Relations of Cognitive Performance and Self-Regulation Across the Adult Life-Span: A Computational Modelling Perspective

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vorgelegt von

Markus Neubeck, M.A.

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Promotionsbetreuerinnen:

JProf. Dr. Tanja Könen, Fachbereich Psychologie, RPTU, Deutschland

Prof. Dr. Julia Anna Glombiewski, Fachbereich Psychologie, RPTU, Deutschland

Vorsitzende der Promotionskommission:

Prof. Dr. Julia Karbach, Fachbereich Psychologie, RPTU, Deutschland

Vom Promotionsausschuss des Fachbereichs Psychologie der Rheinland-Pfälzisch Technischen Universität Kaiserslautern-Landau (RPTU) zur Verleihung des akademischen Grades Doktor der Philosophie (Dr. phil.) genehmigte Dissertation

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II. Abstract

This dissertation project aims to examine the potential of network modelling, an increasingly popular methodology in emotion research (e.g., Fried et al., 2016), to better comprehend age-related differences in structural connections between cognitive processes such as fluid intelligence and executive control functions. Furthermore, it aims to identify the key variables that link self-regulation to executive control functions and age-related discrepancies. Lastly, it seeks to delve into the key variables and correlations between executive control functions, self-regulation, and affect utilizing a longitudinal design in combination with machine learning as a data-driven method.

In study 1, differences between the cognitive performance networks of younger (M = 38.0 years of age, SD = 9.9) and older (M = 64.1 years of age, SD = 7.7) adults were explored. Network modelling showed that while speeded attention is essential throughout the life-span, connections between fluid intelligence and working memory were stronger, and intelligence was more central in the older group. Additionally, confirmatory factor modelling demonstrated that latent correlations were highest between working memory and intelligence, particularly in older adults, whereas inhibition had the lowest correlations with other abilities. This research suggests that the relations of cognitive abilities may differ between younger and older adults, indicating process-specific changes in the cognitive performance network.

In study 2, we investigated the connections of self-regulation (SR) and executive control functions (EF), which are theoretical concepts encompassing various cognitive abilities supporting the regulation of behavior, thoughts, and emotions (Inzlicht et al., 2021; Wiebe & Karbach, 2017). Evidence, however, implies that correlations between self-report measures and performance-based tasks are often difficult to observe (e.g., Eisenberg et al., 2019). We investigated connections and overlap between different aspects of SR and EF in a life-span sample (14-82 years). Participants completed several self-report measures and behavioral tasks, such as sensation seeking, mindfulness, grit, or eating behavior

questionnaires and working memory, inhibition, and shifting tasks. Network models for a youth, middle-aged, and older-aged group were estimated to identify key variables that are well connected in the SR and EF construct space. In general, stronger connections were observed within the clusters of SR and EF than between them, and older adults appeared to have more connections between SR and EF than younger individuals, probably because of declining cognitive resources.

In study 3, we analyzed the intricate links between EF, SR and affect, as well as individual differences in these relations. Bridgett et al. (2013) proposed that EF and self-regulation SR are psychological constructs to support the regulation of cognition and affect. A total of 315 participants, aged 14 to 80, answered questionnaires and took part in behavioral tasks which evaluated EF, SR, and both positive and negative affect two times (one-month apart). Combined X-means and deep learning algorithms aided in the separation of two distinct groups who featured different EF performances, SR tendencies, and affective experiences. Network model analysis was then utilized to confirm the connections between the EF, SR, and affect variables in each of the two groups. The two groups displayed a maximal centrality for variables linked to SR and positive affect. Group membership remained mostly consistent (85%) across both measurement occasions. Logistic regression indicated that age and personality (conscientiousness, neuroticism, and agreeableness) predicted group membership. This sheds light on stable individual differences in the complex relations of EF, SR, and affect.

This dissertation project utilized a combination of standard approaches (such as confirmatory factor analysis; CFA) and advanced approaches (such as network models, machine learning algorithms, and deep learning) to explore the connections between cognitive abilities, EF, SR, and affect. Our findings are in line with the theory of process specific changes in age-dedifferentiation. Findings suggested that connections between SR and EF were stronger within clusters, and positive affect was better connected to SR than EF

measures. Lastly, age and personality traits were found to predict the clusters. These findings suggest that computational modelling is an effective exploratory tool in understanding how cognitive abilities and other psychological constructs may interact. Further research is necessary to gain further insights on the mechanisms behind differences in network structures.

III. German Summary (Zusammenfassung)

Ziel dieses Dissertationsprojektes ist es, mit Netzwerkmodellierung altersbedingte Unterschiede in den strukturellen Verbindungen zwischen fluider Intelligenz und exekutiven Kontrollfunktionen sowie Selbstregulation und Affekt besser zu verstehen. Dabei werden Schlüsselvariablen identifiziert und altersbedingte Diskrepanzen in den Netzwerkstrukturen aufgedeckt. Weiterhin werden anhand von maschinellem Lernen und Deep Learning im Längsschnittdesign interindividuelle Unterschiede in diesen Zusammenhängen untersucht.

In Studie 1 wurden die Unterschiede zwischen den Netzwerken der kognitiven Leistung von jüngeren und älteren Erwachsenen untersucht. Dabei zeigte sich, dass die Zusammenhänge zwischen den Schlüsselvariablen *fluide Intelligenz* und *Arbeitsgedächtnis* bei älteren Erwachsenen stärker waren, was auf prozessspezifische Veränderungen im Netzwerk kognitiver Leistungen hindeutet. Diese Ergebnisse decken sich mit denen einer konfirmatorischen Faktorenanalyse. In Studie 2 wurden Zusammenhänge zwischen Selbstregulation, exekutiven Kontrollfunktionen und verschiedenen kognitiven Fähigkeiten untersucht. Ältere Erwachsene zeigten stärkere Verbindungen zwischen Selbstregulation und exekutiven Kontrollfunktionen als jüngere Personen. In Studie 3 wurden die komplexen Beziehungen zwischen exekutiven Kontrollfunktionen, Selbstregulation und Affekt in verschiedenen Altersgruppen im Längsschnitt mit Netzwerkmodellen und Machine Learning untersucht. Dabei wurde deutlich, dass ältere Erwachsene eine stärkere Verbindung zwischen positivem Affekt und Selbstregulation aufweisen. Alter und Persönlichkeitsmerkmale können die verschiedenen Cluster vorhersagen.

Diese Ergebnisse betonen die Bedeutung von computergestützter Modellierung bei der Untersuchung der Zusammenhänge zwischen kognitiven Fähigkeiten und anderen psychologischen Konstrukten. Weitere Forschung ist erforderlich, um die Mechanismen hinter altersbedingten Unterschieden in den Netzwerkstrukturen besser zu verstehen.

1 Introduction

This dissertation project aims to use computational modelling like network analysis and machine learning algorithms as data-driven approaches to investigate age differences in structural relations of cognitive abilities, connections between self-regulation (SR) and executive control functions (EF), and their connections with affect in a longitudinal design. Network analysis is an increasingly popular approach in emotion research and has been used to model relations between depression and anxiety symptoms (Fried et al., 2016) or to build an integrative psychometric model of emotions (Lange et al., 2020). Furthermore, networks can be used to identify central symptom patterns in therapy (Schemer et al., 2023). Network models are advantageous for exploring and interpreting patterns of dependence among multiple variables (Borsboom et al., 2021). They enable us to detect and assess connections between the variables (Bringmann et al., 2015; Fried et al., 2017; Guyon et al., 2017) and can be used to infer psychological attributes without relying on latent variables (Borsboom, 2017; Dalege et al., 2016). Latent variable models and network models are both useful for studying cognitive performance, SR, and affect. Latent variable models enable researchers to identify correlations based on a shared underlying ability or construct, while network models are better suited for depicting localized interactions between cognitive processes (van Bork et al., 2019) or other variables.

The *age differentiation and dedifferentiation* hypothesis proposes that cognitive abilities become less interrelated during childhood and more associated in late adulthood. However, numerous studies have come to conflicting results concerning how age impacts the connections of cognitive abilities (Tucker-Drob, 2009). While research has established lower average performances in certain fluid or mechanic abilities among older adults relative to younger adults (Baltes et al., 1999; Salthouse, 2012), further evidence is needed to better understand the age differentiation and dedifferentiation of cognitive abilities.

In study 1, we examine how cognitive abilities are connected in groups of younger and older adults. Age dedifferentiation suggests that cognitive changes over the life-span may not only be characterized by declines in performance but also by the reorganization of cognitive functions. To investigate this, we analyzed tests of fluid intelligence, working memory, speeded attention, and inhibition and with network models. Studies on the relationship between EF and SR have been inconsistent. Hofmann and colleagues (2012) proposed that EF plays a part in SR, serving as the cognitive processes that support SR in terms of working memory, behavioral inhibition, and adaptive behavior. Meanwhile, Bailey and Jones (2019) hypothesized a four-component model that included the core regulatory processes of working memory, inhibition, shifting, and attention control, forming three operational domains: cognition, emotion, and social interaction, which, in turn, are the basis of the multi-component skills of EF and SR. Despite this, recent explorations found minimal to no correlation between the two (e.g., Eisenberg et al., 2019; Nęcka et al., 2018; Saunders et al., 2018). Wennerhold and Friese (2020) suggested that differences between maximum and typical performance, measuring a single versus multiple processes, and varying impulsivity across responses in different domains might explain this unexpected result. Moreover, cognitive decline in aging could also be considered as another factor to explore, as it has been widely discussed in the literature (e.g., Baltes et al., 1999; Salthouse, 2012).

In study 2, we explore the relation between EF and SR, which is an area of interest in psychology that has been studied for many years. Despite theories suggesting a connection between the two concepts, empirical evidence has often been difficult to establish. To gain a better understanding of the similarities and differences between the two concepts, we explore associations between SR and EF measures with both self-report questionnaires and behavioral tasks. The associations are explored through network analysis among three age groups: a youth, a middle-aged, and an older-aged group. Through this approach, this study aims to provide insight into how cognitive abilities may change with age and the central role of certain variables that connect SR and EF.

Both EF and SR impact affective states, allowing individuals to manage and regulate their behavior in order to reach their objectives. Research has shown that effortful control and working-memory updating abilities are correlated with lower dispositional negative affect (Bridgett et al., 2013), while poor inhibition is linked with increased negative affect (Shields et al., 2016). Moreover, higher levels of SR are connected with improved emotion management and inhibition of impulsive reactions (Schmeichel & Tang, 2014). Also, SR deficits may form a transdiagnostic dimension for both internalizing and externalizing psychopathology (Santens et al., 2020). Neuropsychological theory (Ashby et al., 1999) shows that higher dopamine levels in the brain due to positive affect can lead to improved cognitive abilities, such as memory consolidation, creative problem-solving and working memory. Negative affect, on the other hand, can lead to a lack of motivation (Gillet et al., 2013), lower working memory performance (Brose et al., 2012) and disengagement from goals (Carver & Scheier, 1990).

In study 3, we explore the theoretically predicted relations between EF, SR, and affect, as well as individual differences in those relations. We collected data with behavioral tasks and self-report measures to assess EF, SR, and positive and negative affect on two occasions. Machine learning and network modelling were used to generate a comprehensive view of the connections between EF, SR, and affect. To check the plausibility of groups found by machine learning, we combine different approaches and predict the grouping with age and personality – demonstrating individual differences in the complex relations of EF, SR, and affect.

In the following Chapter 2 the theoretical and empirical background of EF, SR, and affect as well as their connections with each other are introduced. Chapter 3 presents the research goals and Chapter 4 provides a methodological introduction to the models used to address these goals. The three empirical studies are summarized in Chapter 5, and the results are discussed in Chapter 6.

2 Theoretical and Empirical Background

2.1 Cognitive Abilities and Fluid Intelligence

Cognitive abilities refer to a set of mental capabilities that enable individuals to think, understand, learn, reason, remember, and make decisions. These abilities include, for example, intelligence, problem solving, reasoning, attention, working memory, inhibition, cognitive flexibility, and more. The most recent and prominent theoretical framework of cognitive abilities is the Cattel-Horn-Carrol Theory (CHC; Alfonso et al., 2005; Horn & Blankson, 2005; McGrew, 2005; Schneider & McGrew, 2012). This theory evolved over time, beginning with Spearman (1904), who was the pioneer in identifying positive correlations between diverse cognitive abilities, which then paved the way for his two-factor theory of intelligence. This theory hypothesized that both a general ability (g) and a task specific ability (s) contribute to solve a task (with an undefined number of task specific abilities). Additionally, Horn and Cattell's later works (Cattell 1941, 1971/1987; Horn, 1965) introduced the notion of fluid and crystallized intelligence, followed by Carroll's three stratum theory (1993) that encompasses task-specific, broad, and general factors. Carroll's (1993; 1997) CHC framework (Figure 1) builds on these previous theories and was extended in the recent years (Schneider & McGrew, 2012). Various g abilities are categorized as broad or stratum II abilities, such as Gf and Gc, the two original factors. According to Carroll (1993), these broad abilities are "basic constitutional and long-standing characteristics of individuals that can govern or influence a great variety of behaviors in a given domain" (p. 634). Incorporated in the broad abilities are narrow or stratum I abilities, consisting of approximately 70 identified abilities (Carroll, 1993, 1997). At the most general level of ability in the Gf-Gc model is stratum III, interpreted as a cognitive ability that encompasses both broad (stratum II) and narrow (stratum I) abilities, representing a general factor (i.e., g) and being involved in complex higher-order cognitive processes (Gustaffson & Undheim, 1996; Jensen, 1997; McGrew & Woodcock, 2001).

2.2 Cognitive Aging and Age Dedifferentiation

Much research has demonstrated lower average performance levels in certain fluid or mechanic abilities among older adults compared to younger adults (Baltes et al., 1999; Salthouse, 2012). However, evidence concerning how the connections of cognitive abilities differ as a function of age is mixed (Tucker-Drob, 2009). The *age differentiation and dedifferentiation* hypothesis, which states that cognitive abilities become less interrelated during childhood and then in late adulthood increasingly associated as we age, is based on intelligence theories (Tucker-Drob, 2009). According to Cattell (1987), a single general (fluid) factor is invested in increasing knowledge-based (crystallized) abilities in childhood, which leads to the development of age differentiation, or more independent fluid and crystallized abilities. Conversely, late adulthood is characterized by cognitive decline, which is thought to be caused by global biological constraints that lead to age dedifferentiation or increases in interrelations of abilities (Baltes & Lindenberger, 1997; Li et al., 2004; Lövdén, Ghisletta, & Lindenberger, 2004). It has been suggested that the reduction in cognitive performance seen in late adulthood may be the result of a decrease in efficiency in neurotransmission (Li & Lindenberger, 1999; Li, Lindenberger, & Sikström, 2001). Studies demonstrated different results regarding age dedifferentiation over time, with initial research not providing support (Anstey et al., 2003; Bickley et al., 1995; Lindenberger & Baltes, 1994; Tomer & Cunningham, 1993; Tomer et al., 1994; Schaie et al., 1998), whereas more recent studies have partially (Cunningham, 1980; Cunningham, 1981; Hultsch et al., 1998; Horn & McArdle, 1992; Mitrushina & Satz, 1991; Zelinski & Lewis, 2003) or fully found evidence of such a concept (de Frias et al., 2007; Tucker-Drob et al., 2019).

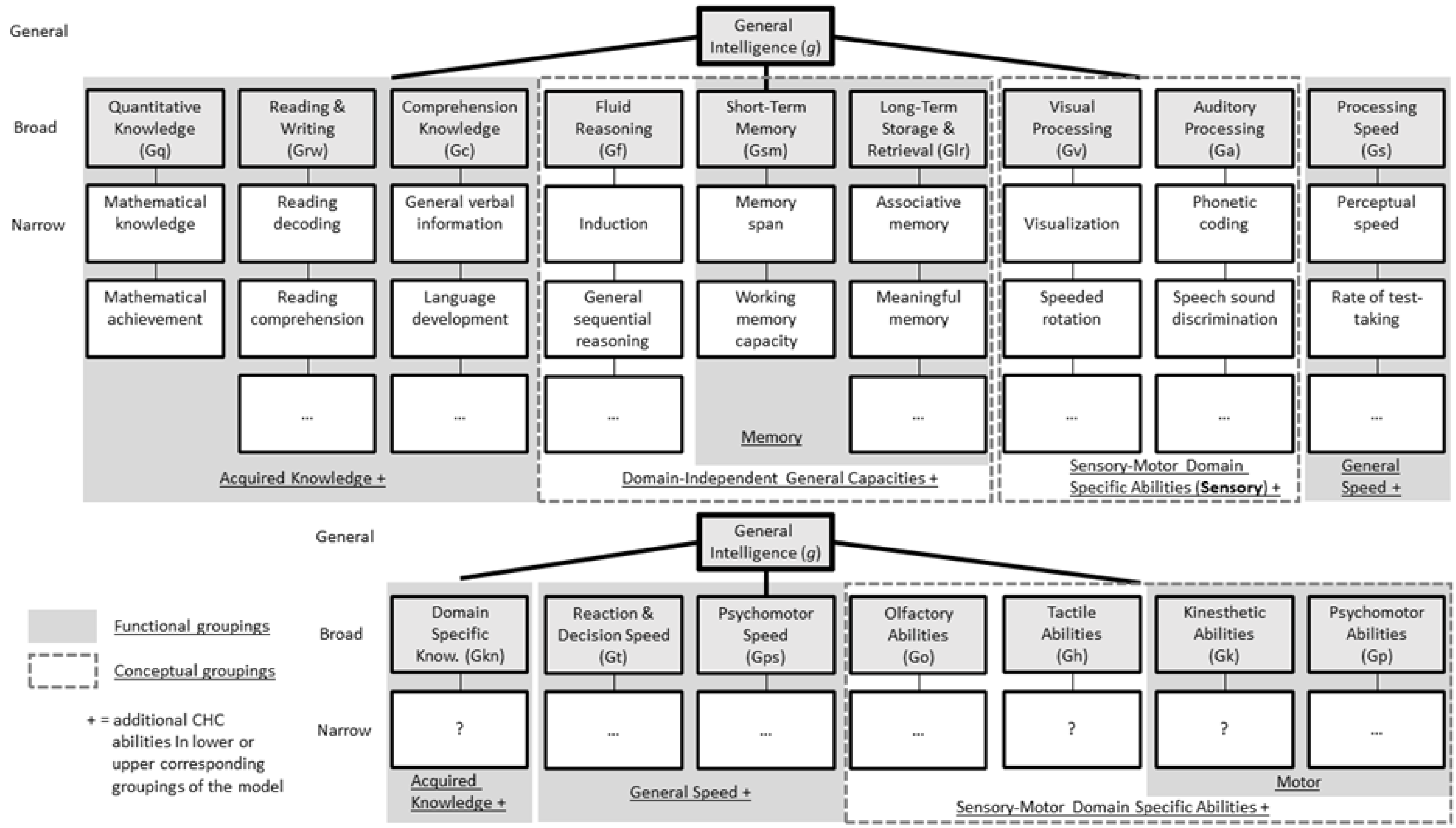

Figure 1. CHC framework adapted and shortened from Schneider and McGrew (2012).

2.3 Executive Control Functions

Executive Control Functions (EF) are part of the Cattell-Horn-Carroll model of cognitive abilities (Floyd et al., 2010; Jewsbury, et al., 2016). They are integral to controlling cognitive processing in complicated tasks and comprise the three core functions working memory, inhibition, and shifting (cf. Bull & Scerif, 2001; Hermida et al., 2015). EF (Figure 2) support higher-order skills like reasoning and planning (Diamond, 2013; Richland & Burchinal, 2013). *Working memory* is limited in capacity and plays a crucial role in complex cognitive tasks, as it allows for the temporary storage and manipulation of information (Baddeley, 1983, 1992, 2010; Ecker et al., 2010). It enables information to be maintained, manipulated, and updated, even when performing demanding cognitive activities. *Inhibition* includes both interference control (i.e. management of distracting or interfering information) and response inhibition (i.e. the deliberate and controlled intervention to suppress certain automatic or prominent replies; Aron, 2007; Diamond, 2013; Friedmann & Miyake, 2004; Miyake et al., 2000; Nigg, 2000). The process of *shifting* entails transitioning between diverse activities, processes, or cognitive orientations (Monsell, 1996). Miyake and colleagues (2000) first introduced the concept of unity and diversity of EF with working memory, inhibition, and shifting being clearly separated but intercorrelated in a latent factor model. Later on, Miyake and Friedmann (2012) extended this model by introducing a common EF factor and two specific factors (updating and shifting). EF develop from a single general factor in early and middle childhood to a three-factorial structure (working memory, inhibition, and shifting) in late adolescence. This transition is linked to corresponding neural development in the prefrontal cortex, where inhibition and shifting mature earlier than working memory, which does not fully develop until late adolescence and shows an earlier age-related decline in older age, followed by shifting and inhibition (Brydges et al., 2014; Chevalier & Clark, 2017; Crone et al., 2017; Karbach & Unger, 2014; Karbach & Unger, 2016; Lehto et al., 2003; Li et al., 2017; Shing et al., 2010; Wiebe & Karbach, 2017).

2.4 Attention

The construct of attention is closely linked to EF and self-regulation, because directed attention is considered as a common resource for both (e.g., Diamond, 2013; Kaplan & Berman, 2010). Models of attention often distinguish perceptual and executive attention (i.e. alertness and focused attention, van Zomeren & Brouwer, 1994). Latent perceptual and executive attention are typically correlated because they both capture the speed of attentional processes (e.g., Moosbrugger, Goldhammer, & Schweizer, 2006). Processing speed measures are thus very similar to attention measures (cf. Moosbrugger et al., 2006), which is highlighted by the term “speeded attention” (e.g., Lamar & Raz 2007), which is also used in this dissertation. Attention is thus indirectly included in the Cattell-Horn-Carroll model of cognitive abilities (which includes processing speed).

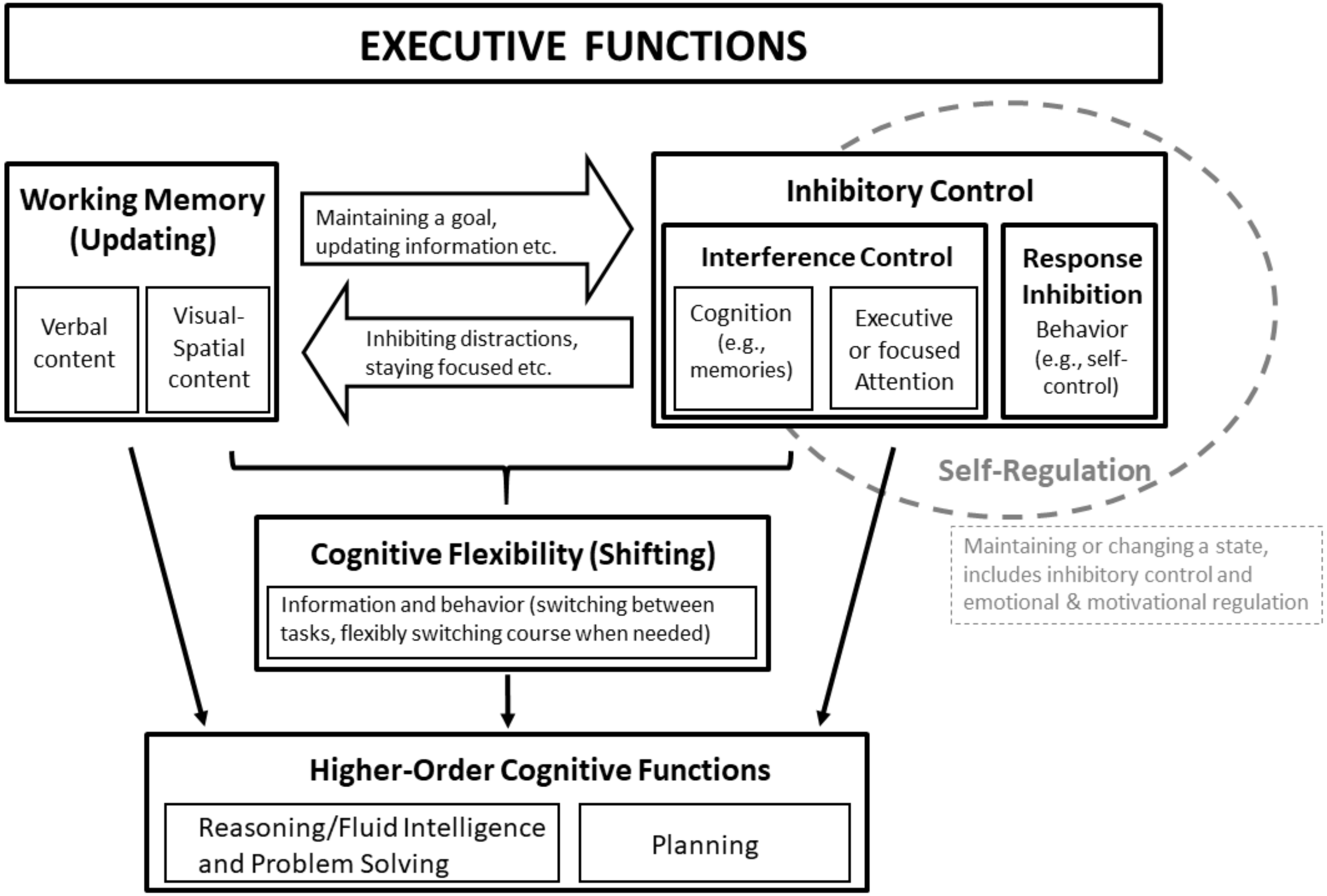

Figure 2. Executive Functions adapted from Diamond et al. (2013).

2.5 Self-Regulation

Hofmann et al. (2012) suggest that EF, such as working memory, behavioral inhibition and shifting, are fundamental processes that can enhance self-regulation (SR) (see Figure 2; Friese et al., 2010; Hofmann et al., 2008; Houben & Wiers, 2009; Payne, 2005). According to Inzlicht et al. (2021), SR is the act of setting and working towards a goal. It involves deciding upon a desired end-state, such as a behavior (e.g., exercise), an attitude (e.g., compassion), or an emotion (e.g., contentment), and implementing strategies that guide one towards that goal. This encompasses a variety of tasks, such as making plans, protecting goals from distraction, and sometimes even giving up on a goal (Fujita, 2011; Gollwitzer, 1999; Ludwig et al., 2019; Shah et al., 2002; Wrosch et al., 2003). Goals can be any form of behavior, thought, emotion, cognitive performance, attentional procedure, or impulse and appetite control (Vohs & Baumeister, 2016).

2.6 Affect

Affect covers both emotions and mood, with the former being directed and transient, and the latter being continuous (Lischetzke & Könen, 2022). Affect can be further classified into positive and negative components (Russell & Caroll, 1999; Diener & Emmons, 1984; Warr et al., 1983). Positive affect is linked with emotions such as joy, happiness, enthusiasm and optimism; it increases well-being, encourages motivation and assists in adaptive functioning. Furthermore, it is also associated with physical health (Pressman & Cohen, 2005). Research has shown that higher levels of SR are associated with improved emotion management, inhibitory control (Schmeichel & Tang, 2014), and lower dispositional negative affect (Bridgett et al., 2013).

2.7 Theoretical Overlap between Self-Regulation and Executive Control Functions

Research on the relations between EF and SR has not yet provided a clear picture. Hofmann et al. (2012) suggested that EF are basic cognitive processes promoting SR. EF have been found to support SR in terms of working memory needed to form mental representations of goals, behavioral inhibition to suppress impulsive behaviors, and shifting to adapt to different goals and scenarios (Friese et al., 2010; Hofmann et al., 2008; Houben & Wiers, 2009; Payne, 2005). Bailey and Jones (2019) suggested a model that incorporates both EF and SR. The model posits that EF comprises four core regulatory processes – working memory, inhibition, shifting, and attention control – which interact to form three regulatory domains: cognition, emotion, and social interactions. From a developmental perspective, it hypothesizes that these core processes gradually differentiate from generic regulatory skills, leading to domain-specific knowledge and increasingly complex behavior in middle and late childhood. This progression would ultimately form the basis for multi-component skills, such as EF and effortful control, and umbrella skills, such as SR, which draw on a variety of cognitive and emotional skills. Thus, this theoretical framework proposes a higher-order factor based on multi-component skills. However, despite this strong theoretical integration, recent evidence found little to no systematic relations between EF and SR measures (e.g., Eisenberg et al. 2019; Nęcka et al., 2018; Saunders et al., 2018). Wennerhold and Friese (2020) suggested that this could be attributed to distinguishing between typical and maximum performance, measuring single versus repeated performance, and varying impulsivity across responses in different domains. A particular factor to be investigated further in the context of aging is the difference between typical and maximum performance, as cognitive functions are known to decline with age (e.g., Baltes et al., 1999; Salthouse, 2012, for reviews).

2.8 Connections of Executive Control Functions, Affect, and Self-Regulation

Research has demonstrated that higher effortful control and working-memory updating abilities are uniquely correlated with lower dispositional negative affect (Bridgett et al., 2013), while poor inhibition is linked with increased negative affect (Shields et al., 2016). Moreover, higher levels of SR are associated with an improved ability to manage emotions and inhibit impulsive reactions (Schmeichel & Tang, 2014). Additionally, SR deficits may serve as a transdiagnostic dimension for internalizing and externalizing psychopathology (Santens et al., 2020). A neuropsychological theory (Ashby et al., 1999) proposes that positive affect can influence cognitive performance by increasing brain dopamine levels. This is proposed to explain enhanced memory consolidation, working-memory performance, and creative problem solving, which is thought to be due to increased dopamine release in the anterior cingulate, improving cognitive flexibility. On the other hand, negative affect incorporates sentiments such as sadness, guilt, anger, and worry. It can inhibit motivation (Gillet et al., 2013), can lead to disengagement from goals (Carver & Scheier, 1990), reduce the willingness to take part in enjoyable activities and be indicative of mental illnesses like depression and anxiety (Brown et al., 1998; Watson et al., 1988). State negative affect is further linked to lower working-memory performance (Brose et al., 2012). Thus, EF and SR both impact affect by permitting individuals to regulate their thoughts, feelings, and behavior in order to reach desired objectives.

3 Summary of Research Goals

The main objective of this dissertation project is to investigate how network modelling, which is a relatively novel approach to cognitive research but already more established in the field of emotion research (e.g., Fried et al., 2016; Giuntoli & Vidotto, 2020; Lange et al., 2020), can:

- Study 1: lead to a better understanding of age-differences in structural relations of cognitive processes like fluid intelligence and executive control functions (EF);
- Study 2: identify key variables that connect self-regulation (SR) and EF as well as age-related differences therein;
- Study 3: zoom in on key variables and connections between EF, SR, and affect in a longitudinal design in combination with a data-driven approach for grouping with machine learning.

4 Methodological Background

4.1 Network Models

Network modelling is already more established in emotion research (e.g., Fried et al., 2016; Giuntoli & Vidotto, 2020; Lange et al., 2020) but is a relatively novel approach in cognitive research, where confirmatory factor analysis (CFA) or in general structure equation modelling (SEM) are more common. Borsboom and colleagues (2021) describe network modelling as advantageous for exploring and interpreting patterns of dependence among multiple variables without having to make strong a priori assumptions about how the data was generated. Such models are powerful tools for exploratory data analysis and visualization of relations in multivariate data since they enable us to detect and assess patterns of conditional connections between variables (and can thus supplement standard exploratory data analysis techniques). According to Guyon and colleagues (2017), network analysis can be used to infer psychological attributes without relying on the assumptions of latent variables (Borsboom et al., 2003; for details). Network analysis plays a meaningful role in psychopathology research (e.g., Bringmann et al., 2015; Fried et al., 2017). However, its usage presents an epistemic challenge for psychological science (Borsboom, 2017; Dalege et al., 2016). Unlike certain traditional models (such as CFA), network analysis does not assume that a psychological attribute is the effect of a single, hidden cause. Instead, it defines it as a complex system of perceptible elements with interactions between every component (Borsboom and Cramer, 2013; Bringmann et al., 2013; Cramer et al., 2010; Dalege et al., 2016; de Schryver et al., 2015; Fried, 2015; McNally et al., 2015; Schmittmann et al., 2013).

Latent variable models, which are a standard procedure in the research of cognitive abilities, as well as network models, which are relatively new to this field, may both be of use in examining cognitive performance, SR, and affect due to their representation of distinct aspects of a phenomenon. Correlations between task scores or questionnaires could result from a shared underlying ability or opinion, which could be reflected through latent variable models, or they might for example, result from localized interactions between cognitive processes, which network models are better suited to depict (van Bork et al., 2019).

Using network models, we aimed to identify key variables contributing to age dedifferentiation (study 1) or the connections of EF and SR in three different age groups (study 2), or the connections of EF, SR, and affect in data-driven clusters (study 3). Key variables are defined by strength and number of connections with other variables on an observed level (as previously shown in the area of emotion research by, e.g., Fried et al., 2016; Giuntoli & Vidotto, 2020; Lange et al., 2020).

4.2 Machine Learning

In study 3, we complemented the network models with machine learning as another exploratory method to find possible clusters with a data-driven approach. There is a growing set of algorithms for supervised and unsupervised machine learning (e.g., Alloghani et al., 2020; Bengio et al., 2012; for reviews). Supervised machine learning utilizes a dataset with known labels (e.g., group memberships) to train a model in order to predict the outcome of unlabeled data. Unsupervised machine learning is when patterns and clusters are determined from data without prior labels.

4.2.1 X-Means

X-means (Pelleg & Moore, 2000) is an extension of the K-means clustering algorithm (Hartigan, 1975; Hartigan & Wong, 1979). It is an unsupervised learning method that attempts to identify distinct clusters of data points in a data set. The algorithm assigns each data point to a random cluster, computes the mean of all the data points in that cluster, and then reassigns each data point to the cluster whose centroid is closest to it. The optimization method sum of squared error (SSE) is used to measure how similar the data points in a cluster are. The objective of the algorithm is to minimize the SSE by iteratively adjusting the cluster centroids until the cluster assignments do not change or the maximum number of iterations is reached. X-means is an extended version of K-means that can detect up to a certain number of clusters.

4.2.2 Neural Networks and Deep Learning

The results of the X-means algorithm have a high dimensionality which makes it difficult to visualize them. To better understand the data, a feedforward neural network can be used as an autoencoder (e.g., Bengio et al., 2012) similar to principle component analysis (e.g., Kramer, 1991). A neural network typically consists of multiple layers: an input and output layer (with, for example, an equivalent number of nodes to the number of variables) and a “bottleneck” layer in the middle (with, for example, only 2 nodes), reducing the dimensionality of the data. During the training process, the network adjusted its weights through backpropagation (e.g., Hecht-Nielsen, 1992) in order to provide reliable output. After training, the values obtained from the “bottleneck” layer can be extracted as deep features for each data point. These values can then be plotted with the group assignments obtained from the X-means algorithms in order to compare their results.

5 The Present Research

The following sections provide a short summary of the three studies conducted in this dissertation project. Please see chapter seven for the full-length manuscripts and their corresponding supplementary material.

5.1 Summary of Study 1

Neubeck, M., Karbach, J., & Könen, T. (2022). Network models of cognitive abilities in younger and older adults. *Intelligence*, *90*, 101601.

Background: While age differences in cognitive performance over the life-span are well documented, less is known about differences in the cognitive performance network. Research on the age dedifferentiation of cognitive functions yielded mixed results. Some studies did not offer support for the concept. Other studies partially supported age dedifferentiation (e.g., process-specific changes), and some research has demonstrated full support for the concept. We investigated how cognitive abilities are connected between younger and older adults by estimating network models. Our goal was to identify which variables are most influential in age dedifferentiation, as indicated by the strength and number of connections with other variables at the observed level.

Methods: We explored differences between younger (M = 38.0 years of age, SD = 9.9, n = 73) and older (M = 64.1 years of age, SD = 7.7, n = 73) adults in the connections of different cognitive abilities. We used the Wechsler intelligence test for adults and the logic component of the *ASK test* to measure fluid intelligence, the *digit span backward task* and the *Corsi block backward task* for working memory, the *digit-symbol substitution test* and the *FAIR-2 for* speeded attention, as well as the *Flanker task* and the *Simon task* to for inhibition.

Results: Results from the network modelling study showed that the link between intelligence and working memory was stronger for the older group, while speeded attention had a higher importance for the younger group. Additionally, confirmatory factor modelling uncovered that the correlations of working memory and intelligence were stronger for the older group, and inhibition had the fewest connections with other cognitive abilities.

Discussion: In sum, there are noticeable differences between the cognitive performance networks of younger and elderly adults, which support the concept of process-specific age-related changes in cognitive abilities.

5.2 Summary of Study 2

Neubeck, M., Johann, V. E., Karbach, J., & Könen, T. (2022). Age-differences in network models of self-regulation and executive control functions. *Developmental Science*, *25*(5), e13276.

Background: Despite the theoretical connection between self-regulation (SR) and executive control functions (EF), recent evidence has suggested that correlations between self-reported measures of SR and performance-based tasks of EF may be elusive. Different psychological disciplines rely on distinct methodologies to measure these concepts, such as self-reports for SR and performance-based tasks for EF, which may account for the difficulty in establishing a clear correlation. Thus, this research explored the associations between a wide range of EF and SR assessments to determine the conceptual similarities and differences between the two concepts. We also examined age-related changes in the connections between cognitive abilities by employing network analyses for a youth, middle-aged, and older-aged group.

Methods: In our study, participants from a life-span sample ($N = 333$; 14–82 years) completed self-report measures and behavioral tasks, which were selected to include a variety of different facets of SR and EF. For SR, the questionnaires were the Barratt Impulsiveness Scale, Behavioral Inhibition System and Behavioral Approach System Questionnaire, Brief Self-Control Scale, Emotion Regulation Questionnaire, Grit Scale, Three-Factor Eating Questionnaire, Mindful Attention and Awareness Scale, Sensation Seeking Scale Form V and

Theories of Willpower Questionnaire. EF were measured with the N-Back Task and the Corsi Block Backwards Task for WM, Task Switching and Wisconsin Card Sorting Task for shifting, as well as the Flanker Task and Stroop Task for inhibition.

Results: Our findings suggest that connections between variables in the networks of youth and middle-aged adults were stronger within the domains of EF and SR, respectively, than between them. The network of the older adults showed more connections across the two domains and more variability within SR. Additionally, measures of EF became more central in the networks with increasing age: The Grit Scale was most central in the youngest age group, the Brief Self-Control Scale in the middle-aged group, and the Wisconsin Card Sorting Task in the oldest group.

Discussion: Using this broad approach, we systematically investigated connections and overlaps of different aspects of SR and EF to increase their conceptual understanding. By comparing network models of a youth, middle-aged, and older-aged group, we identified key variables that are well connected in the SR and EF construct space. In general, we found connections to be stronger within the clusters of SR and EF than between them. However, older adults demonstrated more connections between SR and EF than younger individuals, likely because of declining cognitive resources.

5.3 Summary of Study 3

Neubeck, M., Johann, V. E., Karbach, J., & Könen, T. (2023). Relations of Executive Control Functions, Self-Regulation, and Affect: A Machine Learning and Network Modelling Approach. *Manuscript submitted for publication.*

Background: Executive control functions (EF) and self-regulation (SR) are wide-ranging psychological constructs supporting the regulation of cognition and affect. Despite their theoretical overlap, behavioral tasks and self-report measures of EF and SR are often unrelated. EF and SR both impact affect in that they allow individuals to manage their thoughts, feelings, and behavior in order to reach desired outcomes. To explore the presumably complex interplay of EF, SR, and affect, and individual differences in these relations, we employed a new approach, including machine learning and network modelling. Based on theoretical models and previous evidence, it was hypothesized that the strongest connections would be found within as compared to across domains.

Methods: *N* = 315 participants (14–80 years) completed self-report measures and behavioral tasks that assessed EF, SR, as well as positive and negative affect on two measurement occasions (one month apart). We used a variety of questionnaires to tap different aspects of SR like Barratt Impulsiveness Scale, Behavioral Inhibition System and Behavioral Approach System Questionnaire, Brief Self-Control Scale, Emotion Regulation Questionnaire, Grit Scale, Three-Factor Eating Questionnaire, Mindful Attention and Awareness Scale, and Sensation Seeking Scale Form V and Theories of Willpower Questionnaire. EF were measured with the N-Back Task and the Corsi Block Backwards Task for WM, Task Switching and Wisconsin Card Sorting Task for shifting, as well as the Flanker Task and Stroop Task for inhibition. We used the Positive and Negative Affect Schedule to measure affect and the NEO Five-Factor Inventory to assess personality.

Results: Using X-means and deep learning algorithms, we identified two groups with differential EF performances as well as differential SR and affective experiences. Grouping was predicted with logistic regression by age and personality (conscientiousness, neuroticism, and agreeableness). We further applied network model analysis to investigate the connections between EF, SR, and affect within the two groups and identified well-connected key variables.

Further analysis showed that while there was no significant difference in overall connection strength or level of connectivity between the two groups, the Behavioral Approach System, positive affect, and Behavioral Inhibition System had the highest node strength for group one (older, more conscientious, agreeable, and less neurotic) while the highest node strength varied for group two (younger, less conscientious, less agreeable, and more neurotic) across occasions except for the Behavioral Approach System, which was consistently central.

Discussion: We found that positive affect had a high node strength and was well connected to SR measures like the Behavioral Approach System, while negative affect had no major effect on SR or EF and was not particularly important in the networks examined. This is in line with the *Broaden-and-Build Theory of Positive Emotions* and *the Mood-Behavior-Model.* Age and personality proved to be plausible grouping variables from a theoretical and empirical perspective. Regarding the connections between SR and EF, our findings are in line with studies that found connections between SR and EF to be weak. Further research is needed to gain a more thorough understanding of the processes driving the different network structures revealed by this exploratory approach.

6 General Discussion

The main goal of the present research was to use network modelling to gain a better insight into age-related differences in the relationships between cognitive processes, such as fluid intelligence and EF (study 1). Additionally, this project was aimed at pinpointing key variables which link SR and EF to age-related variations (study 2), as well as focusing on the connections between EF, SR, and affect in a longitudinal design using a data-driven, machine learning-based grouping approach (study 3).

Study 1 investigated the relations of cognitive abilities in younger and older adults. Previous research has offered mixed evidence of age dedifferentiation, with some studies not supporting the concept, others demonstrating partial support, and some offering full support (e.g., Tucker-Drob, 2009). In order to identify which variables are most influential in age dedifferentiation, as measured by the strength and number of connections with other variables, we used network models to test differences in the connections of cognitive abilities between younger and older adults. Network modelling demonstrated that connections between intelligence and working memory were stronger, and intelligence was more central in the older group. When a person's basic functions lack the capability to support higher mental skills such as reasoning, working-memory capacity is assumed to be the deciding factor (Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002; Schweizer & Moosbrugger, 2004; Fukuda et al., 2010). Comparatively, attention proves decisive for the younger generations in that it determines whether and to what degree the information is processed in the first place (Cowan, 1988; Schneider & Shiffrin, 1997). Our findings demonstrated an age-related shift from speeded attention to working memory as the central limiting factor for higher cognitive functioning. This provides evidence for process-specific changes, in line with the conclusions of Zelinski and Lewis (2003), who reported longitudinal evidence for process-specific changes in vocabulary, perceptional speed, working memory, as well as text and list recall. Contrary to the assumption of age-dedifferentiation, our network models resulted in both stronger (centering intelligence) and weaker (centering speeded attention) connections in older adults compared to those of younger adults, suggesting a partial increase or no changes in the relations of some variables.

A first limitation of the present study is that there were relatively few participants (n = 73) for network analysis, thus being unable to compare between old and very old adults. Factors other than age, such as the cohort effect, could also affect the results. As different methodological approaches or statistical fit criteria could lead to different results when conducting age dedifferentiation, this should also be taken into consideration (Zelinski & Lewis, 2003). Future research on cognitive-performance networks could employ a longitudinal design to further elucidate aging processes. Despite the limitations inherent in making cross-sectional and longitudinal comparisons, studies measuring the same birth cohorts at different ages have yielded results similar to those from cross-sectional designs for some cognitive functions (Salthouse, 2014). To maximize the results from the network approach, larger samples and a higher resolution of different age groups, particularly older adults, could be used. In addition, the focus of this research could be expanded to include children and adolescents. Finally, pragmatic abilities could be included among the indicators of mechanical cognitive abilities for a more complete understanding of the involved processes, which could aid the design of effective cognitive training and interventions.

Network models offer the possibility to investigate the correlations between various cognitive capabilities by highlighting the prominent variables involved. Moreover, caution must be employed as a strong theoretical foundation is necessary to gain an understanding of the role of each variable (e.g., attention and working memory in regards to fast and efficient information analysis). In conclusion, network models can present supplementary information to the more traditional approaches like CFA, providing a valuable source of knowledge on the interaction of cognitive qualities.

Study 2 was conducted to examine the connections between EF and SR measures in different age groups utilizing network analyses. The results showed that there was greater clustering within domains of EF and SR in the youth and middle age, while this pattern of clustering had decreased in the networks of the older adults, where there were more links between the two domains. Adolescents displayed greater connectivity within SR than middle-aged adults. Moreover, as age increased, EF measures became more central than SR measures, with the Grit Scale being the most prominent in the youngest group, the Brief Self-Control Scale in the middle-aged group, and the Wisconsin Card Sorting Task in the oldest group. This is likely due to the need to focus on the long-term goals of the participants in school/training/career setting at a young age, as well as the varied SR demands imposed on the middle-aged from work and family life. The Wisconsin Card Sorting Task was pivotal in the oldest group due to its association with shifting, working memory, and inhibition – all processes that are adversely impacted by cognitive aging, as observed in the literature (Gamboz et al., 2009; de Ridder et al., 2012).

In the youth group, our research revealed strong correlations between Theories of Willpower scales, measuring strenuous mental activity and resisting temptations, and the Behavioral Inhibition System. Additionally, we observed a link between Sensation Seeking and the Barratt Impulsiveness Scale, followed by the Brief Self Control Scale and the cognitive control component of the Three Factor Eating Questionnaire. The Mindful Attention and Awareness Scale and Grit Scale also showed high connectivity. All EF tasks demonstrated strong connections with each other, and connections between SR and EF were minimal, with the strongest link being the one between the Mindful Attention and Awareness Scale and the Stroop Task, and the Corsi Span Backward Task. In the middle-aged group, the link between the Theories of Willpower measures, the Brief Self-Control Scale and the Barratt Impulsiveness Scale, and the Mindful Attention and Awareness Scale and Grit Scale was prominent once more. Connections within SR were weaker than in the youth group, and EF tasks were connected to each other but not to SR. Lastly, in the older-aged group, the strongest SR correlations again fell under the Theories of Willpower measures, the Brief Self-Control Scale and the Barratt Impulsiveness Scale, and the Mindful Attention and Awareness Scale and Grit Scale. The EF tasks displayed more connections to each other than in the middle-aged group, and SR-EF connections were more frequent, with the strongest path between Stroop Task and Sensation Seeking Scale and Flanker Task and Grit Scale.

A potential explanation for this pattern of results may be that EF tasks assess maximum performance. Younger participants likely possess sufficient cognitive functioning to achieve their SR goals, and consequently, motivational components are more integral for successful SR among this population. In contrast, aging is associated with decreased cognitive functioning (Tucker-Drob et al., 2019). This could lead to decreased EF capacity, which could detrimentally affect daily SR in the elderly. Nevertheless, our cross-sectional design precludes the establishment of causality, and other factors are likely at play. It is possible that individuals with higher SR may prioritize a healthier lifestyle that enhances cognitive abilities (Lindenberger, 2014), while another potential mechanism is a third variable inducing changes in both EF and SR. According to Roberts et al. (2006) and Wettstein et al. (2017), reliable changes in personality may be a potential mechanism of the closer coupling of SR and EF in older adults. In particular, conscientiousness tends to increase over the adult life-span and is related to long-term cognitive performance (Wettstein et al., 2017) as well as daily health and social goal progress (Hooker et al., 2013). This finding could explain the interplay between SR and EF in later life.

The results of for the youth group are generally in agreement with earlier research demonstrating little or no relations between EF and SR (Allom et al., 2016; Duckworth & Kern, 2011; Nęcka et al., 2018). This may stem from a method effect, considering that the results were obtained through performance measures as opposed to questionnaires (Könen & Karbach, 2020; Meyer et al., 2001). Nonetheless, this applies to both age-groups and the comparatively stronger correlations seen among older participants point to a systematic pattern over and above a method effect. Compared to Eisenberg et al. (2019), our findings showed more connections between EF and SR, yet we analyzed a smaller set of variables. Moreover, the overall age range of our sample (14-82 years) was higher, whereas their sample ranged from 18-50 years.

EF and SR are two key constructs that have been discussed frequently in research, and it is necessary to confirm the relation between them with further research, such as longitudinal designs. Focusing on the variables identified, such as EF and SR, would support in building a more in-depth understanding of the links between these two aspects, as well as the moderating factors that play a role. This could aid in reconciling the discrepancies that exist as to how EF and SR are conceptualized and studied. An improved theoretical framework could also help to create connections between work that stems from different disciplines, such as cognitive psychology and educational psychology, in order to explain the different findings on the correlations of SR and EF, such as different academic abilities (e.g., Diamond, 2013; Hofmann et al., 2012; for reviews). Moreover, a better understanding of these key variables could be useful for guiding more effective interventions that target the underlying abilities involved, with the goal of achieving transfer effects to activities of daily living. These interventions could be utilized with children facing issues in school or with adults facing troubles in managing their everyday tasks.

The aim of study 3 was to examine the links between EF, SR, and affect. We found that age and personality (conscientiousness, neuroticism, and agreeableness) were the most significant predictors for grouping into two distinct groups with different EF, SR, and affective experiences. Using machine learning and network modelling, we found that affect was strongly related with SR measures, whereas the connections between SR and EF were comparably weak. The X-means algorithm was applied to the data gathered on two different occasions, with 85% of participants allocated to the same group across both times. Upon visualizing these clusters, a similar result to that of the X-means analysis was obtained via a deep-learning neural network. The results of the network models indicated no discernible differences in overall connection strength and overall level of connectivity between the two groups at the two given measurement occasions. However, the difference networks unveiled that connections within the domains of EF and SR were stronger than between them, and positive affective states were more strongly interconnected with SR measures than with EF. Centrality analyses revealed that for group one (older, more conscientious, more agreeable, and less neurotic) the Behavioral Approach System (BAS), positive affect, and Behavioral Inhibition System (BIS) had the highest node strength in both occasions, while for group two (younger, less conscientious, less agreeable, and more neurotic), the node strengths varied across occasions except BAS, which was persistently central. BAS was connected to positive affect in both groups on both occasions. This alignment is supported by the *Broaden-and-Build Theory of Positive Emotions* (Fredrickson, 2001), which states that positive emotions can aid in the accomplishment of goals, consequently resulting in more positive emotions. Positive affect was highly influential (in the top 5 in the two groups both times) and was linked to many indicators of SR. This suggests an association between positive affect and better SR, meaning that better SR could potentially result in more positive emotions. Additionally, the *Mood-Behavior-Model* (Gendolla, 2000; Gendolla & Brinkmann, 2005) affirms the idea that one's affective state significantly shapes the selection and application of available resources for SR. It is likewise linked to individual differences in traits like self-esteem, depression, dispositional optimism, dispositional anxiety, extraversion, and neuroticism (Mischel & Shoda, 1995; Gendolla & Brinkmann, 2005). Nonetheless, a closer look into the role of EF could have been conducted if the focus was laid on hot EF tasks (Salehinejad et al., 2021), such as those rewarding or related to affective states.

It has been suggested, yet scarcely studied, that emotion can influence one's ability to self-regulate. This is especially evident in trait models, which theorize that appetitive behavior can result in a larger urge for quicker rewards, which can lead to compromising the attainment of long-term goals. Shields et al. (2016) found that anxiety has an effect on EF without being affected by anger. Therefore, it might be necessary to more precisely distinguish between aspects of negative affect in order to further understand the role of emotion in self-regulation (Inzlicht et al., 2021).

Our findings regarding the personality traits of agreeableness and neuroticism agree with the study of Robinson (2007), which suggested that extraversion and neuroticism were associated with affective memory patterns that favored either positive or negative affect, respectively. Meanwhile, agreeableness was found to be connected to the regulation of hostile thoughts. Furthermore, our study's results were consistent with the previous research, where we found different structures of EF and SR for three different age groups (Neubeck et al., 2022). Regarding the connections between SR and EF, our findings are in line with studies investigating the connections between SR and EF, which often found weak associations between these constructs (Duckworth & Kern, 2011; Saunders et al., 2018; Nęcka et al., 2018; Eisenberg et al., 2019).

The lower reliability of performance-based EF measures compared to SR questionnaires and affect questionnaires (Enkavi et al., 2019) leads to a potential underestimation of the existing links between EF, SR, and affect. This is because the different measurement types (i.e., self-report for SR and affect vs. performance tasks for EF) tend to introduce greater connections between domains than within them.

X-means clustering is a powerful data analysis tool that can uncover complex connections between many variables. However, this technique has the potential downside of converging towards local optima rather than global optima (Pelleg & Moore, 2000). Additionally, these results can be hard to evaluate accurately (Huang, 1998). Therefore, to properly assess the clustering results, we combined this method with visualization, deep learning algorithms, and predictions based on established theoretical control variables such as age and personality (Huang 1998). Despite their advantages in detecting complex connections, machine learning algorithms such as X-means and deep learning can be considered "black boxes" and therefore require a solid data basis, a theoretical understanding of the variables involved, and a combination with other methods to get reliable results.

The two groups showed similarities as well as discrepancies regarding the associations between SR, EF, and affect. They were alike in terms of the relations between EF and SR or between EF and affect. However, distinctions were observed in terms of the relations within the domains of SR and EF. An important next step would be to explore the interplay of the identified key variables longitudinally and investigate the temporal order of effects (e.g., with cross-lagged panel models).

6.1 Connections Between the Studies

The main objective of this dissertation project was to investigate how network modelling leads to a better understanding of age differences in the structural relations of cognitive processes such as fluid intelligence and EF (study 1), identify key variables that connect SR and EF with age-related differences (study 2), and also zoom in on key variables and connections between EF, SR, and affect in a longitudinal design in combination with a data-driven approach for grouping using machine learning (study 3).

In study 1, results from the network modelling indicated that while the relation between intelligence and working memory was more significant for elderly adults, speeded attention was more essential for the younger population. Additionally, confirmatory factor modelling revealed that working memory and intelligence were correlated more strongly for the older individuals, while inhibition was found to be least associated with the other cognitive abilities. Thus, the study implies process-specific changes in cognitive abilities that differ with age (Zelinski & Lewis, 2003).

In study 2, we utilized a broad strategy to assess the linkages between and among distinct characteristics of SR and EF in an effort to augment their understanding. By comparing network models of young, middle-aged, and elderly individuals, we were able to identify key elements that are closely interrelated in the SR and EF construct space. Generally, the connections were stronger among components of SR and EF than between them. Nevertheless, elderly people displayed further connections between SR and EF compared to younger generations, perhaps due to reduced cerebral capabilities (Tucker-Drob et al., 2019).

In study 3, our findings were in line with the *Broaden-and-Build Theory of Positive Emotions* and the *Mood-Behavior-Model* (Fredrickson, 2001; Gendolla, 2000; Gendolla & Brinkmann, 2005), as positive affect had strong relations with SR measures such as the Behavioral Approach System while negative affect had no significant relations with SR or EF. Furthermore, age and personality were demonstrated to be plausible determinants of the networks analyzed in this study. This is in line with other research showing rather weak connections between SR and EF (e.g., Eisenberg et al., 2019; Nęcka et al., 2018; Saunders et al., 2018).

Taken together, our studies help us identify key variables in the respective networks of cognitive abilities that show which variables are presumably involved in core processes (e.g., the interplay of fluid intelligence and working memory in cognitive aging or the centrality of the card-sorting task that taps all basic functions of EF). From an aging perspective, all our studies suggest that age is a relevant factor that can influence the structure of networks of cognitive abilities, which is relevant for age-dedifferentiation. In a similar manner, age can influence the structure of networks of EF and SR, as well as affect in different groups, which is relevant for the interplay of EF and SR. In this regard, it is important to highlight that the older age group in study 2 showed stronger connections between EF and SR, which previous studies did not discover, as they did not split their samples in different age groups (e.g., Enkavi et al., 2019).

Studies 2 and 3 share the possible issue that performance-based EF measures generally have lower reliability compared to SR questionnaires (and affect questionnaires – only for study 3), which could lead to an underestimation of the existing links between EF, SR and affect due to the different measurement types (self-report for SR and affect vs. performance tasks for EF) which favor stronger connections between domains than within them (Enkavi et al., 2019).

6.2 Related Research and Possible Directions

Regarding the plasticity of networks, Menu and colleagues (2022) examined the changes in the structure of EFs in 137 typically developing children (9–10 years) and adolescents (15–17 years) before and after undergoing computerized cognitive training, using the regularized partial correlation network model. Results indicated that the EF network structure differed between age and training groups, with networks after training being more similar to those of the adolescent group than the pre-training networks. These findings provide evidence of structural alterations in EF, which are age and training-dependent, thereby suggesting that the training could advance the developmental stages of some aspects of EFs.

Another analysis approach of network modelling is time-varying network models (e.g., Bringmann et al., 2015; Scholten et al., 2023) that are proving to be useful in the evaluation and treatment of mental disorders like depression or anxiety, as they outline the individual interaction of variables as well as variations in parameters over a period of time. The results showed temporal changes in network topology and the different temporal evolvements of dynamic interactions between variables. Thereby, time-varying network models can provide hypotheses for further exploration and take into account variability over time in mental health problems, making them a valuable tool for clinicians. While time-varying network models were not applicable to our data with two measurement points, this approach could be fruitful in better understanding intensive training and involved transfer processes in the training of EF, which can take place over several weeks with multiple sessions a week.

Time-varying network models are also used in pain research. Vlaeyen and colleagues (2022) describe the pain as more than just a response to physical damage. They argue that it is part of an intricate network that operates on multiple levels - including an emotional experience. Learning to anticipate, circumvent and manage potentially damaging situations is vital in such a model. Network models effectively combine the idea of physical triggers inducing acute pain with the concept that symptoms can reinforce each other, developing chronic complaints. Moreover, individual traits can be explained by such an approach.

In a somewhat familiar data collection setting with SR and affect measures, or emotions in general, time-varying network models could also help uncover situations in daily life (e.g., high-frequency data acquired with mobile devices), which are more demanding in regard to SR and could therefore show higher connections with EF. In combination with qualitative methods, insights could be gained into how participants deal with these demands to develop strategies for those who have difficulty coping with these difficult situations.

In the context of the CHC framework McGrew and colleagues (2023) seek to move beyond the traditional common cause factor analysis-based g-debate approach with network analysis. They argue that network analyses of IQ batteries have shown consistent results according to the multidimensional structure of IQ tests (Bulut et al., 2021; Schmank et al., 2019, 2021; van der Maas et al., 2017). Additionally, network modelling is being used to identify potential mechanisms in target systems and interventions, such as psychosis (Sánchez-Torres et al., 2022) and learning skills (Zoccolotti et al., 2021).

6.3 Limitations and Future Research with Computational Modelling

The network approach used in all three studies is limited in that it does not allow for causal conclusions due to its explorative nature, and the reliability of the centrality indices cannot be assured for closeness and betweenness as these metrics require the “presence of flow and shortest paths” (Bringmann et al., 2019, p. 892). For example, a shortest path between two nodes could not be the path with the strongest connections between these variables and therefore misrepresent the connection between the two variables. The idea of flow is useful for example in logistics (e.g., goods are moved along a path), but it is unclear whether psychological variables interact in a similar manner.

Besides, multiple testing also remains a challenge when applying difference tests for network models (Epskamp et al., 2018). In spite of the advances of modern network structures that can be estimated using standard software, some limitations remain (Borsboom et al., 2021): The treatment of ordinal data, common in the social sciences, is suboptimal and requires further research (Isvoranu & Epskamp, 2021). Additionally, traditionally used estimation techniques such as node wise regularized regression (van Borkulo et al., 2014) and the graphical lasso (Epskamp & Fried, 2018) can result in visually attractive networks. However, these methods are often effective when networks can be anticipated to be sparse (Barber & Drton, 2015; Ravikumar et al., 2011). An alternative to regularized estimation approaches is employing non-regularized techniques based on model selection, as research indicates that they may be more effective in particular circumstances (Williams et al., 2019; Wysocki & Rhemtulla; 2019). Finally, many network modelling techniques do not account for missing data effectively, which can be addressed by more advanced estimation frameworks based on full-information maximum likelihood that can provide an alternative approach (Epskamp et al., 2022).

On the plus side, the combination of network representations and theory formation is beneficial in creating relations between dissimilar areas of research and study. For example, it provided links between exploring inter-individual discrepancies and exploring intra-individual processes (Borsboom et al., 2021). Network models and subsequently associated complex systems approaches have enabled a wide range of interdisciplinary research projects, as these approaches have become more frequent to connect different scientific disciplines with each other. In particular, this has broadened the horizons of psychology by allowing network modelling to build bridges between data analysis and theory formation. Such methods look to create conversations between fields and can be used to tackle different psychological research questions (Borsboom et al., 2021).

Network representations provide a common vocabulary that enables researchers from various disciplines to form connections, opening the door for studying systems composed of networks operating at different levels, such as human behavior. For instance, neuroscience and psychology can both benefit from network models of the brain and psychological responses generated through neuroimaging research. Through these models, a greater understanding of how networks interact can be gained, overcoming any barriers created by the individual disciplines (e.g., Brooks et al., 2020; Bathelt et al., 2020).

7 Conclusion

In this dissertation project, I utilized a combination of standard approaches such as CFA with network models, machine learning algorithms, and deep learning to explore the connections between cognitive abilities, EF, SR, and affect by the means of computational modelling. The findings are in line with the theory of process specific changes in age-dedifferentiation. Furthermore, the results indicated that connections between SR and EF were stronger within the clusters than between them and that positive affect was well connected to SR but not to EF measures. Additionally, age and personality traits were found to predict these clusters. Our findings suggest that computational modelling can be a useful exploratory tool in understanding the interplay between cognitive abilities. Further research is necessary to gain a more detailed understanding of the mechanisms behind differences in network structures.

As psychology has traditionally focused on explaining the causes of behavior, utilizing controlled experiments, Yarkoni and Westfall (2017) propose that a focus on predictions rather than explanations, made possible by techniques like machine learning, can lead to a better understanding of behavior. These methods can be a useful complement to network models, traditional CFA, and sound theoretical background.

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9 Original Manuscripts

9.1 Study 1: Network Models of Cognitive Abilities in Younger and Older Adults.

Network Models of Cognitive Abilities in Younger and Older Adults

Markus Neubeck, Julia Karbach, and Tanja Könen

University of Koblenz-Landau, Landau, Germany

Author note:

Correspondence concerning this article should be addressed to Markus Neubeck, Department of Psychology, University of Koblenz-Landau, Fortstraße 7, 76829 Landau, Germany. Email: neubeck@uni-landau.de

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Abstract

While age-differences in cognitive performance over the lifespan are well documented, less is known about differences in the cognitive performance network. We explored differences between younger (*M* = 38.0 years of age, *SD* = 9.9, *n* = 73) and older (*M* = 64.1 years of age, *SD* = 7.7, *n* = 73) adults in the connections of fluid intelligence, working memory, speeded attention, and inhibition. While speeded attention is well known to be important throughout the lifespan, network modeling demonstrated that connections between intelligence and working memory were stronger, and intelligence was more central in the older group, whereas speeded attention was more central in the younger group. Additionally, confirmatory factor modeling demonstrated that latent correlations were highest between working memory and intelligence, especially in the older group, whereas correlations of inhibition with the other abilities were the lowest. Taken together, we found notable differences in the cognitive performance network of younger and older adults, which is in line with the idea of process-specific changes in the relations of cognitive abilities.

Network Models of Cognitive Abilities in Younger and Older Adults

Introduction

Age-differences in cognitive performance over the lifespan are well documented, with older adults showing a lower average performance level compared to younger adults, particularly in fluid or mechanic abilities (e.g., Baltes, Staudinger, & Lindenberger, 1999; Salthouse, 2012, for reviews). However, evidence regarding age differences in the relations of cognitive abilities is mixed (e.g., Tucker-Drob, 2009). According to Tucker-Drob (2009), the development of the age differentiation and dedifferentiation hypothesis (the assumption of decreasing relations of cognitive abilities during child development and increasing relations of these abilities in later adulthood), is related to the development of *intelligence* theories: Spearman (1904) was the first to observe positive correlations between different measures of cognitive abilities, leading to his two-factor theory of intelligence, with a task-independent general ability (g) and specific abilities (s), being dependent on the task at hand and leading to the development of common factor analysis. The second well-known theory is one of fluid and crystallized intelligence by Horn and Cattell (Cattel 1941, 1971/1987; Horn, 1965), which is a hierarchical theory, with sub-factors like visualization, retrieval, and cognitive speed. The third theory is the closely related three stratum theory by Carroll (1993). The first stratum consists of task-specific factors, the second stratum of broad abilities, and the third stratum of a general factor. As "negative relations of age to cognition are among the strongest individual difference relations in psychology" (Salthouse, 2012, p.220), the structural organization of cognitive abilities might differ as a function of age (resembling age differentiation–dedifferentiation) as well (cf. Tucker-Drob, 2009). The level of ability might be an indicator of these structural organizations (resembling ability differentiation). Theories supporting age differentiation–dedifferentiation are based on theories of cognitive development and aging (Tucker-Drob, 2009): According to Cattel's (1991/1987) investment theory, a single general (fluid) factor is invested in increasing knowledge-based (crystallized) abilities in childhood.

Accumulating specific knowledge and increasing environmental influences then leads to more independent fluid and crystallized abilities (age differentiation). During late adulthood, cognitive decline is attributed to global biological constraints that lead to decreases in cognitive performance and therefore to increases in interrelations of abilities (age dedifferentiation; e.g., Baltes & Lindenberger, 1997; Li et al., 2004; Lövdén, Ghisletta, & Lindenberger, 2004), possibly caused by losses in efficiency in neurotransmission (Li & Lindenberger, 1999; Li, Lindenberger, & Sikström, 2001).

Over time, research on age dedifferentiation has yielded different results, with a shift from some studies that (1) do not support, to studies (2) partially supporting, to studies (3) fully supporting age dedifferentiation. Examples for the first group (1) are a study with more than 2,000 adults (aged 65 and older) finding little evidence for age dedifferentiation of verbal, memory, vision, and hearing factors (Anstey, Hofer, & Luszcz, 2003) and a study with more than 6,000 participants (6 to 79 years old) also finding little evidence for age dedifferentiation in the context of the three-stratum theory (Bickley, Keith, & Wolfle, 1995). Further studies that found little support of age dedifferentiation assessed speed, reasoning, memory, knowledge, fluency, and sensory functioning (Lindenberger & Baltes, 1994) with 156 subjects (70 to 103 years old), or sixteen different speed measures (Tomer & Cunningham, 1993) with 296 participants (18 to 73 years old). Other research focused on tasks related to everyday memory (Tomer, Larrabee, & Crook, 1994) with 273 subjects (50 to 79 years old), or inductive reasoning, spatial orientation, perceptual speed, numeric facility, verbal ability, and verbal recall (Schaie et al, 1998) with 984 participants (mean cohort age ranging from 32 to 76 years old; over seven years).To the second group (2) belongs a study with more than 600 adults (30–97 years old) providing longitudinal evidence for process-specific (i.e. not general) changes in vocabulary, perception speed, working memory, as well as text and list recall (Zelinski & Lewis, 2003). Further studies that found partial support of age dedifferentiation assessed different aspects of memory (Hultsch et al., 1998) starting with

484 participants (55 to 86 years old; over six years), (non)verbal memory, speed, and attention (Mitrushina & Satz, 1991) with 122 participants (57 to 84 years old), verbal comprehension, sensitivity to problems and semantic redefinition (Cunningham, 1980) with 510 participants (15 to 91 years old), verbal comprehension, number facility, perceptual speed, symbolic cognition, and flexibility of closure (Cunningham, 1981) with 524 participants (15 to 83 years old), or eleven scales of the Wechsler Adult Intelligence Scale-Revision (Horn & McAdrdle, 1992) with 1880 participants (16 to 74 years old).Examples for the third group (3) include a meta-analysis combining 22 unique datasets –with a total of more than 30,000 individuals– reporting strong evidence for a general cognitive aging factor (Tucker-Drob, Brandmaier, & Lindenberger, 2019). Furthermore, a longitudinal multi-cohort study with 1000 participants without dementia (initially 35–80 years old) provided evidence for dedifferentiation (in episodic recall, semantic knowledge, semantic fluency, and visuospatial ability) above ~65 years of age (de Frias, Lövdén, Lindenberger, & Nilsson, 2007). Considering the 98 analyzed outcomes in the meta-analysis, 26 were measures of processing speed, 35 of episodic memory, and 12 of reasoning. Only three were measures of working memory and measures of inhibition and attention were not included. By including these variables, we aim to further contribute to the field: Through network analysis, we can provide a detailed view on these measures, which is currently missing. In addition, Tucker-Drob and colleagues (2019) state that their results are in line with the hypothesis that "an ensemble of common sources increasingly dominates development of intellectual abilities" (de Frias et al., 2007, p. 382). Thus, it might be challenging to answer the question of age dedifferentiation with a binary *yes* vs *no* perspective, and answers might be in a spectrum for different processes and domains that are involved.

Latent variable models and network models can complement each other well in the investigation of cognitive performance. Correlations between task scores can either result from their dependence on a common latent ability or their dependence on related cognitive abilities, which can be represented well in latent variable models. Or they may result from local interactions between cognitive processes (cf. van Bork et al., 2019), which can be represented well in network models. For example, working-memory (WM) capacity is known to be a limiting factor for reasoning (e.g., Süß et al. 2002; Fukuda et al., 2010), which is important to understand cognitive aging. First, reduced WM may limit older adults' reasoning on a general ability level (e.g., reduced capacity for multiple types of operations with current information), which can be investigated well with latent variable models. Second, it may limit older adults' reasoning through specific processes (e.g., reduced capacity for spatial and temporal integration), which can be investigated well with network models because such processes may be captured by some tasks only (and not by the common variance of multiple indicators of a latent variable). Third, both general and specific mechanisms may apply. Taken together, both latent variable and network models can be informative when studying the same data set. Therefore, network models can be a tool to investigate which variables are central to understand possible mechanisms of cognitive aging. Therefore, we investigated cognitive abilities from a network perspective and considered age dedifferentiation as one but not the sole potential mechanism contributing to age differences in the cognitive performance network.

In addition to measures of fluid intelligence, we included measures of working memory, speeded attention, and inhibition as they are essential cognitive functions related to fluid intelligence (e.g., Verhaeghen, & Salthouse, 1997; Kane & Engle, 2002; Conway, Kane, & Engle, 2003; Schweizer & Moosbrugger, 2004; Fukuda, Vogel, Mayer, & Awh, 2010) that are characterized by a typical age-related decline (Baltes et al., 1999; Salthouse, 2012) and are important for every day functioning (like remembering and forgetting, e.g., Kliegel et al., 2016; Hering et al., 2020; Zimprich & Kurtz, 2013). In order to get a relatively broad representation of these cognitive domains, we included measures tapping different aspects of the constructs (e.g., the verbal and visuospatial domains of working memory or the response inhibition and interference control domains of inhibition).

Working memory has the function to temporarily store information and allows for this information to be processed while performing complex cognitive tasks (Baddeley, 1992), with the capacity of working memory being a limiting factor for how well a person performs in these complex cognitive tasks. Processing speed measures indicate how fast information can be processed and have been shown to be highly correlated with measures of intelligence (especially gf) by many studies (e.g., Sheppard & Venon, 2008). Attention is a very broad construct with many facets (Schweizer, Moosbrugger, & Goldhammer, 2005). We chose two tasks with different emphasis regarding processing speed and attention but similar task requirements to measure *speeded attention* (e.g., Lamar & Raz, 2007; Krum et al., 2008). We understand *inhibition* as inhibition of dominant or prepotent responses (Miyake et al., 2000).

We focused on age-related differences in the connections of cognitive abilities between younger and older adults. To this end, we estimated network models – a relatively new method in this research field. We aimed to identify key variables contributing to age dedifferentiation, as defined by strength and number of connections with other variables on an observed level (as previously shown in the area of emotion research by, e.g., Giuntoli & Vidotto, 2020; Fried, Epskamp, Nesse, Tuerlinckx, & Boorsboom, 2016; Lange, Dalege, Borsboom, van Kleef, & Fischer, 2020). However, as using network models is an exploratory approach (Lange et al., 2020), we accompany them by multigroup confirmatory factor analysis (CFA) to compare the network model findings with a method that is well established in this research field. For the CFA, the results of the above-mentioned studies are mixed with regard to age dedifferentiation. However, based on these studies, we expected to find significant latent correlations between intelligence and working memory (e.g., Conway et al., 2003; Fukuda et al., 2010) as well as between intelligence and speeded attention in younger and older adults (e.g., Kail & Salthouse, 1994; Kane & Engle, 2002; Schweizer & Moosbrugger, 2004).

Method

Participants

The sample consisted of 146 adults aged between 20 and 86 years of age (M = 51.53 years; 55.5% female). We recruited the participants in a city in south-western Germany. All of them were fluid in German, which was the native language of 95.9% of the sample. 2.1% had a second mother language besides German, and 2.1% spoke another native language. They had the following education level: *basic school graduation*: 11.6%; *finished vocational training*: 19.9%, *high school graduation*: 29.5%; *bachelor's degree*: 6.8%; *master's degree*: 26.7%; *PhD*: 4.8% (*no information*: 0.7%). The participants were included if they were fluent in German, reported no medical conditions impairing cognition and no pervasive developmental or learning disorders, and normal or corrected-to-normal vision and hearing. The sample was divided by a median split (at 52 years) into two groups of 73 younger adults (M = 38.0 years of age, SD = 9.9; 62% female) and 73 older adults (M = 64.1 years of age, SD = 7.7; 49% female).

Procedure

Participants performed two sessions at the lab (total testing time: about 90 minutes). In the first session, we assessed demographics, speeded attention, and working memory capacity. In the second session, which took place on average four days after the first (M = 3.5 days, SD = 3.0), we tested inhibition and fluid intelligence. A psychologist or a trained research assistant instructed the assessment sessions and answered questions. All participants provided written informed consent and received 25 Euro for their participation. There was no dropout.

Power analyses for network models are not trivial, as precise estimates of sensitivity, specificity, and correlations depend on the expected network structure (Epskamp & Fried, 2018). As simulation studies have shown, estimating a lasso regularized network generally results in high specificity, while sensitivity and correlations depend on sample size (e.g., Epskamp, 2016; Foygel & Drton, 2010; van Borkulo et al., 2014). We calculated simulations with 5000 iterations each, using the refitted cognitive abilities networks for the younger and older age group as the true network (see Figure A1 and A2), to estimate sensitivity, specificity and correlations between true and estimated networks for different sample sizes, as well as centrality indices. For $N = 75$ cases, mean correlation with the true network was .72 and mean sensitivity .76, and mean specificity was .62 in both groups. This led us to the assumption that the two samples with $N = 73$ participants each fulfilled the necessary power considerations for the planned network models.

Measures

Please see Tables 2 and 3 for reliability estimates of all measures.

Fluid Intelligence

We used the *matrix test* from the German version of the Wechsler intelligence test for adults, (WIE; von Aster, Neubauer, & Horn, 2006) and the logic component of the *ASK test* (Analysis of reasoning and creative thinking, Schuller & Hell, 2005) to assess two aspects fluid intelligence. The WIE matrix test is a subscale of the WIE and was computer-administered. Participants were instructed to complete an incomplete matrix or row by selecting the missing part from five possible answers. After three practice trials, subjects performed 26 trials. The test score was the number of correct items (0-26).

In the logic component scale of the ASK test, subjects performed three different tasks: First, they were presented with three graphics or tables that contained information. Participants were provided statements and had to determine (within 17 minutes) whether they could be inferred from the given information or not. Second, the subjects were presented with pairs of two sentences which contained a premise and decided whether provided logical conclusions were right or wrong. The time for this task was limited to 3:15 minutes, and the task consisted of five trials with three (in one case four) logical conclusions. Third, twelve short statements were presented in one minute, and participants decided whether they were a fact or an opinion. The test score was the number of combined correct answers for these three tasks (0-41).

Working Memory

We assessed working memory capacity with the *digit span backward task* (Wechsler, 1997), and the *Corsi block backward task* (Kessels, van Den Berg, Ruis, & Brands, 2008) to test verbal and visuospatial working memory, respectively. In the digit span backward task participants had to remember a sequence of digits read by an instructor in one-second intervals and repeat them in the inverted order. They performed two practice trials. The sequence length started with two digits and was increased by one every two trials up to a length of eight digits, resulting in 14 trials (digits did not repeat in one trial). If both trials of the same digit length were solved incorrectly, the task was aborted. The test score was the number of trials answered correctly (0-14).

In the Corsi block backward task, participants were instructed to tap a sequence on nine black-colored cubes mounted on a black board. These cubes were labelled with the digits one to nine, which were only visible to the instructor. The instructor, who was seated in front of the subjects, tapped a sequence on the cubes in one-second intervals, which the participants had to repeat in inverted order. Three practice trials were answered by the subjects. The sequence length varied from two to eight digits and was increased by one after two trials. Fourteen trials were administered, and two wrong answers for trials of the same length lead to the task being aborted. Each digit sequence was generated quasi-randomly, and each digit could be used only once in that sequence. The test score was the number of trials answered correctly (0-14).

Speeded attention

We used the *digit-symbol substitution test* (Wechsler, 1982) and the *FAIR-2* (Frankfurt Attention Inventory, Moosbrugger, Oehlschlägel, & Steinwascher, 2011) to assess speeded attention. The digit-symbol substitution test consists of nine digit-symbol pairs, which were presented to the participants on a sheet of paper. The participants were tasked with completing 100 of these pairs, where the symbols were missing. All items that were correctly completed within 90 seconds were counted as the test score. Thus, higher scores represent better performance.

In the FAIR-2, lines with symbols consisting of combinations of a square or circle outer shape and two or three dots within this shape were presented to the participants. Target symbols were a circle with three dots or a square with two dots. Subjects had to start at the left edge of the sheet at the indicated pencil symbol and draw a continuous line under the symbols to the right. Whenever they found a target symbol, they were instructed to draw a peak into the symbol from below. One line consisted of twenty symbols. After one practice line, participants had to complete two pages with sixteen lines each within three minutes per page. Following the instructions of the test authors, we calculated a score for continuity of attention which is a product of quality (carefulness and relative correctness) and speed as a performance measure.

Inhibition

We used the *Flanker task* (Eriksen & Eriksen, 1974) and the *Simon task* (Simon & Wolf, 1963) to assess interference control and response inhibition as two aspects of inhibitory control. In the Flanker task, a stimulus consisted of five letters (e.g., SSHSS). The goal was to respond to the central target letter (“H” or an “S”) which was surrounded by two “H” or two “S” on both sides.

Subjects used two different keys with their left and right index fingers for their responses and were instructed to respond as quickly as possible while maintaining accuracy. Twenty practice trials were followed by five experimental blocks (with 40 trials each). Stimuli were presented in a randomized order within the experimental blocks.

In the Simon task, participants were presented with either a green or a blue square on the left or right side of the screen. The colors corresponded to two different keys, which subjects had to press with their left and right index fingers while ignoring the stimulus position. They were instructed to respond as quickly as possible while maintaining accuracy. Twenty practice trials were followed by five experimental blocks (with 40 trials each). Stimuli were presented in a randomized order within the experimental blocks. We calculated inverse efficiency scores as proposed by Gärtner & Strobel (2021) using the following formula: $(RT_{incongruent}/[1–ER_{incongruent}]) – (RT_{congruent}/[1–ER_{congruent}]))$.

Data Analyses

Network Models

To identify key variables that are strongly connected in the network of cognitive performances, we estimated two regularized auto correlation network models (one for each age group) with the statistic software R (version 3.6.1; R Core Team, 2019) using the package *bootnet*, following the approach described by their authors (Epskamp, Borsboom, & Fried, 2018; Epskamp & Fried, 2018).

However, we did not use the extended Bayesian information criterion (EBIC; Foygel, & Drton, 2010) by default, which was initially developed for model selection when facing moderate sample sizes in combination with a vast number of covariates (e.g., in genome-wide association studies; Chen & Chen, 2008). As our expected networks were relatively small, we avoided too strict regularization in the graphical lasso algorithm (Friedman, Hastie, & Tibshirani, 2014), resulting in empty networks being estimated. Therefore, we used the ordinary Bayesian information criterion (BIC) instead, following the recommendation of a simulation study by Chen and Chen (2008) for cases where the number of covariates in the model is smaller than the sample size.

We tested network differences between both age groups with the *NetworkComparisonTest* developed by van Borkulo and colleagues (2017). Bootstrapping was used to assess network stability (Epskamp et al., 2018) for edge weights and centrality indices. Furthermore, we calculated a graphical difference network by subtracting the weights of the older group network from the corresponding weights of the younger group network, inspired by a procedure described by Southworth and colleagues (2009).

Multigroup Confirmatory Factor Analysis

To accompany the results of the network models with an analysis method that is well established in the field, we conducted a multigroup confirmatory factor analysis. All models were estimated using *M*plus 8 (Muthén & Muthén, 2017) with full maximum likelihood estimation (FIML). While 0.7% of the data were missing (one person had no WIE-data), FIML estimation allowed for the use of all observed data points in the analyses. Following Beauducel and Wittmann (2005), we used the χ^2 test, the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR) to evaluate model-fit. For model identification, the first loading of each factor was fixed to 1. All latent factors were allowed to correlate. Metric measurement invariance across groups was established using chi² difference ($\Delta\chi^2$) testing. The significance level for all analyses was $\alpha = .05$. In consideration of the sample size, we estimated the model also with bootstrapping with 500 and 1000 draws to evaluate the stability of the estimation.

Results

Descriptive Statistics

Please see Table 1 for descriptive statistics for both age groups. Correlations between the cognitive variables are presented in Table 2 for the younger group and in Table 3 for the older group (as well as Table A1 for the entire sample).

Network analysis

First, we estimated one network model per age group (Figure 1 and 2) and tested for network structure invariance, which revealed that the difference between the network structures in both groups was not significant (M = 0.282, p = .44), which is a basis for calculating a difference network. The test for invariance of global strength showed no significant difference (S = 0.96, p = .07). Thus, as the overall connection strength and overall level of connectivity are comparable, specific differences between networks are less likely measurement artifacts (e.g., differential measurement error/noise in the age groups) and more likely of content-related nature (e.g., differential importance of nodes in the age groups).

On this basis, we calculated a difference network using the difference of corresponding edge-weights in both models (Figure 3). The younger group network (Figure 1) showed speeded attention (FAIR) as a central variable with strong connections to the other speeded attention variable (Digit-symbol substitution task), fluid intelligence (WIE), inhibition (Simon task). In the older group network, relationships were strong in a cluster grouped around fluid intelligence (especially WIE) with connections to working memory (Corsi block and Digit span backward) and speeded attention (especially Digit-symbol substitution task). The difference network (Figure 3) showed a shift from speeded attention (FAIR) to stronger connections between intelligence and working memory as a function of age.

The centrality indices node strength, betweenness, and closeness[1], mainly confirmed these observations (Figure 4) and hinted to the following key variables as being strongly connected and central in the network of cognitive abilities (Figure 4): Speeded attention (FAIR) seemed to be most prominent in the younger group, followed by fluid intelligence (WIE). In the older group, fluid intelligence (WIE) seemed more central in general but were followed by speeded attention (Digit-symbol substitution task and FAIR).

In the next step, we tested whether the observed network structures and the centrality indices could be assumed as stable. Therefore, we calculated bootstrapped confidence intervals for the edge-weights of both networks (Figure A3 and A4), often indicating no overlapping confidence intervals of strong and weak edge-weights, but of middle-sized edge-weights. In the younger group, the connection between the measures of speeded attention were the strongest edge weights. The strongest connections in the older groups involved speeded attention, the intelligence measures, and the working memory measures. An extensive comparison of the size of the edge weights within the networks of each age group is provided in Figures A5 and A6.

Bootstrapped centrality indices (Figure A7) were quite stable if the sample size was lowered – except for betweenness in the older group. Similar difference tests can be conducted for the centrality indices and are reported only for node strength (Figure A8), as the tests for closeness and betweenness showed no significant results. In the younger group, speeded attention measures (FAIR and digit-symbol substitution test) had a node strength, which was significantly different from all other nodes. In the older group, fluid intelligence (WIE) and working memory (Corsi span and Digit span backwards tasks) had significantly larger node strengths than other tasks. As discussed by Epskamp and colleagues (2018),

[1] *Node strength* quantifies the direct connection to other nodes, *closeness* quantifies the indirect connection to other nodes, and *betweenness* quantifies the role in the average path between two other nodes.

multiple testing is a known but still unresolved issue in the research field of psychological network estimation, which must be considered in the context of the difference tests mentioned above.

Multigroup confirmatory factor analysis

A multigroup model with metric measurement invariance across the age groups demonstrated a good global fit to the data [χ^2 (df = 34) = 41.87, p = .16; CFI = .97; RMSEA = .06 (90 % CI = .01–.11); and SRMR = .08]. Metric measurement invariance was established by comparing this model to a model with configural invariance [$\Delta\chi^2$ (df = 4) = 6.29, p = .18, ΔCFI = .007, and ΔMc = .008]. (ΔCFI < .01 and ΔMc < .02; as suggested by Cheung and Rensvold, 2002) (Figure 5). All reported factor loadings and latent correlations in both age groups were significant (α = .05), except for the latent correlations between inhibition and attention as well as between inhibition and fluid intelligence in the older age group. However, the factor loadings in both groups were quite small for the Simon task. Latent correlations were highest between working memory and fluid intelligence, especially in the older group. The correlations between inhibition and fluid intelligence were the lowest. In addition, estimating the model with bootstrapping with 500 and 1000 draws showed that the stability of the estimation was good as all main findings were robust. Only one latent correlation between working memory and inhibition in the younger group with a p-value of .045 in maximum likelihood estimation was not significant when using bootstrapping.

Discussion

The key findings of our analysis using network models are that in terms of strength and number of connections to other variables, speeded attention (FAIR and digit-symbol substitution test) seemed to be the most prominent variable in the younger group, followed by fluid intelligence (WIE). In the older group, fluid intelligence (WIE) seemed more central in general but was followed by speeded attention (FAIR). The measures of speeded attention (digit-symbol substitution test and FAIR) are variables with very high strength in both groups, supporting the fact that speeded attention plays an important role in cognitive aging. However, Figures 1 and 2 show that the high node strength is heavily impacted by the high correlation of this tasks (see also Tables 1 to 3). This may be caused by highly similar demands of the two tasks which must be taken into account when assessing the centrality of speeded attention. In the CFA, we found trends of lower (in older compared to younger adults) or fairly stable latent correlations of all factors, except for the latent correlation between working memory and fluid intelligence where the latent correlation was even stronger.

One possible explanation for intelligence being the most strongly connected variable in the older adults' network models might be that reasoning is more limited by basic processes (e.g., working-memory capacity, speeded attention). Thus, some older individuals showed intact basic processes, whereas other older individuals demonstrated reduced basic functioning, inadequate to fully support higher cognitive abilities like reasoning. Working-memory capacity is known to be related to reasoning and to be a limiting factor for it (e.g., Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002; Schweizer & Moosbrugger, 2004; Fukuda et al., 2010). This may have resulted in a stronger connection of intelligence with other functions in older adults. In younger individuals, attention was more strongly connected to other nodes as it might be a more decisive limiting factor for other cognitive functions while basic processes are broadly intact. Still, attentional resources might determine whether information enters the system at all (e.g., Cowan, 1988; Schneider & Shiffrin, 1997).

With intelligence being the most strongly connected variable in the older adults' network, we found evidence for both stronger (centering intelligence) and weaker (centering speeded attention) connections in old age in comparison with the younger adults' network. Thus, our results are more in line with process-specific changes as described by Zelinski and Lewis (2003) as with general age dedifferentiation. They reported longitudinal evidence for process-specific (i.e. not general) changes in vocabulary, perception speed, working memory, as well as text and list recall and provide an extensive review of studies investigating age dedifferentiation. While using different samples (age groups) and a variety of methodological approaches (like manifest vs latent variables, cross-sectional vs longitudinal comparisons, and varying statistical fit criteria), the reviewed studies come to mixed conclusions – mostly partial increases and no changes in relationships among variables. As no network models were used, direct comparisons with our findings are not possible. However, our results are in line with and can complement the idea of process-specific changes. Our data suggest a possible switch from speeded attention (younger adults) to working memory (older adults) as central limiting factor for higher cognitive functioning.

Regarding limitations of our findings, one first limitation of the present study is that the number of participants was relatively small for network analysis (with n = 73 per age group), and we could not investigate differences between old and very old adults. Also, the sample consisted of community-dwelling adults and therefore did not allow to distinguish between normal aging processes and individuals with strong cognitive decline caused by one or several diseases, which might lead to different trajectories of cognitive decline in this group (as interindividual differences might be higher in very old age when non-normative sources of heterogeneity outweigh normative age-related change; de Frias et al., 2007). Considering the cross-sectional design, typical limitations like the cohort effect (shared factors other than age;

e.g., Salthouse, 2014) apply. Different methodological approaches (design or statistical fit criteria) can lead to different results when using CFA in the context of age dedifferentiation (Zelinski & Lewis, 2003). This must be taken into consideration when interpreting the results of our CFA. At the same time, the network models are not free of these limitations, as the used algorithm allows for the specification of similar parameters, too (e.g., amount of regularization of the edge weights). The usage of centrality indices is also not a fully developed approach and needs to be interpreted with caution (e.g., Bringmann et al., 2019), especially as closeness and betweenness assume the ‘presence of flow and shortest paths’, which might not be always applicable in psychological networks. Furthermore, the stability of all centrality measures can be problematic in the network approach (which we investigated with bootstrapping, see Figure A7). Another known and unresolved issue that applies when using difference tests for network models is multiple testing (Epskamp et al., 2018). In addition, the network models we estimated are an exploratory analysis and our research design, in general, does not allow for causal conclusions. Finally, we have to point out that the FAIR had higher correlations with WIE and ASK than expected from other measures of speeded attention and fluid intelligence in the literature (e.g., Schweizer, Moosbrugger, & Goldhammer, 2005). Therefore, the strength of the connection between FAIR and WIE as well as ASK in the network models has to be interpreted with caution: The connection strength between speeded attention and fluid intelligence measures might differ as a function of the measures used to assess the abilities.

In future research on cognitive-performance networks, a longitudinal design could lead to an even better understanding of involved aging processes. However, when trying to account for the known limitations of cross-sectional and longitudinal comparisons by testing people of the same birth cohorts at different ages for the first time, results from several studies showed closer similarity to those from cross-sectional designs for some cognitive functions (Salthouse, 2014). The network approach might further benefit from a larger sample with a more refined resolution for the different age groups, especially for the older adults. Future research could also include children and adolescents as long as measurement instruments lead to valid comparisons with the adults. While the focus of this research was on better understanding underlying basic cognitive information processes, future research could greatly benefit from adding indicators of pragmatic abilities to complement the indicators of mechanical cognitive abilities. Combined with a sound theoretical understanding of the involved processes, the identification of key variables can help with the design of cognitive trainings and interventions, highlighting tasks which might be promising candidates to foster transfer and hinting to relevant mechanisms for intervention success.

In summary, network models have the potential of being a useful tool when analyzing the connections of different cognitive domains, as they highlight central variables very well. At the same time, a strong theoretical basis is necessary to understand the function of variables (e.g., knowledge about the roles of working memory for intelligence and of attention for fast and effective information processing). Therefore, network models can provide information about the interplay of cognitive abilities that is complementary to the knowledge gained by standard approaches such as CFA.

Table 1

Descriptive statistics for both age groups

	Younger Adults				Older Adults			
	M	*SD*	*Min*	*Max*	*M*	*SD*	*Min*	*Max*
Intelligence								
WIE reasoning matrices	19.77	2.97	11	25	15.57	4.21	4	23
ASK reasoning component	26.18	5.19	15	37	19.68	6.98	5	35
Working memory								
Corsi span backward	9.58	1.96	4	14	7.79	1.95	3	13
Digit span backward	7.67	2.07	4	12	6.51	1.87	4	12
Inhibition								
Simon task	-45.44	33.72	-162.55	19.57	-59.80	49.39	-186.94	54.93
Flanker task	-68.93	32.80	-156.46	-17.94	-78.33	89.18	-346.10	184.69
Speeded attention								
Digit symbol	59.45	10.21	28.00	90	46.21	10.08	19	68
FAIR	356.12	100.63	25.10	586.06	261.43	101.87	0.24	486.08

Notes. Scores for the Simon task, Flanker tasks, and task switching are recoded (to enhance the readability of correlations across cognitive performance indicators). WIE = reasoning matrix subscale of the Wechsler intelligence test for adults; ASK = Analysis of reasoning and creativity (only reasoning was used); FAIR = Frankfurt Attention Inventory 2.

Table 2

Correlations among the cognitive variables in the younger age group

	1	2	3	4	5	6	7	8
Intelligence								
1. WIE reasoning matrices								
2. ASK logical component	.25*							
Working memory								
3. Corsi span backward	.30*	.06						
4. Digit span backward	.26*	.16	.26*					
Inhibition								
5. Simon task	.34*	.15	.28*	.14				
6. Flanker task	.32*	-.03	-.04	.23*	.35*			
Processing speed								
7. Digit-symbol	.41*	.33*	.32*	.26*	.24*	.13		
8. FAIR	.49*	.28*	.36*	.33*	.41*	.26*	.63*	

Notes. *p < .05. Scores for the Simon task, the Flanker task, and task switching are recoded (to enhance readability). WIE = reasoning matrix subscale of the Wechsler intelligence test for adults; ASK = Analysis of reasoning and creativity (only reasoning was used); FAIR = Frankfurt Attention Inventory 2. Internal consistencies are: WIE: .70; ASK: .79; working memory: .80; inhibition: .74; speeded attention: .77.

Table 3

Correlations among the cognitive variables in the older age group

	1	2	3	4	5	6	7	8
Intelligence								
1. WIE reasoning matrices								
2. ASK logical component	.60*							
Working memory								
3. Corsi span backward	.48*	.33*						
4. Digit span backward	.58*	.47*	.41*					
Inhibition								
5. Simon task	.16	.06	.13	.08				
6. Flanker task	-.13	-.07	.03	.09	.32*			
Processing speed								
7. Digit-symbol	.54*	.57*	.30*	.38*	-.17	-.11		
8. FAIR	.49*	.52*	.44*	.37*	-.15	-.06	.75*	

Notes. **p* < .05. Scores for the Simon task, the Flanker task, and task switching are recoded (to enhance readability). WIE = reasoning matrix subscale of the Wechsler intelligence test for adults; ASK = Analysis of reasoning and creativity (only reasoning was used); FAIR = Frankfurt Attention Inventory 2. Internal consistencies are: WIE: .80; ASK: .87; working memory: .83; inhibition: .77; speeded attention: .85.

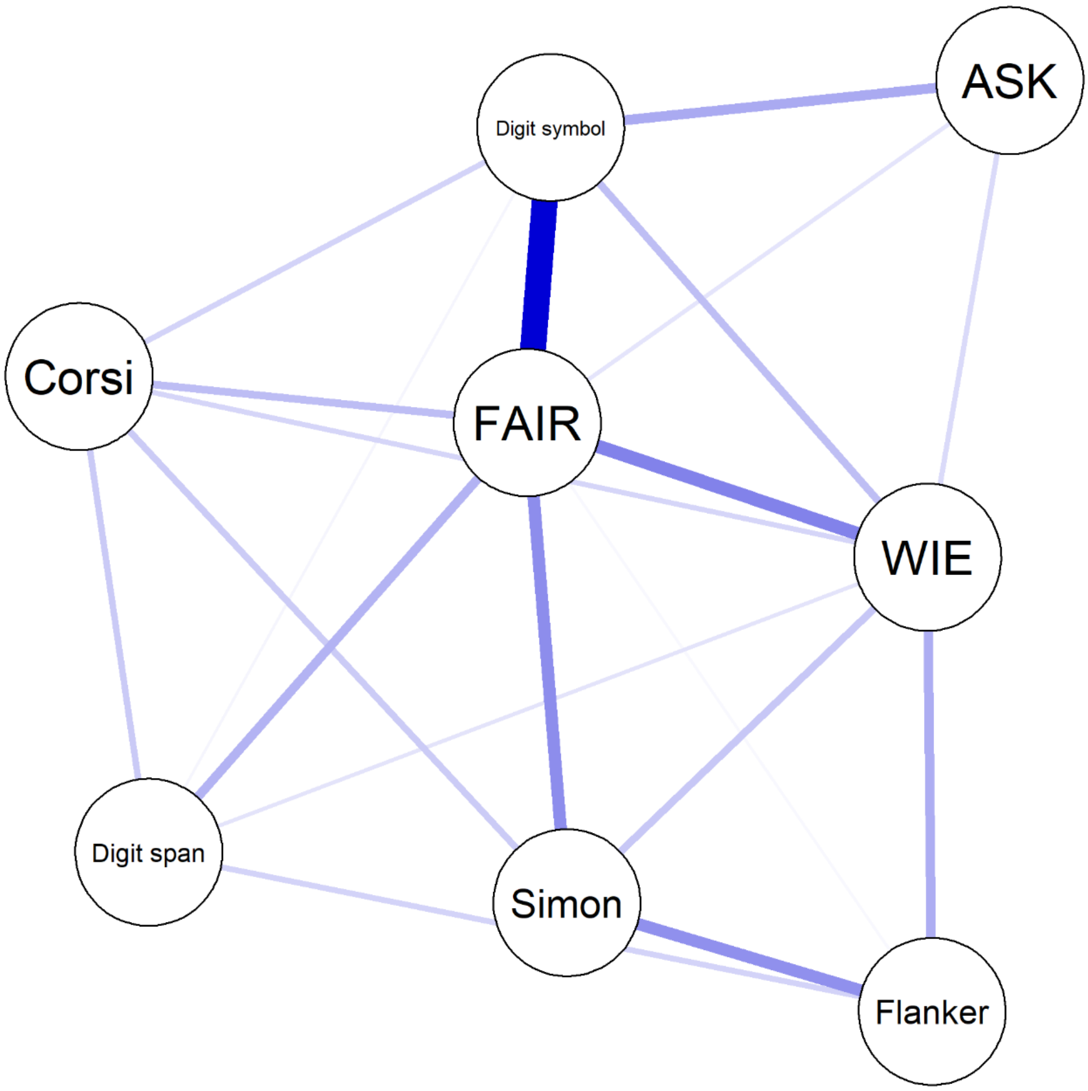

Figure 1. Network model for the group of younger adults. Darker blue corresponds to stronger connection strengths. The centrality of a variable is not necessarily implied by being placed in the centre of the plot, but by number and strength of connections. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

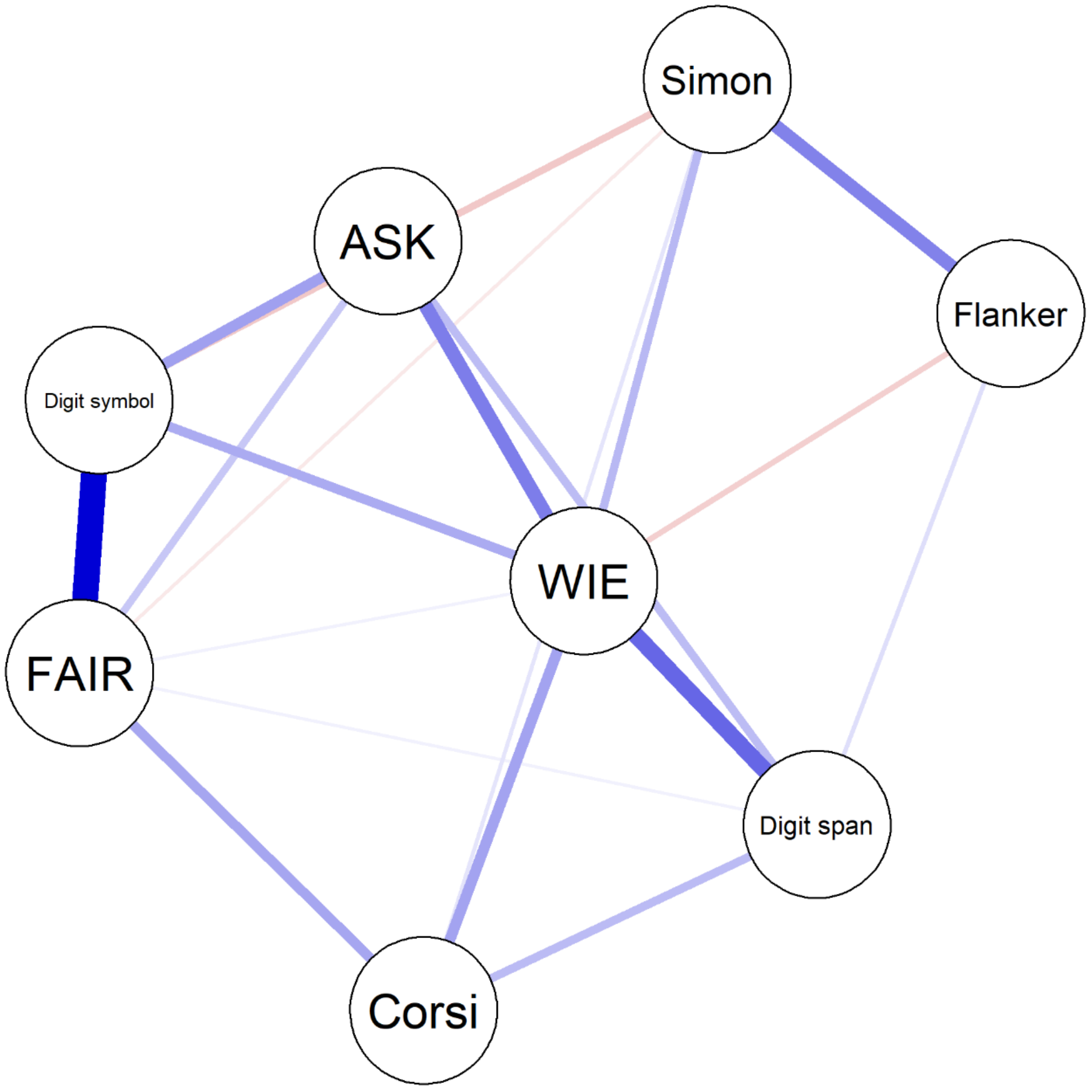

Figure 2. Network model for the group of older adults. Darker blue corresponds to stronger connection strengths. Darker red corresponds to stronger negative connection strengths. The centrality of a variable is not necessarily implied by being placed in the centre of the plot, but by number and strength of connections. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

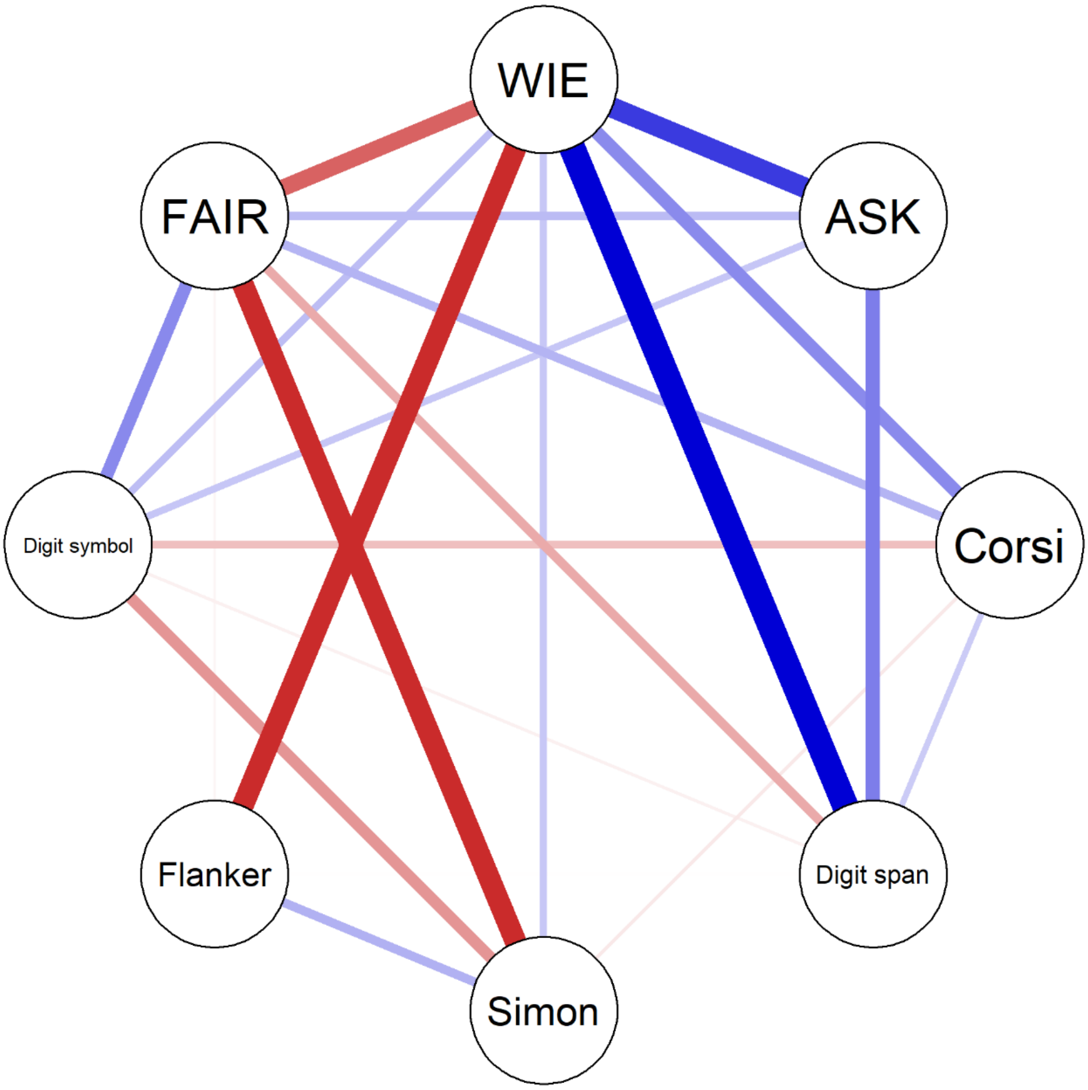

Figure 3. Difference between networks for the younger and the older group. Red corresponds to a decrease in connection strength from younger to an older age. Blue corresponds to an increase in connection strength from younger to an older age. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

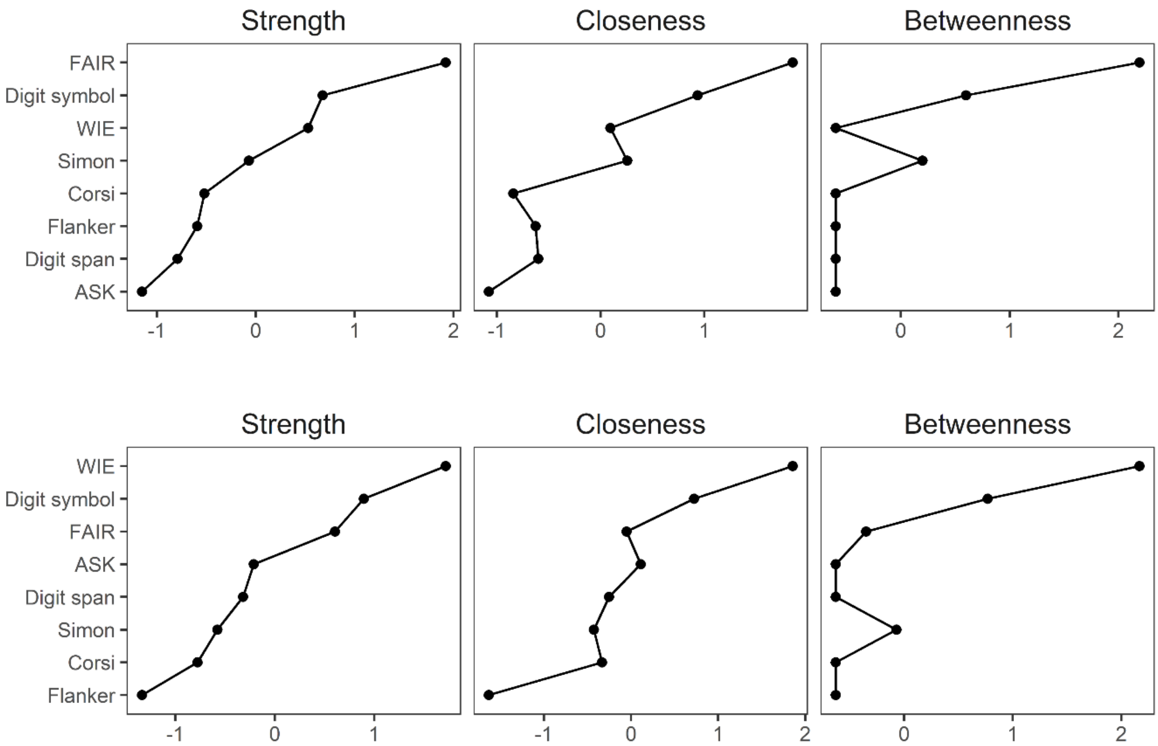

Figure 4. Centrality indices as standardized *z*-scores for the younger age group (above) and the older age group (below). Node strength quantifies the direct connection to other nodes, closeness quantifies the indirect connection to other nodes, and betweenness quantifies the role in the average path between two other nodes. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

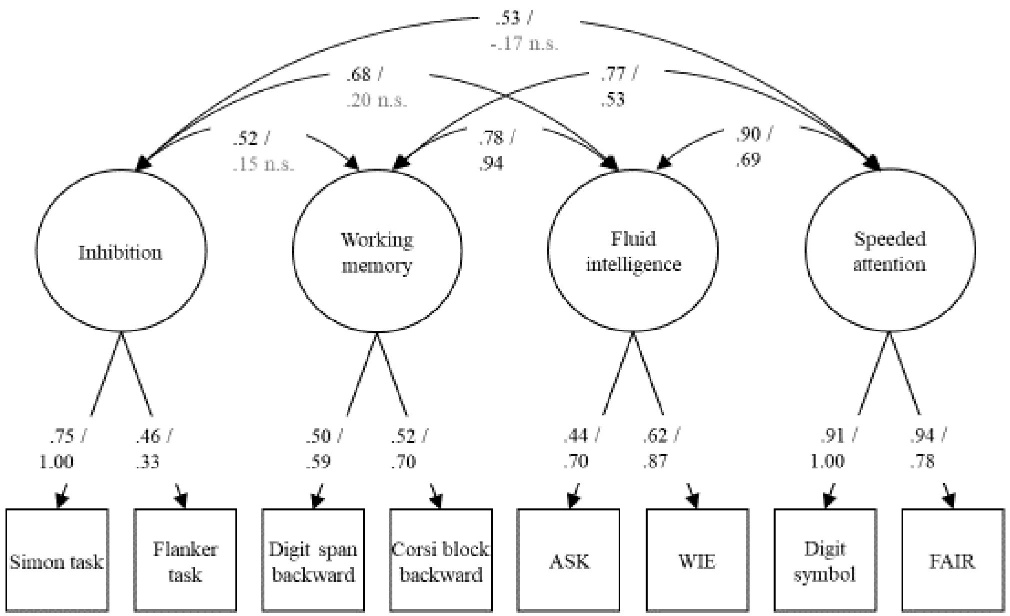

Figure 5. Multigroup confirmatory factor analysis with metric measurement invariance. Latent correlations and factor loadings are presented for both age groups as “younger adults” (above)/“older adults” (below). All parameters are standardized. The squares represent observed variables, and the circles represent latent variables. All factor loadings were significantly different from zero ($p < .05$). FAIR = Frankfurt Attention Inventory 2; ASK = Analysis of reasoning and creativity (only reasoning); WIE = Wechsler logical matrices; Digit symbol = Digit-symbol task; n.s. = not significant.

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9.2 Supplementary Material for Study 1

Table A1

Correlations among cognitive variables for the entire sample

	1	2	3	4	5	6	7	8
Intelligence								
1. WIE reasoning matrices								
2. ASK logical component	.60*							
Working memory								
3. Corsi span backward	.52*	.37*						
4. Digit span backward	.50*	.41*	.41*					
Inhibition								
5. Simon task	.27*	.16	.24*	.14				
6. Flanker task	.00	-.02	.04	.13	.33*			
Speeded attention								
7. Digit-symbol	.62*	.60*	.46*	.41*	.09	.00		
8. FAIR	.59*	.53*	.51*	.43*	.14	.05	.76*	

Notes. *$p < .05$. Scores for the Simon task, the Flanker task, and task switching are recoded (to enhance readability). WIE = reasoning matrix subscale of the Wechsler intelligence test for adults; ASK = Analysis of reasoning and creativity (only reasoning was used); FAIR = Frankfurt Attention Inventory 2. Internal consistencies are: WIE: .82; ASK: .84; working memory: .83; inhibition: .82; speeded attention: .87.

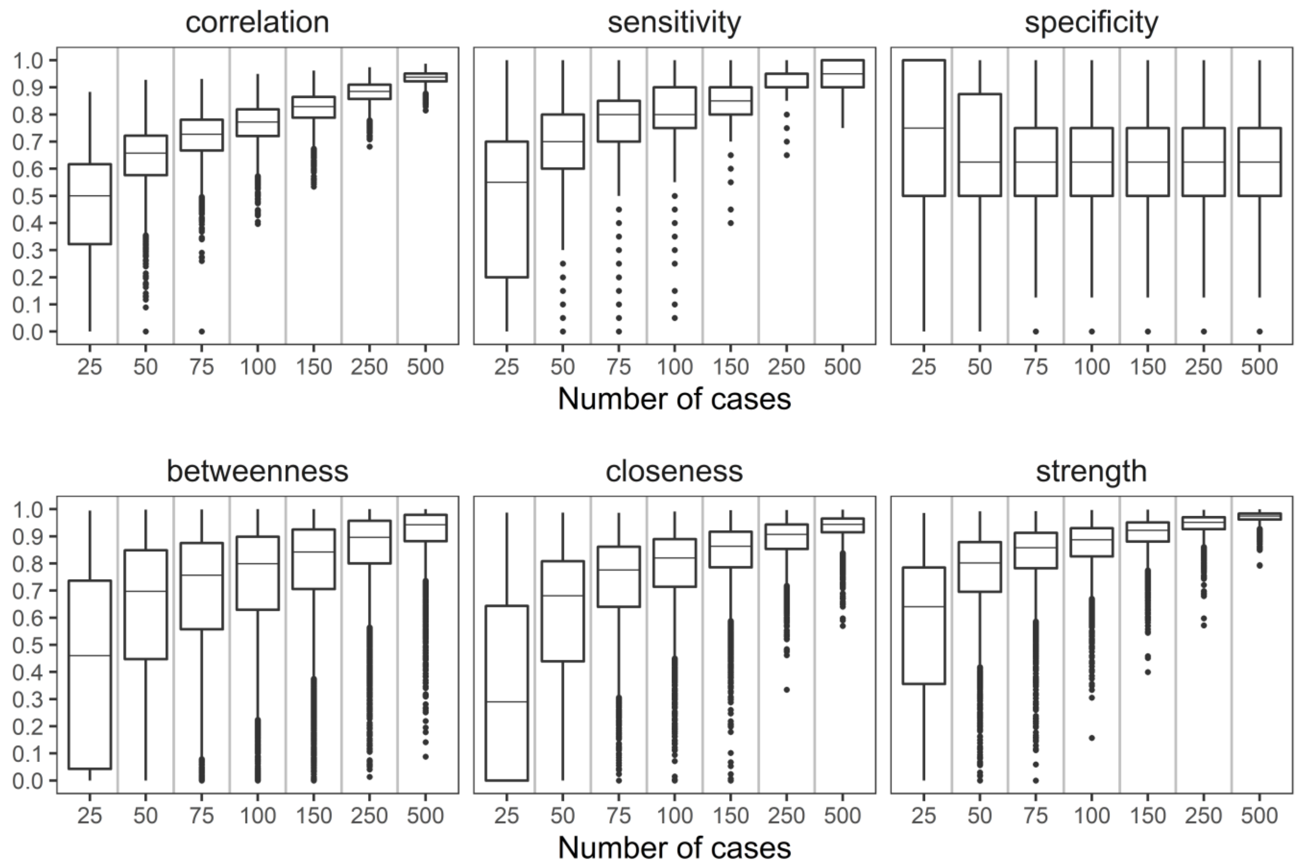

Figure A1. Simulation results using the estimated refitted cognitive abilities networks for the younger age group as true network structure. Sensitivity, specificity and correlation between true and estimated networks can be evaluated in the top panel and the correlation between true and estimated centrality indices in the bottom panel.

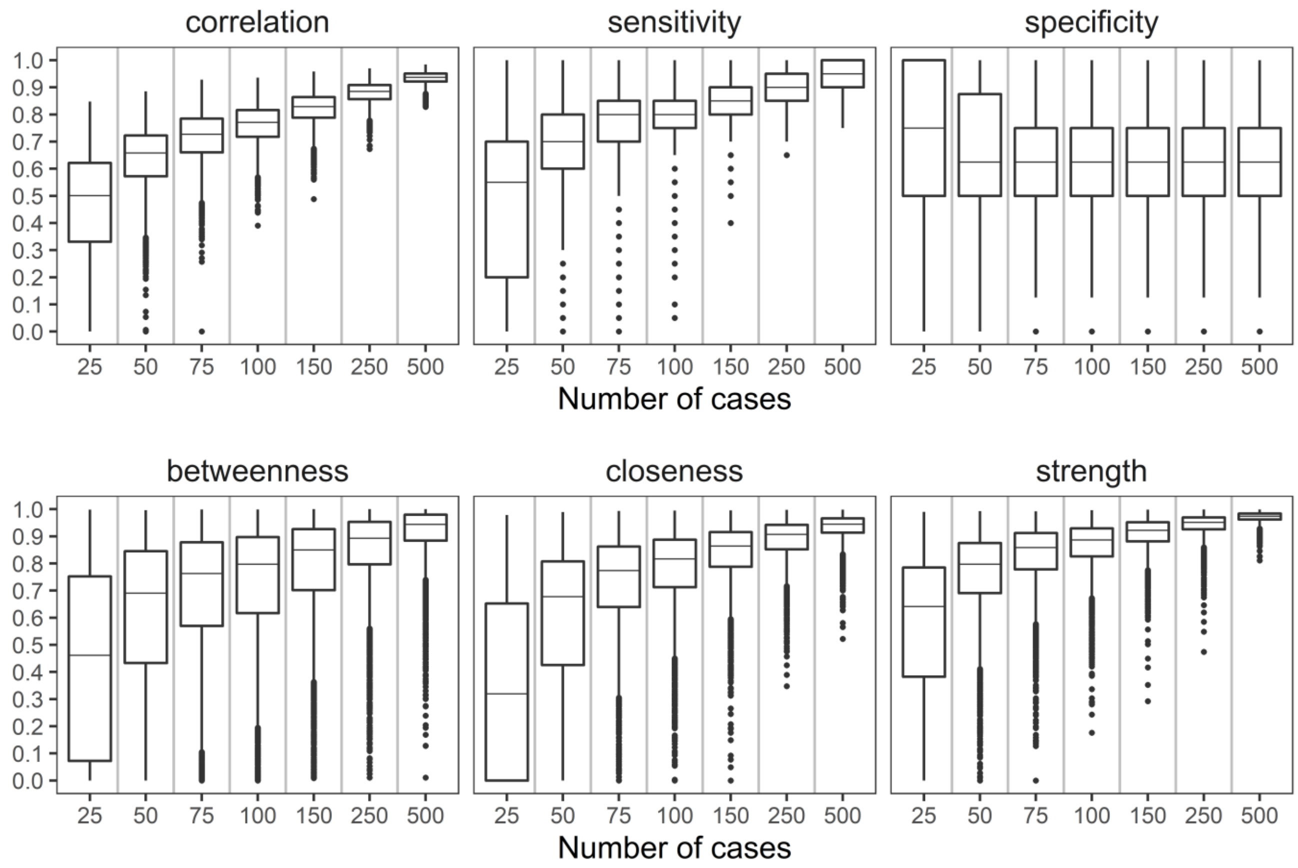

Figure A2. Simulation results using the estimated refitted cognitive abilities networks for the older age group as true network structure. Sensitivity, specificity and correlation between true and estimated networks can be evaluated in the top panel and the correlation between true and estimated centrality indices in the bottom panel.

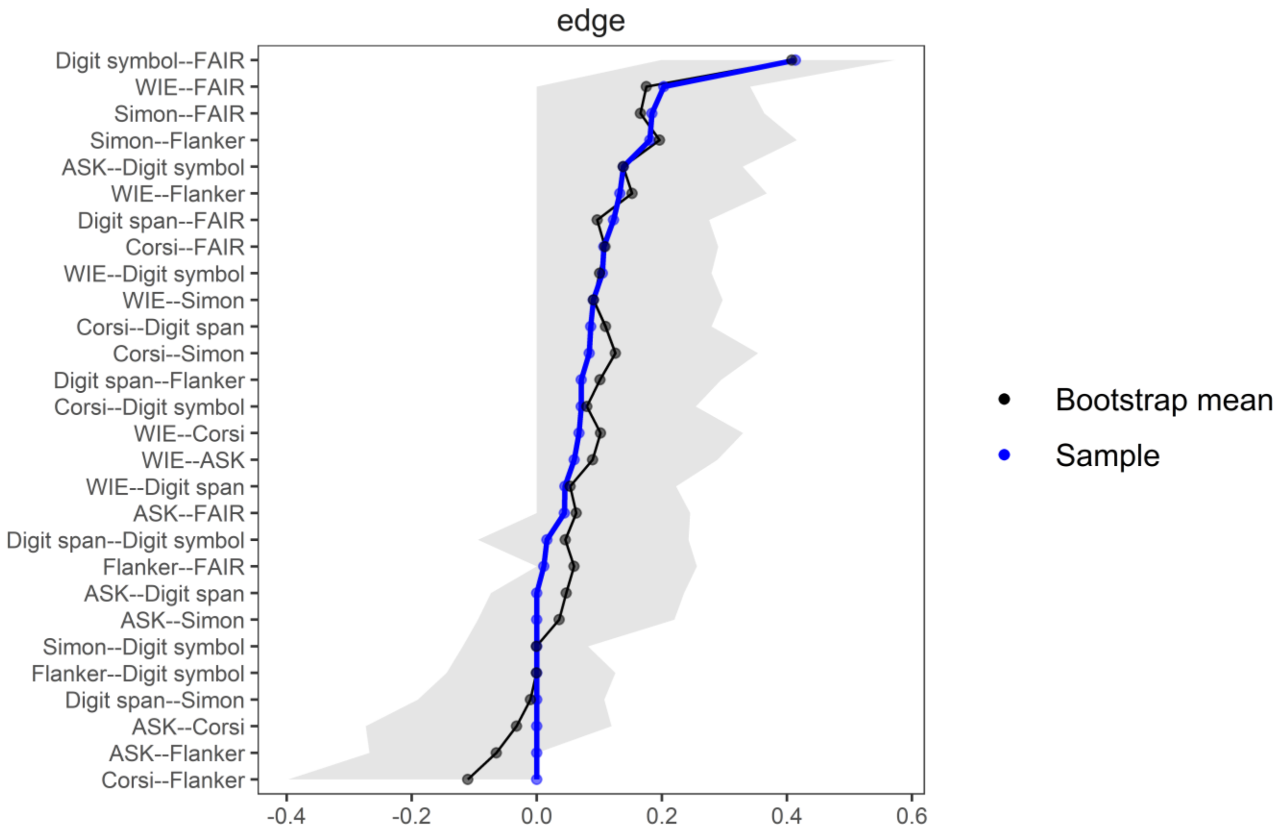

Figure A3. Bootstrapped confidence intervals for estimated edge-weights in the estimated network of 8 cognitive abilities for the younger age group. The blue line indicates the sample values and the grey area the bootstrapped 95% CIs. Horizontal lines represent network edges, ordered from highest edge-weight to the lowest edge-weight. Please note that edge weights in network models are regularised with a penalty by the graphical lasso algorithm and are therefore smaller than correlations or partial correlations. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

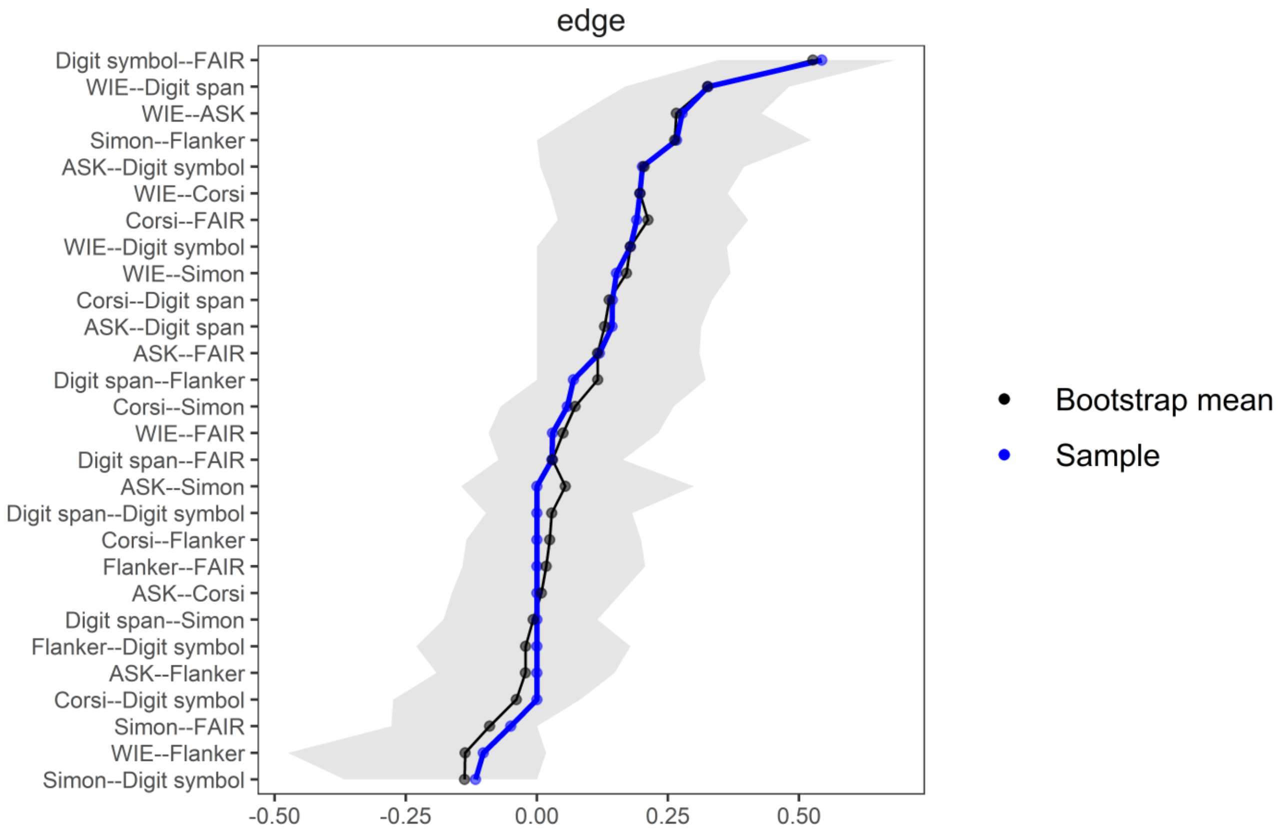

Figure A4. Bootstrapped confidence intervals for estimated edge-weights in the estimated network of 8 cognitive abilities for the older age group. The blue line indicates the sample values and the grey area the bootstrapped 95% CIs. Horizontal lines represent network edges, ordered from highest edge-weight to the lowest edge-weight. Please note that edge weights in network models are regularised with a penalty by the graphical lasso algorithm and are therefore smaller than correlations or partial correlations. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

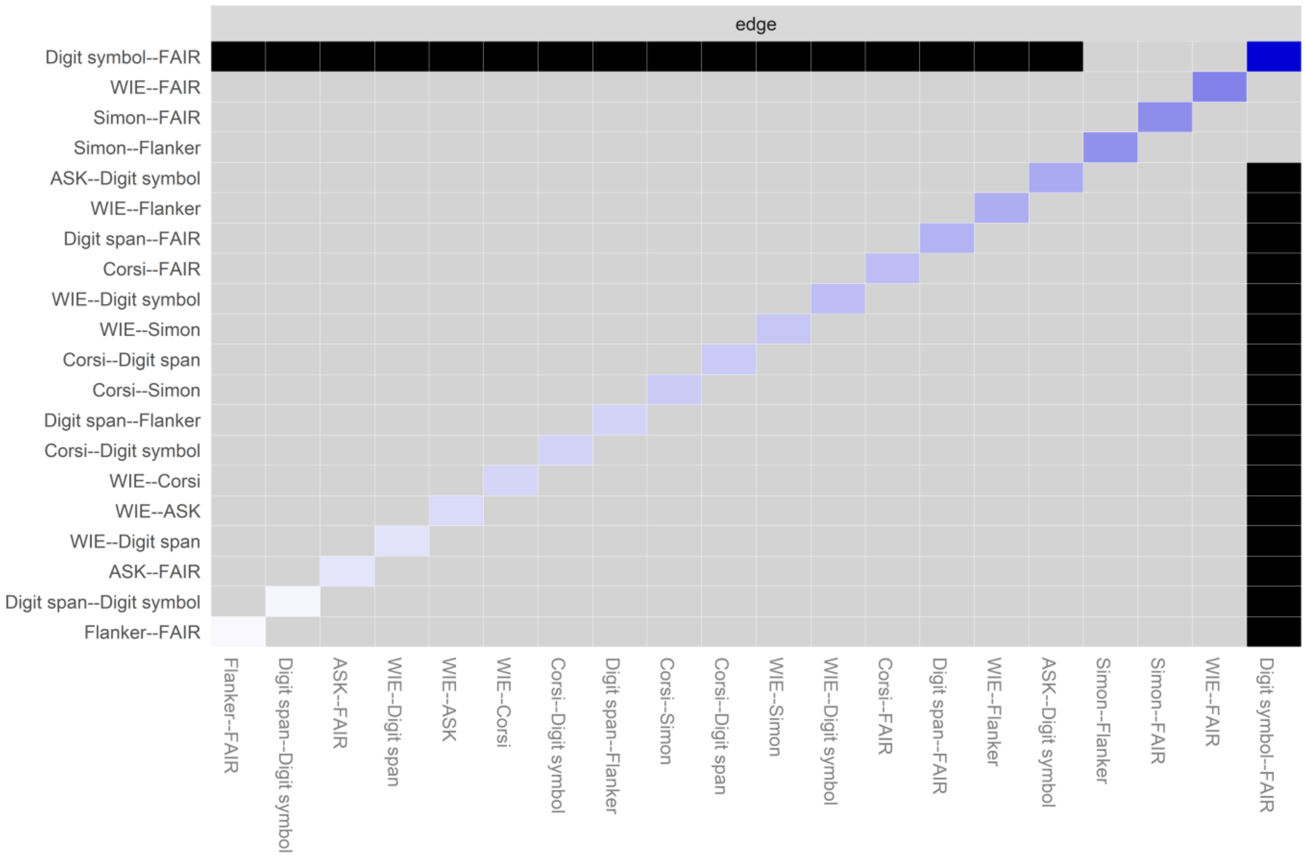

Figure A5. Bootstrapped difference test (α =.05) for all edge-weights in the younger group. Blue colour coding corresponds to the colour of edge-weights in the network plots. Black parcels indicate edge-weights that differ significantly from one another, whereas grey parcels do not differ significantly. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

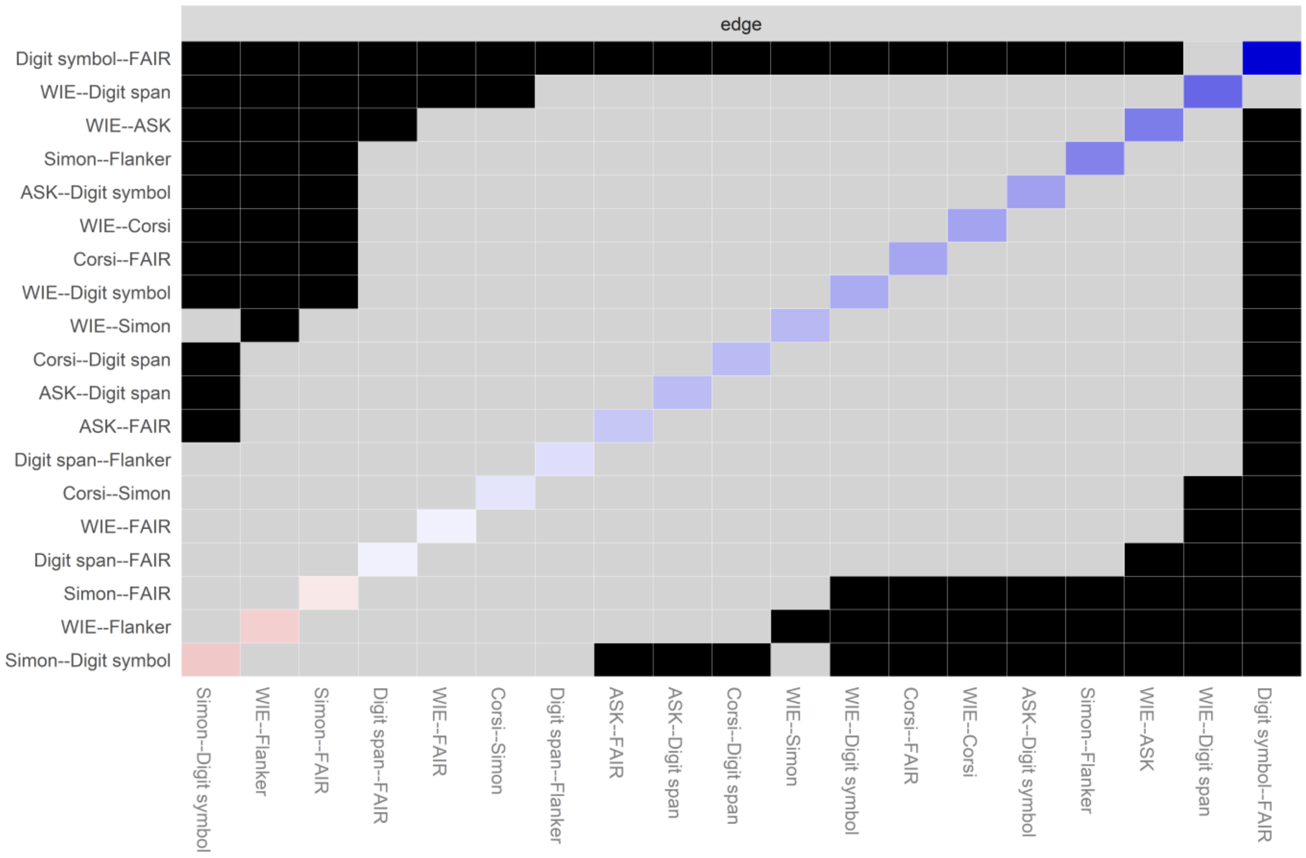

Figure A6. Bootstrapped difference test (α =.05) for all edge-weights in the older group. Blue colour coding corresponds to the colour of edge-weights in the network plots. Black parcels indicate edge-weights that differ significantly from one another, whereas grey parcels do not differ significantly. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

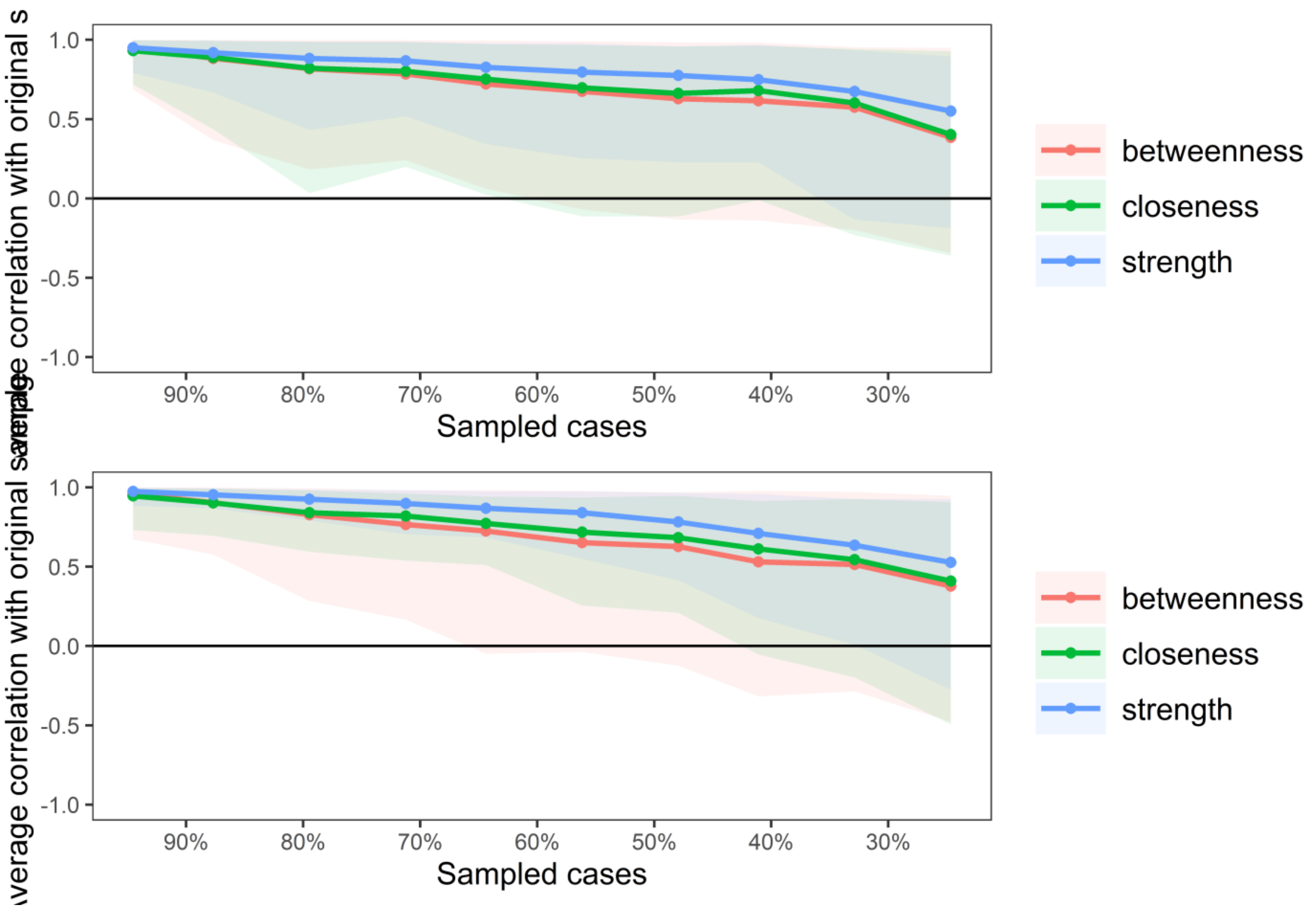

Figure A7. Centrality stability for the younger group network (above) and the older group network (below) as average correlations between the centrality indices of networks while reducing sample size in comparison with the original sample. Lines correspond to the means and areas to the range between the 2.5th and the 97.5th quantile.

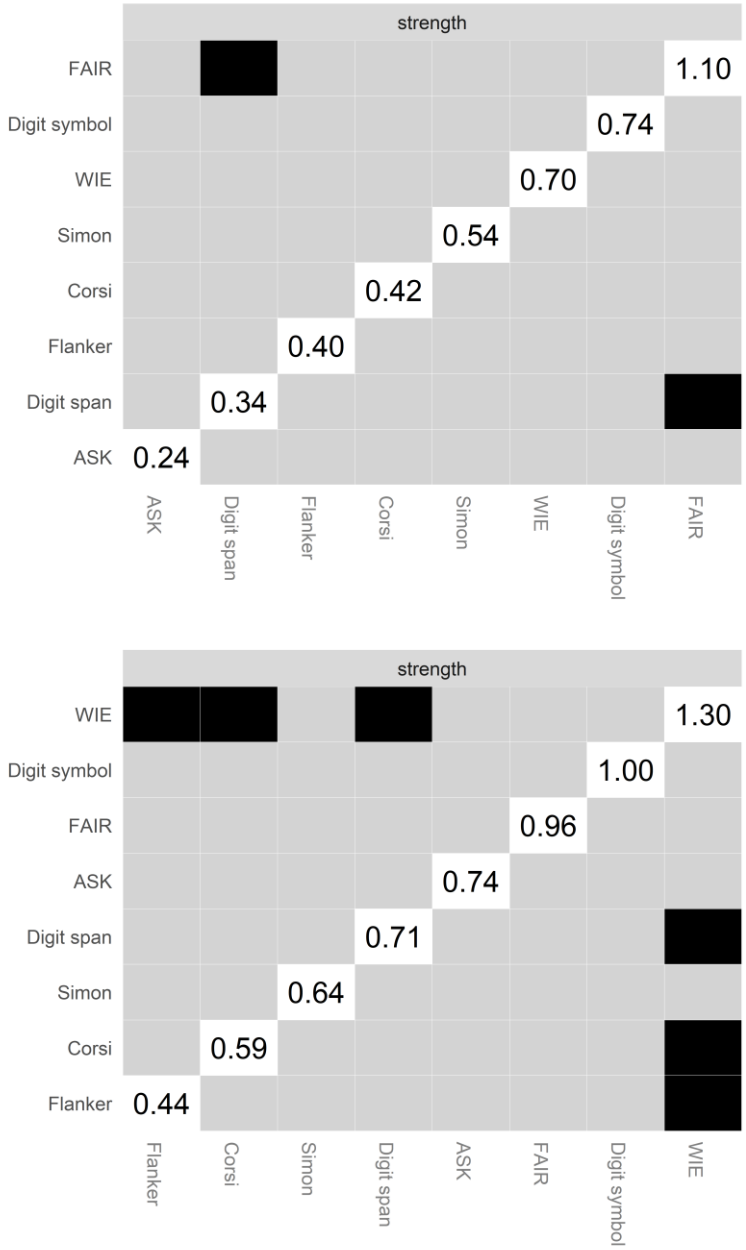

Figure A8. Bootstrapped difference test (α =.05) for centrality index node strength (younger group = above; older group = below). Black parcels mark node strengths that differ in a significant way from one another, whereas grey parcels do not differ significantly. In the white diagonal, the value of the node strength can be found. FAIR = Frankfurt Attention Inventory; WIE = Wechsler logical matrices; Corsi = Corsi block backward; Digit span = Digit span backward; Simon = Simon task; Flanker = Flanker task; ASK = Analysis of reasoning and creativity (only reasoning); Digit symbol = Digit-symbol task.

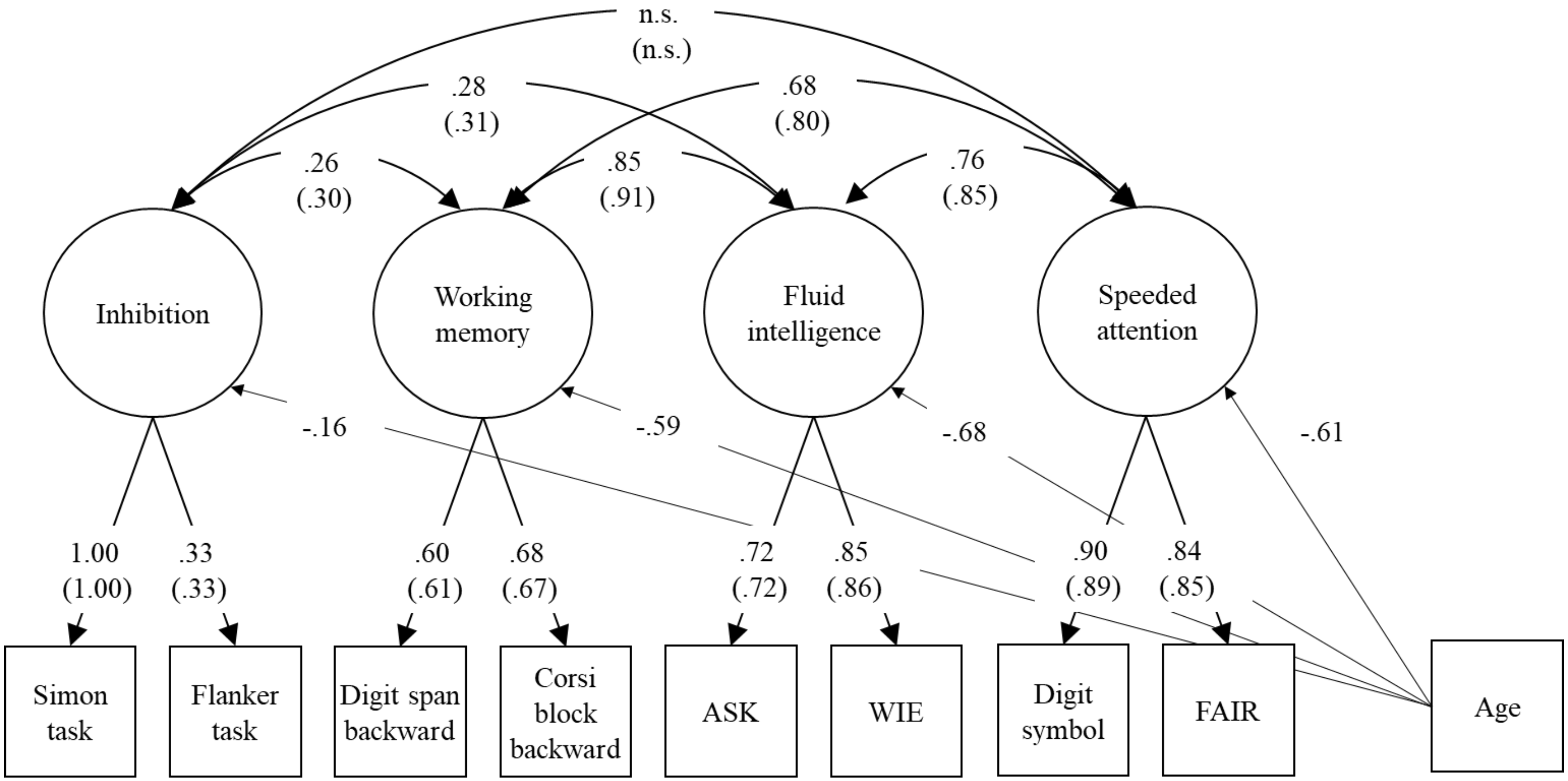

Figure A9. CFA models with (and without) age as a continuous predictor variable. The values in brackets show the estimates for the model without controlling for age. All factor loadings were significantly different from zero ($p < .05$). Both models demonstrated a good fit to the data [e.g., the more complex model including age: χ^2 ($df = 31$) = 43.64, $p = .07$; CFI = .98; RMSEA = .05 (90 % CI = .01–.09); and SRMR = .04]. There are no differences in the factor loadings except for minimal differences in the working-memory loadings. The comparison demonstrates the close relation of age with all cognitive abilities. When controlling for age, the latent correlations tend to be smaller than in the model without this control variable, but the general pattern of correlations stays the same. FAIR = Frankfurt Attention Inventory 2; ASK = Analysis of reasoning and creativity (only reasoning); WIE = Wechsler logical matrices; Digit letter = Digit-letter task; Digit symbol = Digit-symbol task; n.s. = not significant.

9.3 Study 2: Age-Differences in Network Models of Self-Regulation and Executive Control Functions.

Age-Differences in Network Models of Self-Regulation and Executive Control Functions

Markus Neubeck, Verena E. Johann, Julia Karbach, and Tanja Könen

University of Koblenz-Landau, Landau, Germany

Author note:

Correspondence concerning this article should be addressed to Markus Neubeck, Department of Psychology, University of Koblenz-Landau, Fortstraße 7, 76829 Landau, Germany. Email: neubeck@uni-landau.de

We declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

We declare that all used procedures comply with the Declaration of Helsinki, ethical standards of the German Psychological Society, and EU General Data Protection Regulation as required by the local ethics committee at the Department of Psychology (University of Koblenz-Landau).

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Research Highlights

- Different network structures of self-regulation and executive functions for a youth, middle-aged, and older-aged group
- Stronger connections within clusters of different aspects of self-regulation and executive functions than between them
- Older adults demonstrated more connections between self-regulation and executive functions than younger individuals, likely because of declining cognitive resources

Abstract

Self-regulation (SR) and executive control functions (EF) are broad theoretical concepts that subsume various cognitive abilities supporting the regulation of behavior, thoughts, and emotions (c.f. Inzlicht et al., 2021; Wiebe & Karbach, 2017). However, many of these concepts stem from different psychological disciplines relying on distinct methodologies, such as self-reports (common in SR research) and performance-based tasks (common in EF research). Despite the striking overlap between SR and EF on the theoretical level, recent evidence suggests that correlations between self-report measures and behavioral tasks can be difficult to observe (e.g., Eisenberg et al., 2019). In our study, participants from a life-span sample (14-82 years) completed self-report measures and behavioral tasks, which were selected to include a variety of different facets of SR (e.g., sensation seeking, mindfulness, grit, or eating behavior) and EF (working memory, inhibition, shifting). Using this broad approach, we systematically investigated connections and overlap of different aspects of SR and EF to improve their conceptual understanding. By comparing network models of a youth, middle-aged, and older-aged group, we identified key variables that are well connected in the SR and EF construct space. In general, we found connections to be stronger within the clusters of SR and EF than between them. However, older adults demonstrated more connections between SR and EF than younger individuals, likely because of declining cognitive resources.

(221 words)

Keywords: self-regulation, executive functions, cognitive control, cognitive aging, age-differences, network analysis

Age-Differences in Network Models of Self-Regulation and Executive Control Functions

Introduction

Executive control functions (EF) and self-regulation (SR) subsume various cognitive abilities supporting the regulation of behavior, thoughts, and emotions (Inzlicht et al., 2021; Wiebe & Karbach, 2017). However, the term EF has mostly been used in neurocognitive research, while the term SR is more common in educational and clinical psychology, for instance. The aim of this study was to bridge this gap and systematically assess the connections between a number of well-established EF and SR measures in order to learn more about the conceptual overlap and differences between EF and SR. Given that both constructs are subject to significant age-related changes across the lifespan (e.g., Geldhof et al., 2010; Lindenberger, 2014, for reviews) and because the correlations between cognitive abilities change as a function of age (e.g., Tucker-Drob et al., 2019, for a meta-analysis), we also investigated age-differences in the associations between EF and SR measures by means of network analyses.

Executive control functions and self-regulation

According to Miyake and colleagues (2000), EF are involved in controlling cognitive processing in complex tasks through the three basic functions working memory, inhibition, and shifting (cf. Bull & Scerif, 2001; Hermida et al., 2015). *Working memory* allows for the storage and manipulation of information required for other cognitive processes (Baddeley, 1992). The capacity of working memory varies across individuals and is a limiting factor for performance in complex tasks. *Inhibition* refers to the process of deliberate and controlled suppression of a prepotent, automatic, or dominant response and the control of distracting and interfering information (Miyake et al., 2000). *Shifting* is a process involved in switching between different tasks, operations, or mental sets (Monsell, 1996). From a mechanistic perspective, EF have been considered facets of memory and speed that are linked to corresponding white brain matter in the hierarchical watershed model of fluid intelligence (Fuhrmann, Simpson-Kent, Bathelt, CALM Team, & Kievit, 2020).

As summarized by a recent review, SR ‘is abroad term that refers to the dynamic process of determining a desired end state (i.e., a goal) and then taking action to move toward it while monitoring progress along the way’ (cf. Inzlicht et al., 2021, p. 321). Such goals can be, for example, desired behaviors, thoughts, emotions, task performances, attentional processes, or regulating impulses or appetites (cf. Vohs & Baumeister, 2016). Thus, there is striking overlap between SR and EF on the theoretical level (e.g., controlling attention or mental sets).

Despite the similarity of the constructs, neurocognitive research has long used performance-based behavioral measures to assess EF, while SR is typically assessed by self-report questionnaires. Considering their theoretical overlap, it seems reasonable to assume that empirical measures of EF and SR should be substantially correlated. However, recent evidence suggests that correlations between performance on behavioral EF tasks and SR self-report measures can be difficult to observe: Duckworth and Kern (2011) investigated their convergent validity in a meta-analysis (k = 282 samples, N = 33,564 subjects) and found ‘moderate convergence as well as substantial heterogeneity in the observed correlations. Correlations within and across types of self-control measures were strongest for informant-report questionnaires and weakest for executive function tasks’ (Duckworth & Kern, 2011, p. 259). Saunders and colleagues (2018) found in a small meta-analysis (five data-sets; N = 2,641) little to no relations between two indicators for the EF component inhibition (Stroop Task and Flanker Task) on the one side and the Self-Control Scale as indicator for SR on the other side. Another study (Nęcka et al., 2018) also showed no relations between latent EF and latent SR measures (N = 296). Similarly, Eisenberg and colleagues (2019) had 522 subjects aged between 18 and 50 years complete behavioral EF tasks (129 variables), and SR questionnaires (64 variables). They found that measures were mostly unrelated across EF and SR domains using a data-driven approach with a graphical lasso algorithm.

Thus, the empirical evidence for the relationship between EF and SR is not as straightforward as theoretical accounts on this issue suggest. Hofmann and colleagues (2012) argue for the integration of both concepts as EF might be basic processes supporting SR, contributing to outcomes as a predictor, process moderator, or mediator: (1) Working memory might be necessary for SR to provide mental representations of goals and related information. As attention is a limited resource, distracting stimuli might compete with goals in working memory, and studies support the idea that subjects with higher working-memory capacity might have a higher ability to resist distractions in their processing such as ruminative thoughts, unwanted affect, desires, or cravings (e.g., to consume sweets; 2012; Friese et al., 2010; Hofmann et al., 2008;). (2) Behavioral inhibition should be necessary for SR as it helps to suppress prepotent impulses or bad habits competing with goals (e.g., impulsive behavior, Houben & Wiers, 2009; Payne, 2005). (3) Shifting could be beneficial for SR with regard to abandoning suboptimal goals and adapting to new, more relevant ones. However, it could also be detrimental for SR when neglecting an SR goal in favor of tempting alternatives (Hofmann et al., 2012).

A recent model that integrates EF and SR was proposed by Bailey and Jones (2019). They integrated the concepts of EF and effortful control, a construct predominantly used in temperament research, referring to the ability to intentionally manage thoughts, attention, emotions, and behavior. In their model, they complemented the core EF abilities working memory, inhibition, and shifting with attention control as fourth regulatory core process. These abilities are assumed to form the basis for three domains of regulation: cognition, emotion, and social interactions. From a developmental perspective, they argue that the core processes start to differentiate from generic regulatory skills that are present in early childhood. Those core processes are then more and more applied in the three regulatory domains, which leads to domain-specific learning in middle to late childhood. Through this development, the authors propose integrating the regulatory domains into what they call a 'regulatory gestalt that supports increasingly more complex and sophisticated behavior' (Bailey & Jones, 2019, p. 10). The model assumes four levels of complexity: 1) simple skills, such as working memory, inhibition, shifting, and attention control, 2) complex skills, such as planning or emotion regulation, that integrate multiple simple skills and additional knowledge (cf. Doebel, 2020), 3) multi-component skills, such as EF and effortful control, that draw on simple skills, and 4) umbrella skills, such as self-regulation, that are based on a set of diverse cognitive and emotional skills. Thus, Bailey and Jones (2019) proposed a higher-order factor based on multi-component skills, such as EF.

Given the sophisticated theoretical models for the integration of EF and SR, the question arises why recent empirical studies do not show stronger interrelations of EF and SR measures. Wennerhold and Friese (2020, p. 1) discussed this for one EF ability (inhibition) and suggested that the lack of connections between SR and inhibition could be related to the following reasons: '(1) the distinction between typical and maximum performance, (2) the measurement of single versus repeated performance, and (3) differences between impulses in different domains.' Especially the difference between typical and maximum performance is an issue that should be investigated in the context of aging because cognitive functions are known to decline over the lifespan (e.g., Baltes et al., 1999; Salthouse, 2012, for reviews).

Age-related changes in executive functions and self-regulation

The development of EF follows a multidirectional and multidimensional course across the lifespan (Wiebe & Karbach, 2017). In early and middle childhood, EF evolve from a more general EF ability, best described as a general factor (Brydges et al., 2014), to a differentiated three-factorial structure (with working memory, inhibition, and shifting; Lehto et al., 2003; Shing et al., 2010) that already resembles the EF structure found in adulthood. In this transition, performance on the corresponding tasks improves considerably, and fundamental changes occur in the cognitive systems that enable EF. This process is closely linked to the development of corresponding neural networks in the prefrontal cortex that are associated with EF (Chevalier & Clark, 2017; Karbach & Unger, 2014). While all three core functions develop rapidly in early and middle childhood, inhibition and shifting mature earlier than working memory, which is not fully developed until late adolescence (Crone et al., 2017). In older age, working memory is also the first core EF showing age-related decline, mirroring age-related changes in the underlying neural circuits (Karbach & Unger, 2016; Li et al., 2017), followed by a decline in shifting and inhibition.

The development of SR follows a similar trajectory (Geldhof et al., 2010): Before adolescence, SR develops primarily as a function of attention and inhibition, which can reach adult levels at the end of childhood. In contrast, the ability to perform SR in more complex tasks continues to develop into adulthood. In middle adulthood, SR reaches its highest levels and remains at a stable plateau over a longer period of time. Changes in SR occur mainly as fine-tuning of already existing capabilities. In later adulthood, SR is affected by cognitive decline but might also be involved in moderating effects of this decline (Freund & Baltes, 2000). SR might show bigger declines in domains that rely on fluid abilities, whereas those relying on crystallized abilities might be less impacted.

The present study

The first aim of this study was to systematically test the connections between EF and SR across a range of well-established performance-based behavioral and self-report measures by means of network analyses. As theoretical models differ in terms of the level of analysis (e.g., trait vs. state), the extent to which they emphasize conflict (including emotions), and the type of cognitive functions they stress (Inzlicht et al., 2021), we included a broad range of measures for different facets of SR as well as for the three core EF. The SR measures in the present study were chosen to include different foci on conflict (e.g., Brief Self-Control Scale vs. Sensation Seeking) and to include emotional aspects (Emotion Regulation Questionnaire).

Regarding EF, we chose six well-established tasks assessing working memory, inhibition, and shifting (Miyake et al., 2000).

As previous studies on the relationship between EF and SR did not include differentiated models for different age groups, the second aim of this study was to examine whether networks of EF and SR showed different structures in youth, middle age, and older age. Therefore, we recruited a sample with a large age range (14-82 years of age). Following a comprehensive review published in The Lancet by Sawyers and colleagues (2012; 2018) and recommendations from the United Nations, we defined youth as individuals up to 24 years of age and compared them to a middle-aged group (25-49 years of age) and an older-aged group (50+ years of age). We investigated differences in the connections of EF and SR between these three age groups by estimating network models. These exploratory models allowed us to identify key variables and patterns of connections in the respective age groups' networks on an observed level. Network models are a relatively new method in this area of research (only the study by Eisenberg and colleagues, 2019, used a network approach) whereas they are already more established in the field of emotion research (e.g., Fried et al., 2016; Giuntoli & Vidotto, 2020; Lange et al., 2020). Based on previous evidence (Allom et al., 2016; Duckworth & Kern, 2011; Eisenberg et al., 2019; Nęcka et al., 2018) and theoretical models (Bailey & Jones, 2019; Hofmann et al., 2012), we expected to find cluster structures of EF and SR measures in terms of stronger connections within than between/across domains. However, given that we included a large age range, patterns of connections might differ from previous findings, e.g., with regard to the distinction between typical and maximum performance, where stronger connections between EF and SR could be possible due to decline of cognitive functions in older age. As the network model analysis is as of now a primarily exploratory method, our approach does not allow for hypotheses testing. Therefore, assumptions derived from theoretical models cannot be tested against the data.

Method

Participants

The sample consisted of 333 participants aged between 14 and 82 years (M = 38.65 years, SD = 18.87; 58.0% female). They were recruited online; 16.5% were school students, 21.9% university students, 50.7% employees, and 13.5% were retired. They had the following education level: *without basic school graduation*: 9.3%, *basic school graduation*: 6.0%, *finished vocational training*: 29.1%, *high school graduation*: 13.2%; *bachelor's degree*: 13.2%; *master's degree*: 22.2%; *PhD*: 3.0% (other: 3.9%, *no information*: 0.1%) Participants were included if they were fluent in German and reported no diagnosed mental or physical conditions impairing cognitive performance or self-regulation. The sample was divided into three age groups: the youth group (14–24 years of age; M = 19.25, SD = 3.06; 62.6% female; n = 107), the middle-aged group (25–49 years of age ; M = 34.54, SD = 7.97; 53.0% female; n = 117), and the older-aged group (50–82 years of age ; M = 62.11 years, SD = 8.34; 58.7% female; n = 109). Between-group comparisons (χ^2-test) showed no differences between the three groups in terms of gender distribution (p = .34).

Procedure

Participants were recruited online and registered by answering an online demographic questionnaire. From 1067 registered persons, 625 candidates were invited to participate in the study. They were randomly selected if they fulfilled the inclusion criteria with the restriction that age groups were represented equally well. Of 506 individuals who started the study, 167 aborted the study (about 33% dropout), and six did not provide a valid answer for their age and were therefore excluded from the analysis, resulting in a final sample of 333 participants

The study comprised two online sessions (total testing time: about 120 minutes). We used nine questionnaires to assess 12 different facets of self-regulation as well as six different tasks measuring EF. All questionnaires and tasks were administered online and completed on computers or laptops (no tablets or smartphones). Each session consisted of three EF tasks and three of the SR questionnaires plus further control variables on day one and six SR questionnaires on day two. The order of the EF tasks was balanced by the domain of EF (day one: Corsi Block Backwards, Flanker Task, Task Switching; day two: Wisconsin Card Sorting Task, Stroop Test, N-Back Task). For each session, the order of SR and EF measures was counterbalanced across participants (i.e., 50% started with the SR measures). All participants provided written informed consent – for minors, parents provided informed consent as well. They were compensated with 10€ in total or course credit for completing the two sessions.

As precise estimates of sensitivity, specificity, and correlations depend on the expected network structure, power analyses for network models are not trivial (Epskamp & Fried, 2018). According to simulation studies, estimating a lasso regularized network generally results in high specificity, while sensitivity and correlations depend on sample size (e.g., Epskamp, 2016; Foygel & Drton, 2010; van Borkulo et al., 2014). Therefore, we calculated simulations with 5000 iterations each, using the refitted networks for the three age groups as the true network (see Figure A1, A2, and A3), to estimate sensitivity, specificity, and correlations between true and estimated networks for different sample sizes, as well as centrality indices. For $N = 100$ cases, mean correlation with the true network was .76, .81, and .77 (for the youth group, middle-aged group, and older-aged group) and mean sensitivity .76, .76, and .78, and mean specificity was .81, .89, and .76. Therefore, we concluded that for the planned network models, the three samples with $N > 100$ participants each fulfilled the necessary power considerations.

Measures

Self-Regulation Questionnaires

Barratt Impulsiveness Scale (Preuss et al., 2003; Patton et al., 1995)

The German version of the *Barratt Impulsiveness Scale* (Preuss et al., 2003) was administered to measure impulsiveness. Participants rated how often they showed a specific behavior like ‘I do things without thinking.’. The items were rated on a scale from 1 (never/rarely) to 4 (almost always/always). The scale consisted of 30 items. We calculated one mean impulsiveness score, which showed an acceptable internal consistency (Cronbach's alpha = .76).

Behavioral Inhibition System and Behavioral Approach System Questionnaire (Strobel et al., 2001; Carver & White, 1994)

We used the German adaption of the Behavioral Inhibition System and Behavioral Approach System Questionnaire (Strobel et al., 2001) to measure behavioral inhibition and behavioral approach as two systems that underlie behavior and affect. Participants indicated whether or not seven statements like 'Even if something bad is about to happen to me, I rarely experience fear or nervousness.' for behavioral inhibition or 13 statements like 'When I want something, I usually go all-out to get it.' for behavioral approach described them well. The items were rated on a scale from 1 (does not apply at all) to 4 (applies exactly). Four additional items were dummies. The items of both scales were aggregated by calculating mean scores and internal consistencies (Cronbach's alpha) were .81 for behavioral inhibition and .73 for behavioral approach.

Brief Self-Control Scale (Bertrams & Dickhäuser, 2009; Tangney et al., 2004)

The German version of the Brief Self-Control Scale (Bertrams & Dickhäuser, 2009) was administered to measure dispositional self-control capacity. Participants chose how much a statement like 'I am good at resisting temptation' reflected how they typically behaved. The items were rated on a scale from 1 (not at all) to 5 (very much). We calculated a mean brief self-control score, which showed good internal consistency (Cronbach's alpha = .84).

Emotion Regulation Questionnaire (Abler & Kessler, 2009; Gross & John, 2003)

We used the German adaption of the Emotion Regulation Questionnaire (Abler & Kessler, 2009), which tests for the two common regulation strategies *reappraisal* and *suppression*. Participants were asked to which extend they agreed to six statements like 'I control my emotions by changing the way I think about the situation I'm in.' for reappraisal and four statements like ‘I control my emotions by not expressing them.’ for suppression. The items were rated on a scale from 1 (strongly disagree) to 7 (strongly agree). The items of both scales were aggregated by calculating mean scores and internal consistencies (Cronbach’s alpha) were .85 for reappraisal and .76 for suppression.

Grit Scale (Schmidt et al., 2017; Duckworth & Quinn, 2009)

The German version of the Grit Scale (Schmidt et al., 2017) was used to measure the ability to persistently pursue long-term goals while overcoming challenges or obstacles. Participants had to indicate whether statements like ‘I often set a goal but later choose to pursue a different one.’ described them well. The scale consisted of eight items. The items were rated on a scale from 1 (does not apply at all) to 4 (applies exactly). We calculated one mean grit score, which showed acceptable internal consistency (Cronbach’s alpha = .77).

Three-Factor Eating Questionnaire (Löffler et al., 2015; Karlsson et al., 2000)

From a German adaption of the Three-Factor Eating Questionnaire (Löffler et al., 2015), which covers cognitive restraint, disinhibition, and hunger as three domains of eating behavior, we only used the six items for *cognitive restraint*. The questionnaire was translated to German followed by a back-translation. Participants expressed how much they agreed to statements like ‘I deliberately take small helpings as a means of controlling my weight.’, scoring from 1 (definitely true) to 4 (definitely false). We calculated a mean score for eating cognitive restraint, which showed good internal consistency (Cronbach’s alpha = .85).

Mindful Attention and Awareness Scale (Michalak et al., 2008; Brown & Ryan, 2003)

We used the German adaption of the Mindful Attention and Awareness Scale (Michalak, et al., 2008) to measure consciousness. Participants were asked to rate how often they currently had a specific experience like ‘I could be experiencing some emotion and not be conscious of it until some time later.’. The items were rated on a scale from 1 (almost always) to 6 (almost never). We calculated one mean mindful attention and awareness score, which showed good internal consistency (Cronbach's alpha = .86).

Sensation Seeking Scale Form V (Beauducel et al. 2003; Zuckerman, 1971)

The German version of the Sensation Seeking Scale (Beauducel et al., 2003) was used to assess the tendency to have diverse, new, complex and intensive experiences and the willingness to take physical, social, legal, and financial risks in order to have these experiences (Zuckerman, 1994). Participants chose between 40 statements like 'I prefer quiet parties with good conversation.' and 'I like 'wild' uninhibited parties.', which were encoded as 0 or 1, with 1 representing stronger sensation-seeking behavior. We calculated one mean general sensation-seeking score, which showed good internal consistency (Cronbach's alpha = .83).

Theories of Willpower Questionnaire (Job et al., 2010)

We used a German version of the Theories of Willpower Questionnaire (Job et al., 2010) to assess the capacity to exert self-control with the two dimensions strenuous mental activity and resisting temptations. The questionnaire was translated to German followed by a back-translation. Participants indicated how much they agreed with statements like 'After a strenuous mental activity, your energy is depleted and you must rest to get it refueled again' or 'Resisting temptations makes you feel more vulnerable to the next temptations that come along.'. The items were rated on a scale from 1 (strongly agree) to 6 (strongly disagree). Each scale comprised six items. The items of both scales were aggregated by calculating mean scores and internal consistencies (Cronbach's alpha) were .81 for strenuous mental activity and .74 for resisting temptations.

EF Tasks

Verbal-visual WM: N-Back Task (Gevins & Cutillo, 1993)

Participants saw a sequence of stimuli and were to indicate whether the currently presented stimulus matched the one presented *n* steps earlier in the sequence or not by pressing one of two response keys. They started with one practice block of 10 2-back trials and continued with two experimental 2-back blocks of 24 trials as well as two 3-back blocks of 24 trials. Pictures were presented for 1000ms and participants had a maximum of 2000ms to answer. The score was aprime as a combined value of hits and false alarms in the 2-back and 3-back blocks. To adjust the skewness of the distribution we computed ln(1+1-aprime).

Visuospatial WM: Corsi Block Backwards Task (Kessels et al., 2008)

In the Corsi Block Backward Task, participants remembered a sequence of green squares that was presented on a black background on four different positions, which corresponded to four different response keys on the computer keyboard. Participants repeated this sequence in inverted order by pressing the respective response keys. The sequence started with a length of two squares and adapted after one correct response by increasing the sequence length by one additional square. After two consecutive wrong responses, the block ended. The whole task consisted of one practice and one experimental block, and the test score was the maximum correct sequence length in the experimental block. To adjust the skewness of the distribution we computed ln(maximum correct sequence length).

Shifting: Task Switching (Rogers & Monsell, 1995)

For Task Switching, participants were presented with numbers from one to nine and had to decide if the numbers were odd vs. even (Task A) or if the numbers were smaller or larger than five (Task B) by pressing corresponding response keys. In single-task blocks, they were instructed to perform either task A or task B. In mixed-task blocks they were to switch tasks after three trials (AAABBB). The task consisted of two single-task practice blocks (9 trials, respectively) and one mixed-task practice block (18 trials), followed by two single-task experimental blocks (24 trials, respectively) and two mixed-task experimental blocks (48 trials, respectively). We computed mean reaction times (RT) in switch and stay trials (trials not requiring to switch the task) to calculate specific switch costs (switch – stay).

Shifting: Wisconsin Card Sorting Task (Berg, 1948)

Participants were required to identify a card sorting rule by trial and error. A card had a (1) number of objects in a unique (2) shape on it as well as a unique (3) background. One card was presented on the top of the screen, and four different cards that matched all possible sorting rules were shown below, and the participant had to press keys on the computer keyboard corresponding to these four cards. After each response, participants received informative feedback. The sorting rule constantly changed after nine cards. The task started with one practice block with 27 cards. After that, the participants completed two blocks with 54 cards, respectively. The test score was the percentage of perseveration errors. To adjust the skewness of the distribution we computed ln(percentage of perseveration errors + 0.5).

Inhibition: Flanker Task (Eriksen & Eriksen, 1974)

Stimuli consisted of five arrows, all oriented in the same direction (congruent trials), or the middle arrow was oriented in the opposite direction (e.g., left-left-right-left-left; incongruent trials). The goal was to respond to the central target arrow (left or right). Participants were instructed to respond as quickly as possible by pressing the corresponding response keys while maintaining accuracy. Six practice trials were followed by five experimental blocks with 20 trials each. Stimuli were presented in a randomized order within the experimental blocks. We calculated inverse efficiency scores as proposed by Gärtner and Strobel (2021) using RT and error rates (ER) from congruent and incongruent trials with the following formula: $(RT_{incongruent}/[1–ER_{incongruent}]) – (RT_{congruent}/[1–ER_{congruent}]))$. To adjust the skewness of the distribution we computed ln(inverse efficiency score + 300).

Inhibition: Stroop Task (Stroop, 1935)

Participants were presented with color words (red, green, blue, and yellow) written in the same (congruent trials) or a different color (incongruent trials). They had only to pay attention to the color and not to the word's meaning and press a corresponding response key. Participants were instructed to respond as quickly as possible while maintaining accuracy. Twelve practice trials were followed by four experimental blocks with 24 trials each. We calculated inverse efficiency scores as described above for the Flanker Task, using RT and ER from congruent and incongruent trials. To adjust the skewness of the distribution we computed ln(inverse efficiency score + 200).

Data Analyses

Network Models

We estimated three regularized auto correlation network models of SR and EF (one per age group), using the statistic software R (version 4.0.4; R Core Team, 2021) using the package *bootnet*, following the approach described by its authors (Epskamp et al., 2018; Epskamp & Fried, 2018). However, instead of the default extended Bayesian information criterion (EBIC; Foygel & Drton, 2010), we used the ordinary Bayesian information criterion (BIC) for model selection. EBIC was initially developed for the case of a combination of moderate sample sizes and a large number of covariates (e.g., in genome-wide association studies; Chen & Chen, 2008). In comparison, our networks are relatively small, and therefore, we wanted to avoid too strict regularization in the graphical lasso algorithm (Friedman et al., 2014), which otherwise could lead to networks without connections being estimated. Furthermore, to adjust for non-normality in the data, we selected the corresponding option in the model estimation for Gaussianization to help relax the assumption of normality. Differences between age groups were tested with the *NetworkComparisonTest* developed by van Borkulo and colleagues (2017). We used bootstrapping to assess network stability (Epskamp et al., 2018) for edge weights and centrality indices. In addition, following

Southworth and colleagues (2009), we calculated graphical difference networks between the youth and middle-aged group as well as between the middle-aged and older group-aged by subtracting the weights of one group from the corresponding weights of the other group.

Results

Descriptive Statistics

Please see Table A1 for descriptive statistics for all three age groups. Correlations between the EF and SR measures are presented in Table A2 for the youth group, in Table A3 for the middle-aged group, and in Table A4 for the older-aged group.

Network analysis

First, we estimated one network model per age group (Figure 1, 2, and 3) and tested for network structure invariance, which revealed that the differences between the network structures between the youth and middle-aged group (M = 0.290, p = .137) as well as between the middle- and older-aged group (M = 0.190, p = .895) were not significant, which is a basis for calculating difference networks. Tests for invariance of global strength showed no significant differences between the age groups (youth and middle-aged group: S = 1.936, p = .486; middle- and older-aged group: S = 1.078, p = .669). Thus, as the overall connection strength and overall level of connectivity are comparable across age groups, specific differences between networks are less likely measurement artifacts (e.g., differential measurement error/noise) and more likely of content-related nature (e.g., differential importance of nodes in the age groups). On this basis, we calculated difference networks using the difference of corresponding edge-weights in the respective groups' network models (Figure 4 and 5).

For the youth group (Figure 1) as well as for the middle-aged group (Figure 2), connections were stronger within EF and SR measures than between them. When comparing these two networks, the level of connectivity strength within the SR measures was lower in the middle-aged group than in the youth group, which is also supported by the difference network (Figure 4), where we found few increasing connections and many decreasing connections. In the network for the older-aged group, connections still tend to be strong within EF and SR measures. At the same time, we found more connections (more than in both younger groups) between EF and SR measures, which is also supported by the difference network between the middle- and older-aged group, with few decreasing connections and many increasing connections (Figure 5).

The centrality index node strength[2] (Figure A4) shows that SR measures were most central in the youth group, with Grit Scale, Theories of Willpower resisting temptation, and Behavioral Inhibition System being in the top three. As shown in the youth network model (Figure 1), all three demonstrated multiple connections to other SR measures. Theories of Willpower resisting temptation and Behavioral Inhibition System were closely connected to each other and Grit Scale was closely connected to Mindful Attention and Awareness Scale. In the middle-aged group, SR measures are still most central, but centrality of EF increases, with Brief Self-Control Scale, Grit Scale, and n-back Task being in the top three. As shown in the network model (Figure 2), all three demonstrated multiple connections of moderate size to other variables. Besides, Brief Self-Control Scale was closely related to the Barratt Impulsiveness Scale, Grit Scale was closely connected to Mindful Attention and Awareness Scale (as found for the youth group) and n-back Task was closely connected to Flanker task. This trend for increased centrality of EF continues when looking at the node strength of the older-aged group. Now Wisconsin Card Sorting Task, Stroop Task, and Grit Scale were in the top three. As shown in the network model (Figure 3), all three demonstrated multiple connections to other variables. Wisconsin Card Sorting Task was closely related to n-back Task. Notably, Stroop Task had a close connection to Sensation seeking and Grit Scale had a close connection to Flanker task, demonstrating a close link between EF and SR measures.

In the next step, we tested whether the observed network structures and the centrality index node strength could be assumed as stable. Therefore, we calculated bootstrapped confidence intervals for the edge-weights of all three networks (Figure A5), often indicating

[2] Node strength quantifies the direct connection to other nodes.

no overlapping confidence intervals of strong and weak edge-weights (but of middle-sized edge-weights).

If the sample size was lowered the bootstrapped centrality index node strength was quite stable in all three networks (Figure A6). Difference tests can be conducted for the centrality index node strength (Figure A7). In the youth group, Grit Scale, Theories of Willpower resisting temptation, and Behavioral Inhibition System had a node strength, which was significantly different from other nodes. In the middle-aged group, Task Switching, Flanker Task, and Eating Questionnaire (cognitive control) had significantly smaller node strengths than some other tasks. In the older-aged group, Wisconsin Card Sorting Task, Stroop Task, Grit Scale, Behavioral Inhibition System, N-Back Task, and Theories of Willpower resisting temptation had a node strength, which was significantly different from other nodes. As discussed by Epskamp and colleagues (2018), multiple testing is a known but still unresolved issue in the research field of psychological network estimation, which must be considered in the context of the difference tests mentioned above.

Discussion

The aim of this study was to test connections between executive function (EF) and self-regulation (SR) measures in different age groups by means of network analyses. Consistent with our expectations, we found that in youth and middle adulthood connections between variables were stronger *within* the domains of EF and SR (Figure 1 and 2), whereas this pattern of clustering within domains was less pronounced in the older adults' network and more connections *between* the two domains were present (Figures 3 and 5). The youth sample demonstrated more connectivity within SR than middle-aged adults (Figure 4). Further, when looking at node strength as a measure of centrality, we found that EF measures became more central than SR measures with increasing age. In the youngest age group, the Grit Scale was most central, in the middle-aged group the Brief Self-Control Scale, and in the oldest group the Wisconsin Card Sorting Task. As the Grit Scale measures perseverance of long-term goals, its high centrality in the youngest group fits well with the life stage of the participants at this age, who are in school and training settings or at the beginning of their professional career, for which this skill is very important. Because the Brief Self-Control Scale measure is associated with various domains like, for example, personal relations, well-being, planning, decision making, eating, work, and addictions (de Ridder et al., 2012), its high centrality in the middle-aged group fits well with the heterogenous SR requirements in middle adulthood (e.g., regarding work and family life). The Wisconsin Card Sorting Task may be a key variable in older age, as it draws not only on its main process shifting ability, but also on the other EF domains working memory and inhibition (e.g., Gamboz et al.2009) – which are all affected by cognitive aging (as discussed in the next section).

In the youth group, we found high connectivity for the two scales measuring Theories of Willpower strenuous mental activity and resisting temptations. The latter one was also highly connected with the Behavioral Inhibition System. Another connection path within SR spans from Sensation Seeking to Barratt Impulsiveness Scale, to Brief Self Control Scale, and ends at the cognitive control component of the Three Factor Eating Questionnaire. Mindful Attention and Awareness Scale and Grit Scale show a high connection as well. There were multiple strong connections within EF and across the three EF domains. The highest connections between SR and EF were the ones from the Mindful Attention and Awareness Scale to Stroop Task and Corsi Span Backward Task, which could be interpreted as supportive relationship between SR attention and EF inhibition and working memory. In the middle-aged group, we again found strong connections between the two Theories of Willpower measures, between Brief Self-Control Scale and Barratt Impulsiveness Scale as well as between Mindful Attention and Awareness Scale and Grit Scale, which were strong in the youth group, too. Connections within SR tended to be generally weaker than in the youth group. On the EF side, all tasks showed connections except Flanker Task and Task Switching. Between SR and EF, there was only one very small connection between N-Back Task and Sensation Seeking Scale. For the older-aged group, we again found the strongest SR connections between Theories of Willpower measures, between Brief Self-Control Scale and Barratt Impulsiveness Scale, as well as between Mindful Attention and Awareness Scale and Grit Scale. The EF tasks demonstrated more connections to each other than in the middle-aged group. In contrast to the other two age groups, we found more and stronger connections between SR and EF, with the strongest path between Stroop Task and Sensation Seeking Scale and between Flanker Task and Grit Scale.

A possible explanation for this pattern of findings could be that the EF tasks measure maximum performance. Most younger participants likely demonstrate sufficient cognitive functioning to support their SR goals and thus, motivational aspects should be more critical for successful SR in this age group. As cognitive abilities are known to decline with age (e.g., Tucker-Drob et al., 2019, for a meta-analysis), older subjects with lower maximum EF performance can reach the point where their reduced EF capabilities impact their everyday SR processes. This may have resulted in the stronger connections between the two domains and higher centrality of EF measures in the older adults' group compared to the younger groups. However, our cross-sectional design does not allow for causal conclusions and there are of course other explanations: Participants with higher SR may pay more attention to a 'healthy lifestyle' in comparison with participants with lower SR, engaging for example, in more physical and cognitive demanding activities and therefore preventing or at least delaying more substantial cognitive decline (e.g., Lindenberger, 2014, for an overview). A combination of both explanations is likely as well.

Another plausible mechanism would be that changes in a third variable impact both, EF and SR. For example, reliable personality changes develop over the life span (Roberts, Walton, & Viechtbauer, 2006, for a meta-analysis) which are closely related to the development of cognitive abilities (Wettstein, Tauber, Kuzma, & Wahl, 2017). For example, conscientiousness increases over the adult life span up to old age (Roberts et al., 2006). Thus, although older adults experience cognitive decline on average, they also gain functional resources which may foster the interplay between SR and EF. Conscientiousness was not only related to later long-term changes in cognitive performance (Wettstein et al., 2017), it was further related to daily health goal and social goal progress (Hooker, Choun, Mejía, Pham, & Metoyer, 2013) – indicating one of many possible mechanisms behind a closer coupling of SR and EF in old age.

For the youth group, our findings are primarily in line with previous research reporting that connections are low between EF and SR (Allom et al., 2016; Duckworth & Kern, 2011, Nęcka et al., 2018). The low relationship between EF and SR could also be caused by a method effect (performance measure vs questionnaires; Könen & Karbach, 2020; Meyer et al., 2001). However, the fact that the effect is less pronounced among the elderly could indicate that a method effect alone is not a sufficient explanation. Compared to the results from another study that used a network approach with a graphical lasso algorithm, we found more connections between the two domains (EF and SR) than Eisenberg and colleagues

(2019). However, they included far more variables and might therefore have chosen a stricter approach regarding regularization. At the same time, the general idea of regularization is to highlight strong connections and discard weak connections, which could lead to weak connections having a higher chance to be present in smaller networks than in larger ones, where many strong connections within the two domains of EF and SR are already present. Moreover, results are not fully comparable as they did not differentiate between different age groups and had an overall smaller range of age (18-50 vs. 14-82 years), but a larger total sample (N = 522 vs. 333).

Limitations of the present study include the fact that the older-aged group was still relatively young (mean age of around 62 years), which prevented us from investigating differences between old and very old adults (in which cognitive decline should even be more pronounced). A general limitation of performance-based EF measures is that their reliability is lower than that of SR questionnaires (Enkavi et al., 2019), facilitating the identification of stronger connections within the SR domain as compared to the EF domain. Furthermore, it is important to stress that the different measurement types (self-report for SR vs. performance tasks for EF) favor stronger connections between the domains of EF and SR than within them, which means that the existing connections might be underestimated. However, this effect is present in all age-groups and should not affect age-related differences.

There are also specific limitations to the network approach, because it is an explorative method that does not allow for causal conclusions in a cross-sectional research design. Furthermore, the centrality indices need to be interpreted cautiously because the approach is not yet fully developed (e.g., Bringmann et al., 2019). Therefore, we only reported node strength and not closeness and betweenness, as the latter two require the assumption of 'presence of flow and shortest paths' (Bringmann et al., 2019, p. 892) which might not hold in psychological networks. In the network approach, stability of centrality measures can be problematic (we investigated this possible issue with bootstrapping, see

Figure A6). When using difference tests for network models, multiple testing is a known and, till now, unresolved issue (Epskamp et al., 2018). For future research, it could be worthwhile to increase the age range as well as the number of participants to allow a finer resolution of age in terms of more groups and more comparisons (e.g., adding children and very old adults). The current research uses a cross-sectional design and could benefit from adding a longitudinal perspective investigating development over time (e.g., Salthouse, 2014).

Well-connected key variables of EF and SR are a starting point for further confirmatory research (e.g., with longitudinal designs). They provide a clear focus for testing specific hypotheses on the interplay of EF and SR to better understand the relations of these broad constructs and their modulating factors. Focused confirmatory research is necessary to generate an improved theoretical framework and overcome some of the inconsistencies in the way EF and SR have been defined and studied. Understanding the relations between SR and EF might also help building bridges between research from different disciplines such as cognitive or neurocognitive psychology and educational psychology. Thus, divergent results regarding correlates of SR and EF such as academic abilities could be better explained. Regarding practical applications, the key variables are promising candidates for designing interventions. As these variables are well connected with other facets of EF and SR, interventions targeting the underlying abilities could be most effective in achieving near (e.g., to similar cognitive tasks) and far transfer effects (e.g., to related tasks or activities of daily living). Those interventions could be used to support children struggling in school or older adults showing first difficulties in coping with their day-to-day tasks.

Conclusion

By comparing network models of a youth, middle-aged, and older-aged group, we identified key variables that are well connected in the SR and EF construct space. Network models can highlight the strength and number of connections between SR and EF and can be a helpful explorative tool to perform theory-driven analyses of connections between the variables of interest. We generally found stronger connections within the clusters of SR and EF than between them, but also substantial age differences in the network models with older adults demonstrating more connections between SR and EF than younger adults – likely because of declining cognitive resources. As the results are exploratory, further research is needed to understand the precise mechanisms behind these differential network structures – beyond established broad mechanisms such as cognitive aging.

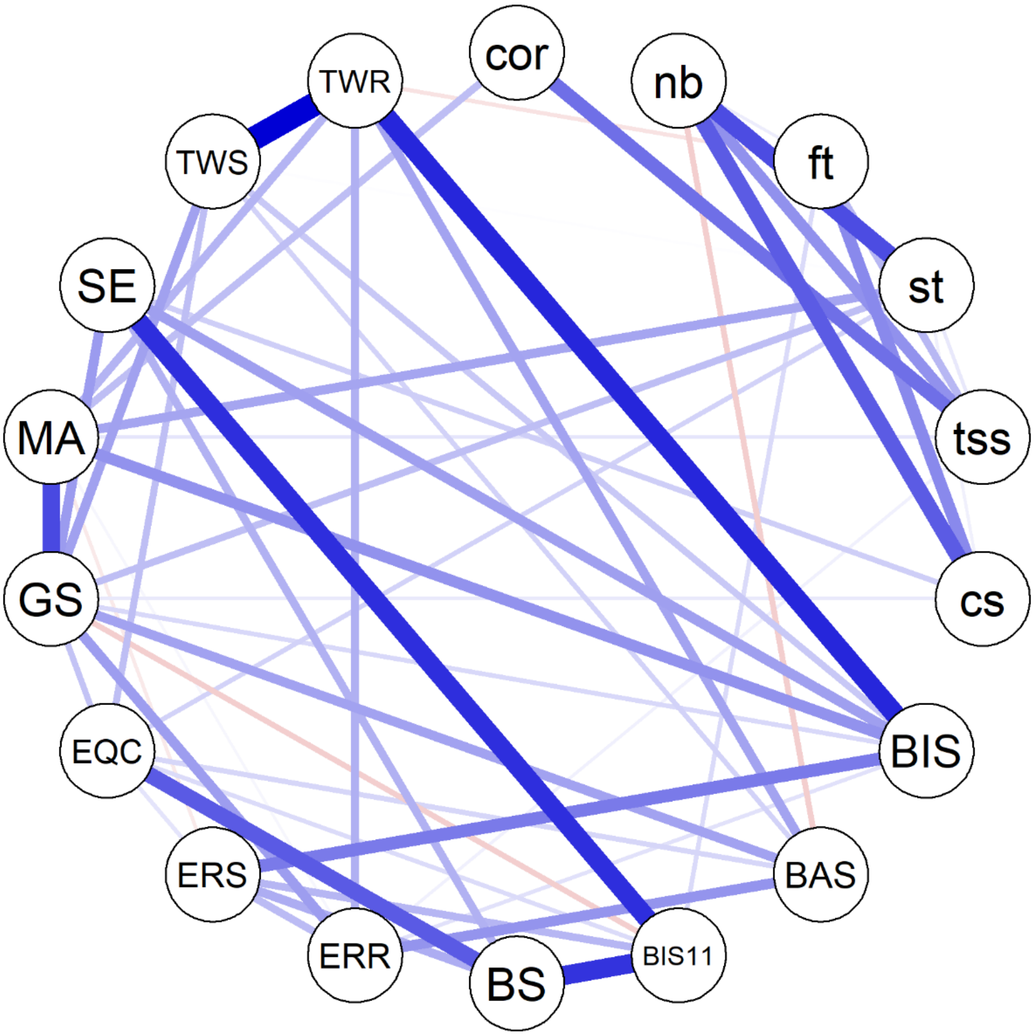

Figure 1. Network model for the youth group. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations). For comparability across age groups, networks are presented in a circular layout. Please find the structured network in the appendix (Fig. A8).

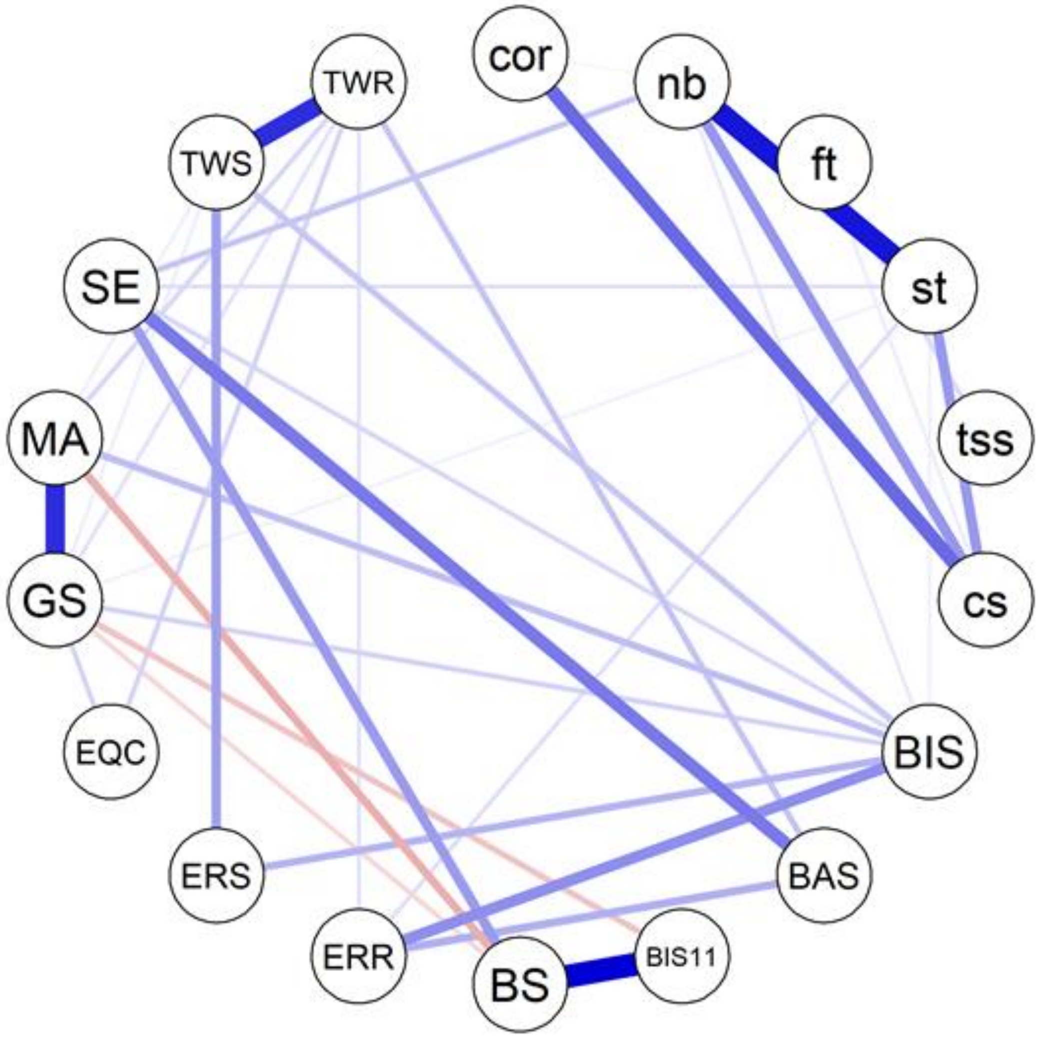

Figure 2. Network model for the middle-aged group. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations). For comparability across age groups, networks are presented in a circular layout. Please find the structured network in the appendix (Fig. A9).

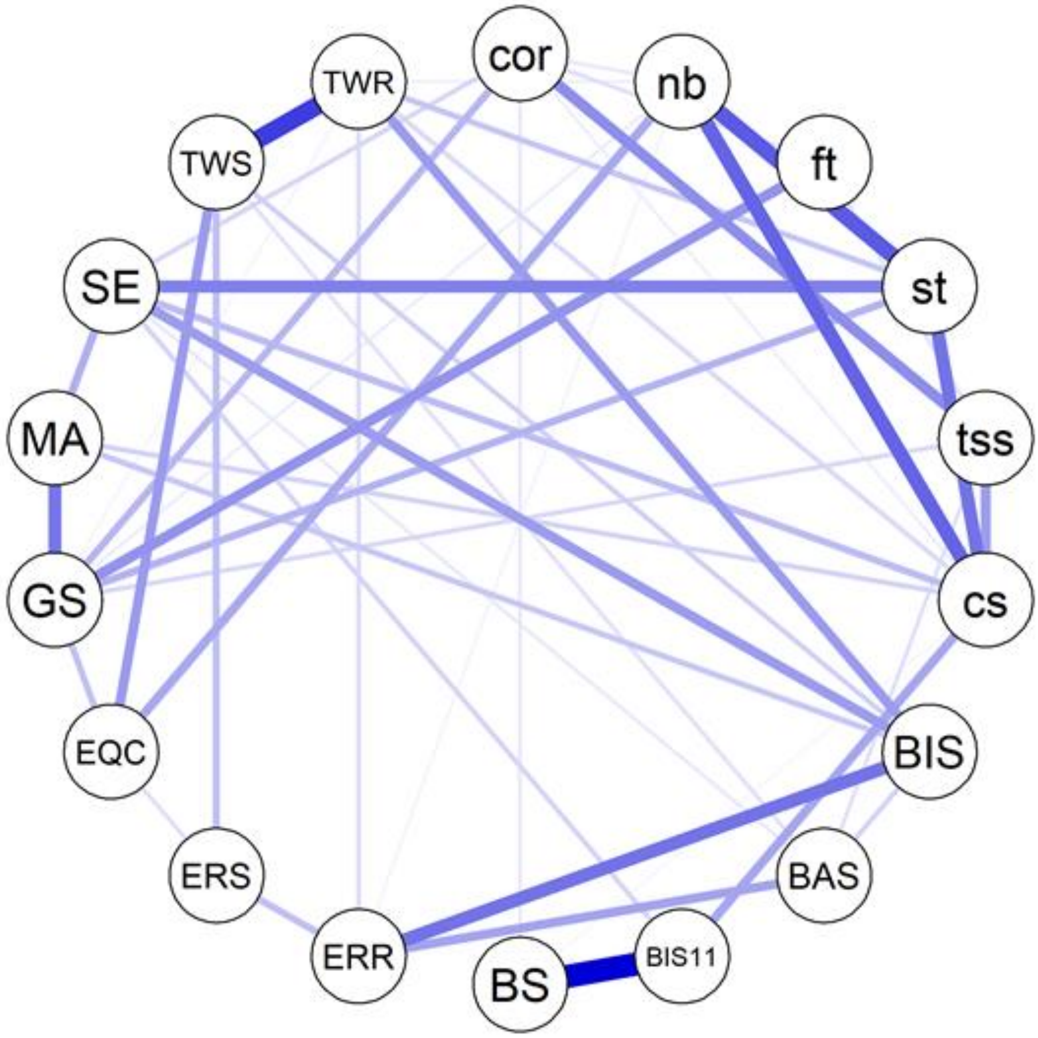

Figure 3. Network model for the older-aged group. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations). For comparability across age groups, networks are presented in a circular layout. Please find the structured network in the appendix (Fig. A10)

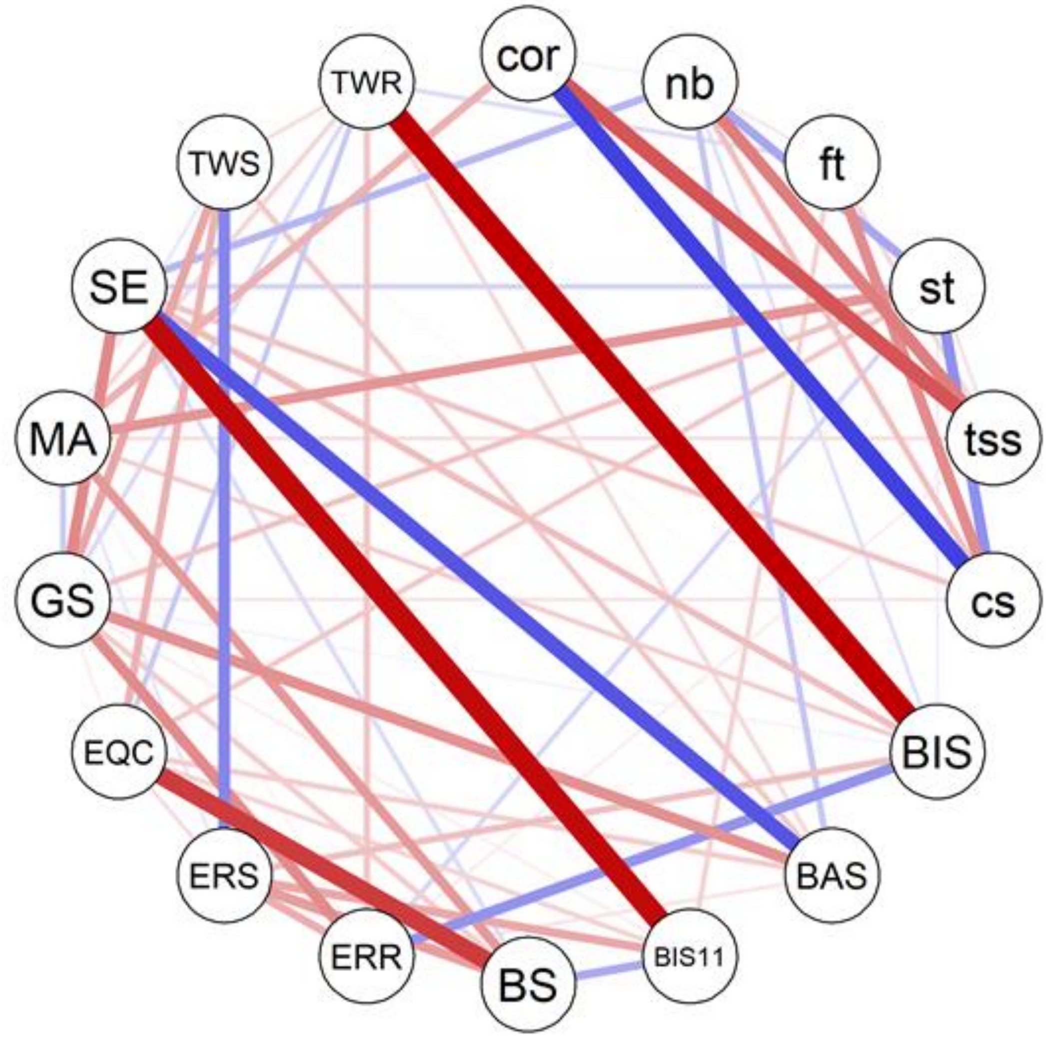

Figure 4. Difference between networks for the youth and the middle-aged group. Red corresponds to a decrease in connection strength from younger to an older age. Blue corresponds to an increase in connection strength from younger to an older age. Executive control functions are written in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations).

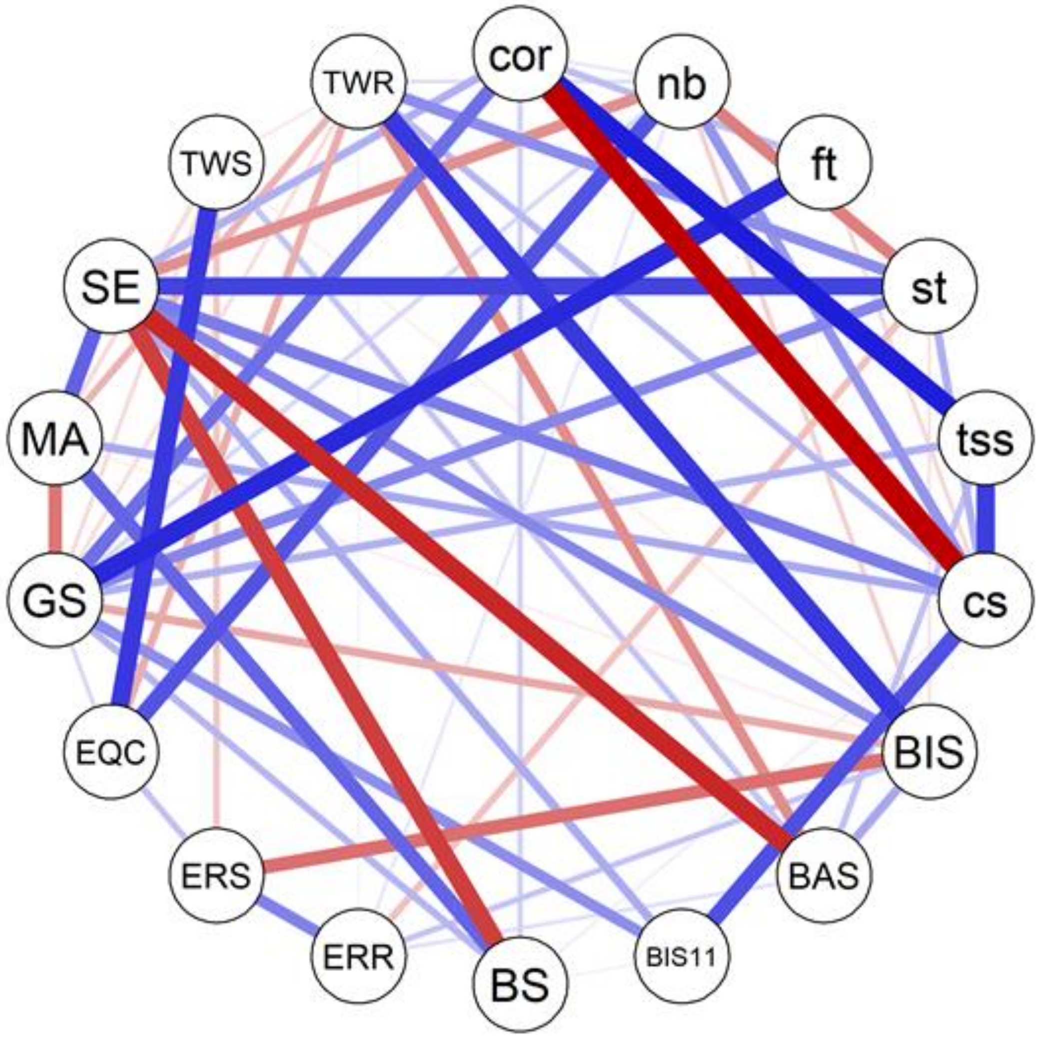

Figure 5. Difference between networks for the middle and older-aged group. Red corresponds to a decrease in connection strength from younger to an older age. Blue corresponds to an increase in connection strength from younger to an older age. Executive control functions are written in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations).

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9.4 Supplementary Material for Study 2

Table A1

Descriptive statistics for the three age groups

	Youth		Middle-Aged		Older-Aged	
	M	*SD*	*M*	*SD*	*M*	*SD*
Executive Control Functions						
Corsi Block Backwards Task	6.02	2.36	5.50	2.16	3.99	2.84
n-back Task	0.85	0.10	0.84	0.11	0.82	0.10
Flanker Task	58.66	33.00	51.63	27.54	44.38	31.58
Stroop Task	215.72	160.03	259.20	163.43	345.96	295.06
Task Switching	162.22	80.19	176.73	84.99	207.54	122.04
Wisconsin Card Sorting Test	0.05	0.04	0.05	0.05	0.08	0.06
Self-Regulation Measures						
BIS	2.99	0.63	2.95	0.50	2.87	0.48
BAS	3.14	0.31	3.02	0.32	2.99	0.35
BIS11	2.09	0.27	2.04	0.27	2.02	0.26
Brief Self-Control	3.06	0.35	2.92	0.36	2.81	0.31
ERQ Reappraisal	4.51	1.17	4.60	1.20	4.65	1.02
ERQ Suppression	3.99	1.30	3.72	1.26	3.64	1.35
Eating Cognitive Control	2.14	0.69	2.04	0.67	2.31	0.61
Grit Scale	3.24	0.65	3.41	0.59	3.49	0.48
MAAS	2.99	0.68	2.95	0.65	2.66	0.62
Sensation Seeking	0.52	0.14	0.44	0.16	0.35	0.15
TW Strenuous Mental Activity	2.78	0.86	2.79	0.82	3.00	0.82
TW Resisting Temptations	3.76	0.82	3.97	0.85	4.05	0.74

Note. Some scores are recoded for readability as they initially express costs. BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; ERQ = Emotion Regulation; MAAS = Mindful Attention and Awareness Scale; TW = Theories of Willpower.

Table A2

Correlations of executive control functions and self-regulation measures for youth

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. cor																	
2. nb	.02																
3. ft	.05	.01															
4. st	.03	**.29**	-.03														
5. tss	.19	.12	.09	.15													
6. cs	**.20**	**.24**	**.27**	.10	-.01												
7. BIS	-.02	-.01	.00	.00	-.10	-.01											
8. BAS	.09	-.18	.01	.06	.06	-.08	-.16										
9. BIS11	.00	-.09	.08	**-.21**	-.11	.03	.01	-.04									
10. BS	.07	.01	-.14	-.18	.02	-.04	-.18	.02	**.32**								
11. ERR	.01	.04	.08	.11	.08	.19	.10	.14	-.16	-.17							
12. ERS	-.03	-.08	-.12	**-.21**	-.16	-.06	.12	-.13	.17	**.21**	.03						
13. EQC	-.06	.02	-.18	.04	-.06	-.11	-.10	.11	.04	.15	-.05	.07					
14. GS	-.04	-.01	-.08	.15	-.09	-.05	**.30**	**.29**	**-.46**	**-.38**	**.26**	-.06	.01				
15. MA	**.21**	.03	.06	.12	.02	-.09	**.39**	-.03	**-.36**	**-.36**	.15	**-.31**	-.12	**.32**			
16. SE	.09	-.01	.03	-.07	-.03	.19	**.34**	.05	**.29**	.15	-.01	-.04	-.05	.06	-.05		
17. TWS	-.03	-.08	.15	.18	-.13	.08	**.20**	.10	-.16	-.06	-.01	-.08	.13	**.26**	.15	.09	
18. TWR	-.16	-.02	-.04	.15	-.01	-.04	**.39**	.13	**-.29**	**-.23**	.14	-.05	-.07	**.26**	**.25**	.03	**.46**

Note. Executive control functions are labelled in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations). Significant correlations are presented in bold typeface (p < .05).

Table A3

Correlations of executive control functions and self-regulation measures for middle-aged group

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. cor																	
2. nb	.12																
3. ft	-.11	-.10															
4. st	.10	**.36**	**-.21**														
5. tss	.03	-.16	.10	.01													
6. cs	**.33**	**.28**	**-.40**	**.33**	-.16												
7. BIS	.00	.02	.04	.10	.06	-.18											
8. BAS	.00	-.04	.12	.04	.06	-.06	.12										
9. BIS11	-.15	**-.21**	.00	-.17	-.10	-.05	-.03	.04									
10. BS	-.01	-.17	.05	-.01	-.01	-.05	-.11	.00	**.50**								
11. ERR	-.01	.05	-.05	.16	.04	.00	**.25**	**.21**	**-.22**	-.05							
12. ERS	.09	.01	.00	.12	.06	.04	**.22**	-.18	-.16	.04	.02						
13. EQC	-.13	**-.25**	-.02	-.06	.07	-.11	-.09	-.02	-.08	-.09	.03	-.11					
14. GS	-.04	.00	-.08	.11	.00	.00	**.22**	.15	**-.51**	**-.50**	.16	.04	.15				
15. MA	-.08	.07	.00	.00	-.01	-.06	**.27**	-.05	**-.45**	**-.52**	.02	-.18	-.03	**.44**			
16. SE	.01	-.02	.03	.17	.07	.03	.17	**.36**	.08	**.23**	.13	-.02	-.02	-.03	-.14		
17. TWS	.04	-.13	.04	-.14	-.04	-.13	**.21**	-.05	**-.31**	**-.25**	.09	**.25**	.08	**.24**	**.26**	-.16	
18. TWR	-.11	-.01	.00	.08	-.19	.01	.09	.19	**-.24**	**-.27**	.17	-.08	**.26**	**.27**	**.28**	.00	**.42**

Note. Executive control functions are labelled in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations). Significant correlations are presented in bold typeface ($p < .05$).

Table A4

Correlations of executive control functions and self-regulation measures for older-aged group

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. cor																	
2. nb	.14																
3. ft	.07	-.02															
4. st	.10	**.21**	.04														
5. tss	.15	-.01	.00	.10													
6. cs	**.21**	**.60**	.02	**.26**	**.23**												
7. BIS	.12	.13	-.04	.08	-.12	.01											
8. BAS	.01	-.01	-.05	.05	.10	-.05	.10										
9. BIS11	.06	-.05	.00	.03	.09	.16	-.04	.10									
10. BS	.04	-.03	-.02	-.11	-.03	-.06	**-.24**	.05	**.42**								
11. ERR	-.02	.13	-.20	-.04	-.09	-.15	**.26**	.17	-.01	.03							
12. ERS	-.10	-.06	**-.26**	-.16	-.17	-.10	-.01	-.19	-.10	.00	.07						
13. EQC	**-.26**	.09	.10	-.16	-.13	-.09	-.05	.03	**-.29**	-.09	.08	.14					
14. GS	.18	.12	**.24**	.14	.11	-.01	.08	.01	**-.45**	**-.42**	.07	-.09	.09				
15. MA	-.01	-.04	-.02	.11	-.09	.07	**.27**	-.10	-.18	**-.30**	-.01	-.17	-.17	**.25**			
16. SE	.14	.10	.00	**.29**	.00	**.21**	**.32**	.15	.19	.03	.06	-.11	-.14	-.04	.15		
17. TWS	.03	-.02	-.06	.01	-.04	-.04	.15	.08	-.11	-.03	-.08	.06	.19	.09	-.05	-.09	
18. TWR	.09	.17	-.04	**.24**	.00	.18	**.24**	-.05	-.17	**-.21**	.07	-.13	.02	.17	.14	.03	**.34**

Note. Executive control functions are labelled in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations). Significant correlations are presented in bold typeface ($p < .05$).

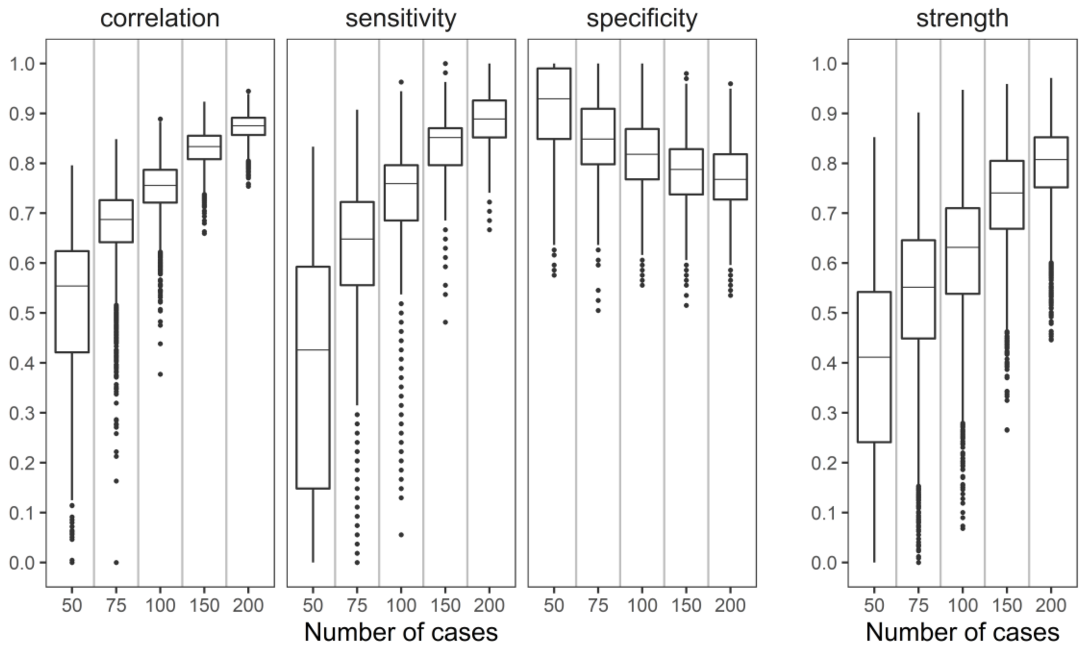


Figure A1. Simulation results using the estimated refitted networks for the youth age group as true network structure. Sensitivity, specificity, and correlation between true and estimated networks can be evaluated in the left side and the correlation between true and estimated centrality index node strength on the right side.

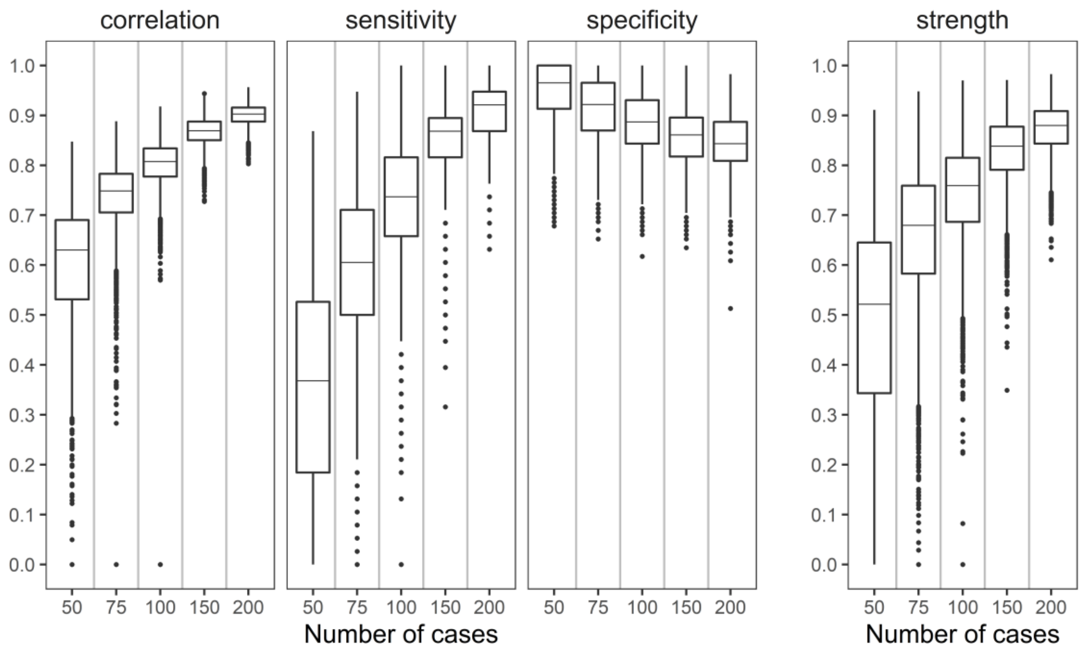


Figure A2. Simulation results using the estimated refitted networks for the middle-aged group as true network structure. Sensitivity, specificity, and correlation between true and estimated networks can be evaluated in the left side and the correlation between true and estimated centrality index node strength on the right side.

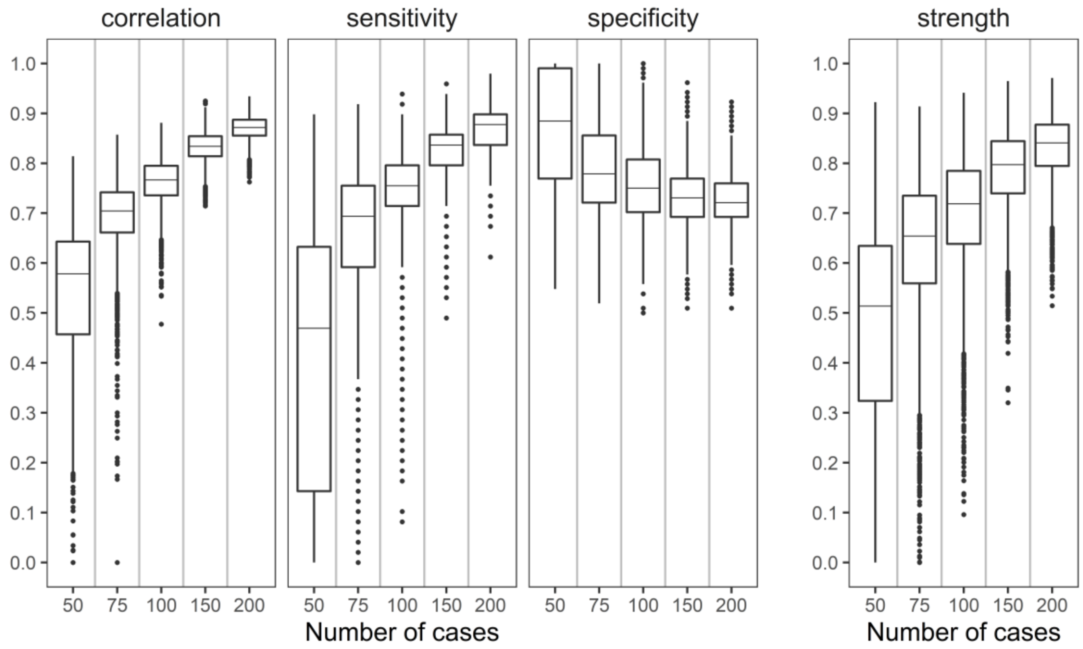


Figure A3. Simulation results using the estimated refitted networks for the older-aged group as true network structure. Sensitivity, specificity, and correlation between true and estimated networks can be evaluated in the left side and the correlation between true and estimated centrality index node strength on the right side.

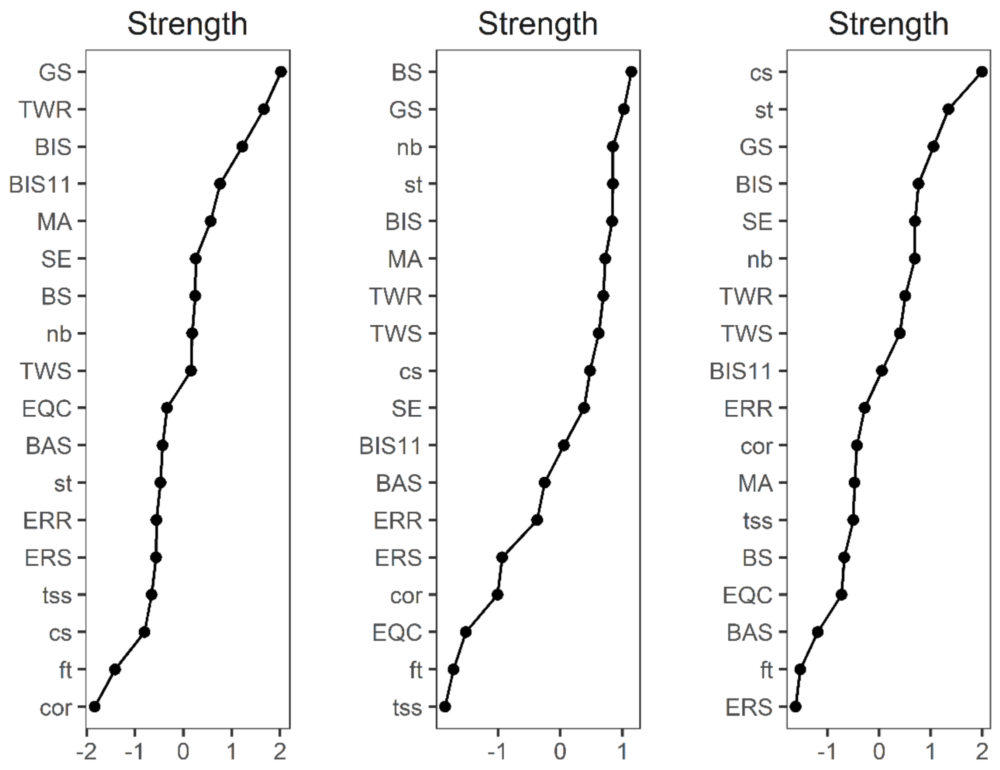


Figure A4. Centrality index node strength as standardized z-scores (left side: youth; middle: middle-aged group; right side: older-aged group). Node strength quantifies the direct connection to other nodes. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching (specific switch costs); cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation (suppression); EQC = Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations).

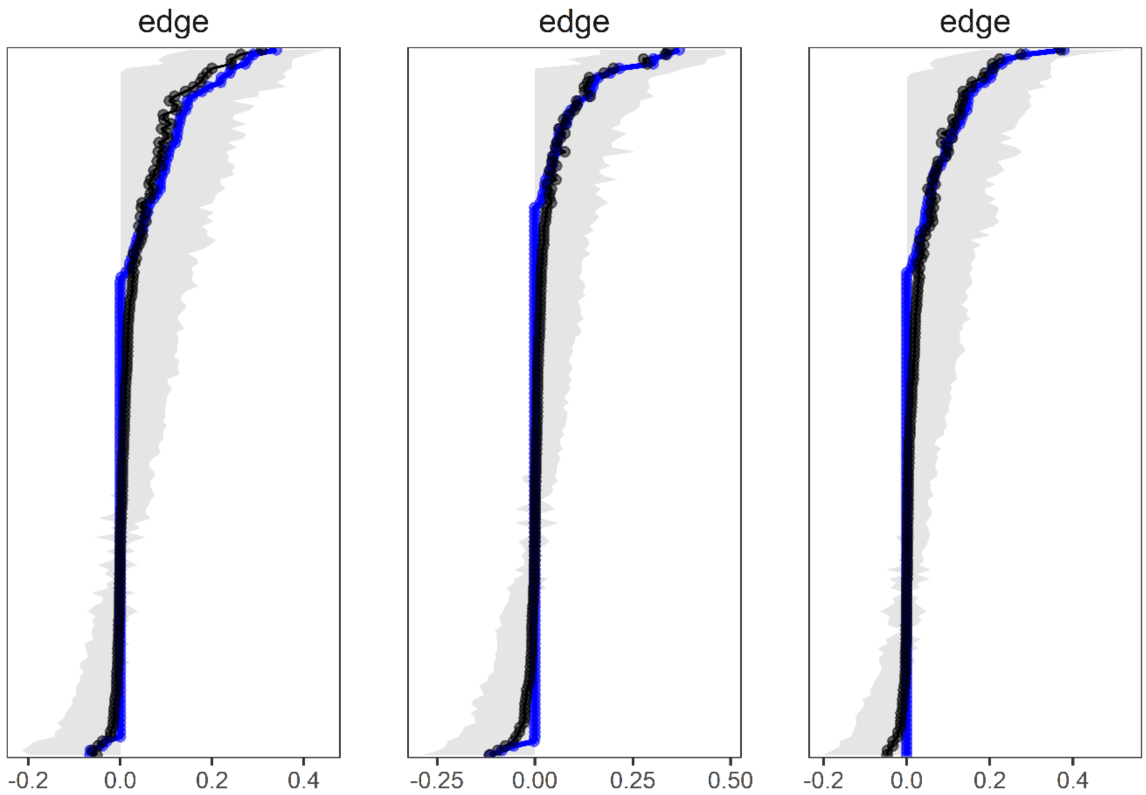


Figure A5. Bootstrapped confidence intervals for estimated edge-weights in the estimated networks (left side: youth; middle: middle-aged group; right side: older-aged group). The blue line indicates the sample values and the grey area the bootstrapped 95% CIs. Horizontal lines represent network edges, ordered from highest edge-weight to the lowest edge-weight. Please note that edge weights in network models are regularized with a penalty by the graphical lasso algorithm and are therefore smaller than correlations or partial correlations. The y-axis labels have been removed to avoid cluttering.

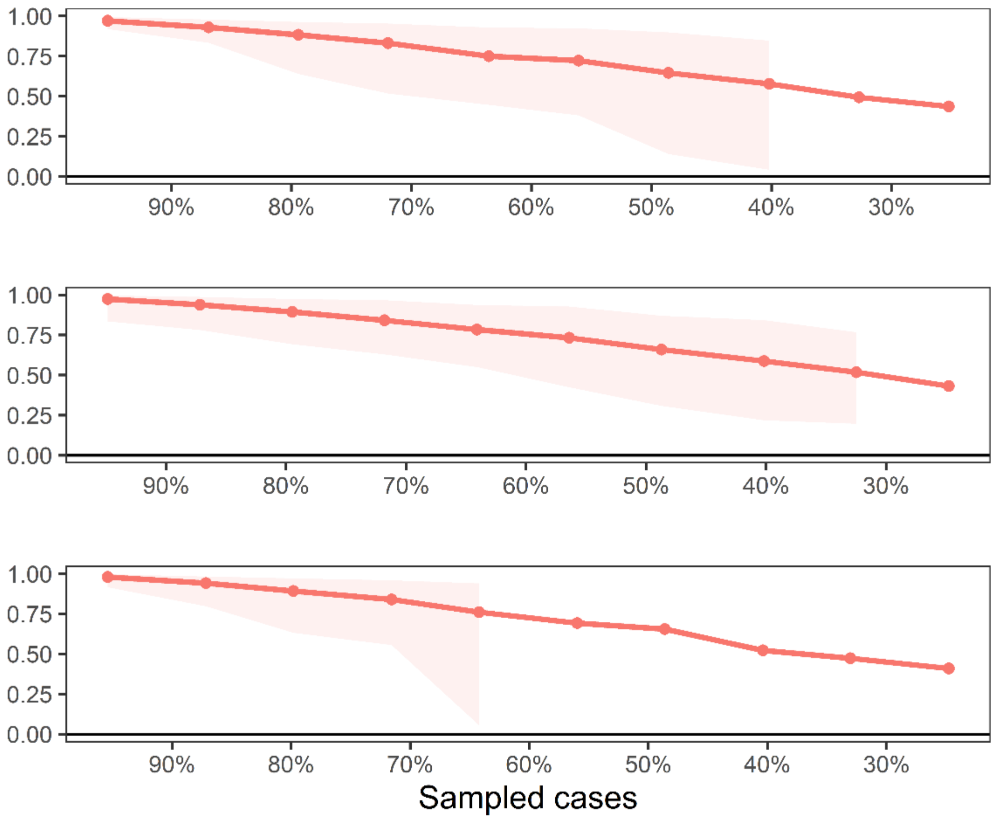
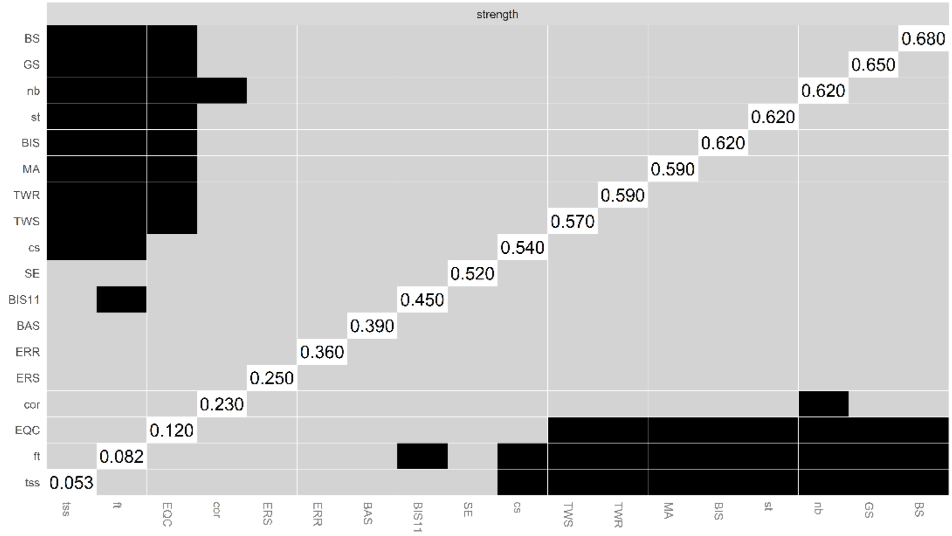


Figure A6. Centrality stability for all networks as average correlations between the centrality indices of networks while reducing sample size in comparison with the original sample (youth = above; middle-aged group = middle; older-aged group = below). Lines correspond to the means and areas to the range between the 2.5th and the 97.5th quantile.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0.680
0.650
0.620
0.620
0.620
0.590
0.590
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0.520
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0.390
0.360
0.250
0.230
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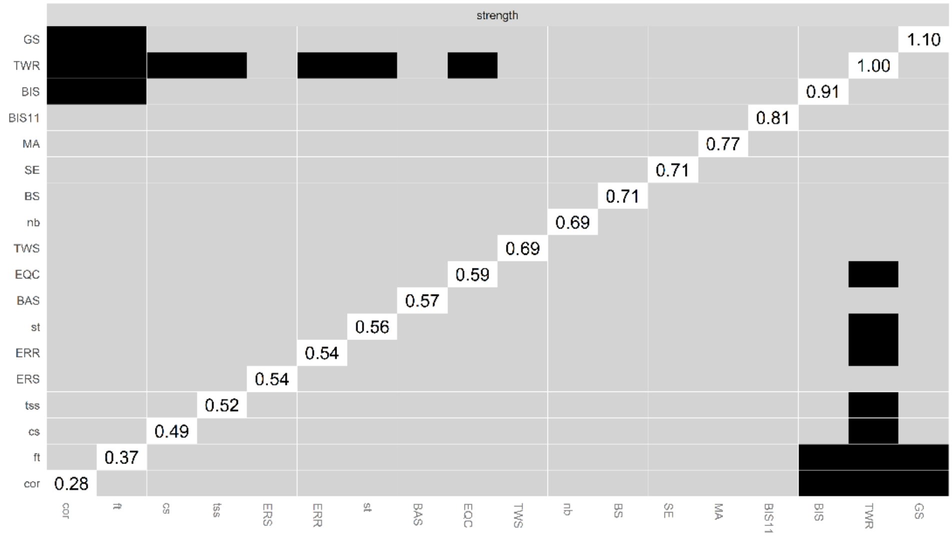
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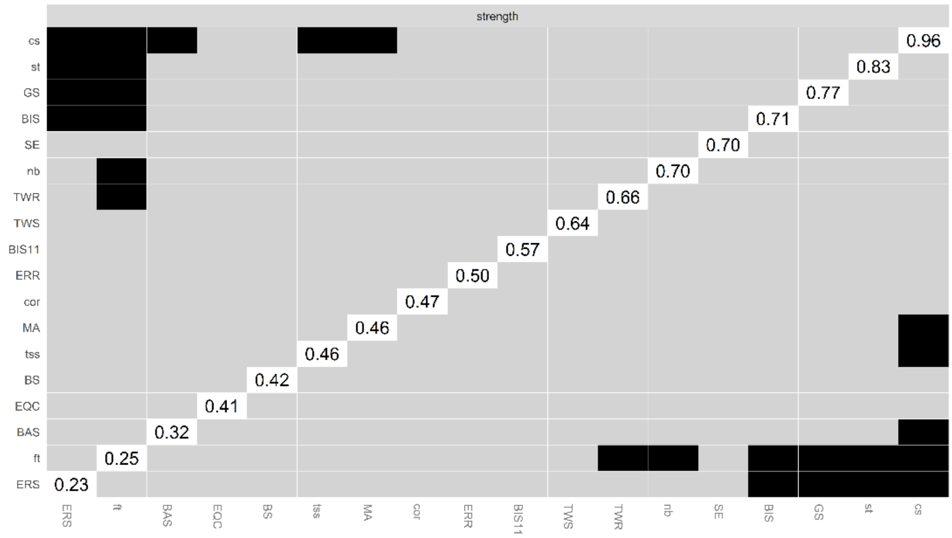
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Figure A7. Bootstrapped difference test (α =.05) for centrality index node strength (youth = above; middle-aged group = middle; older-aged group = below). Black parcels mark node strengths that differ in a significant way from one another, whereas grey parcels do not differ significantly. The value of the node strength is in the white diagonal. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations).

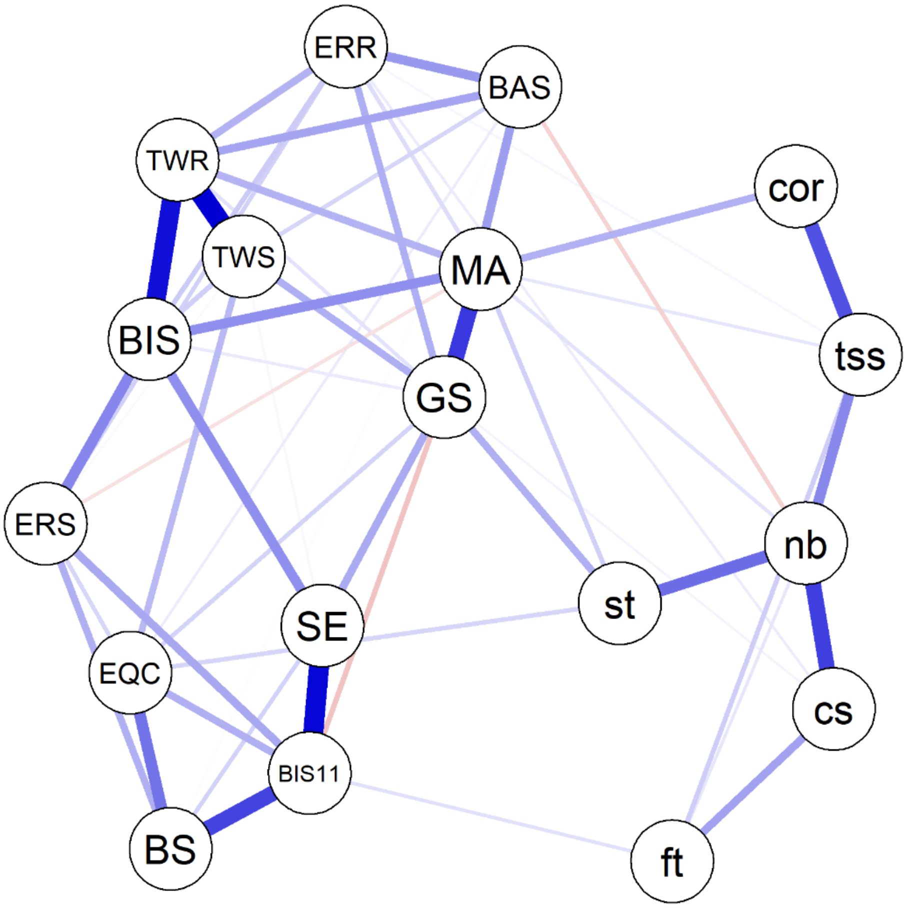

Figure A8. Network model for the youth group. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations).

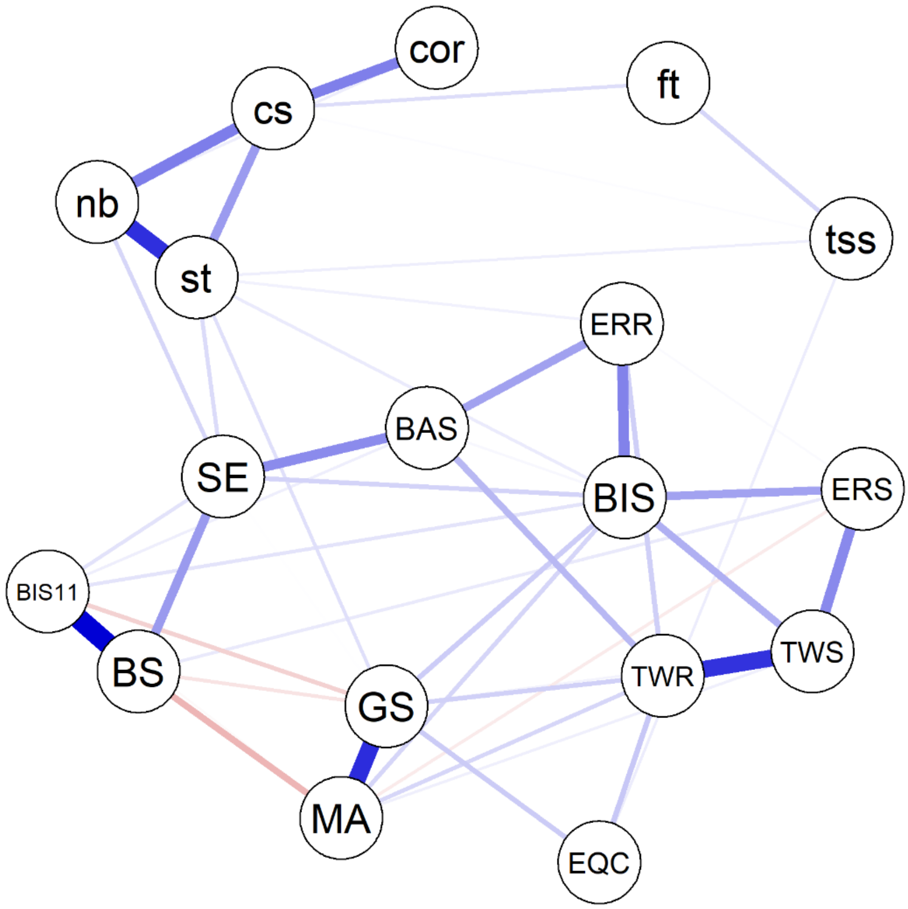

Figure A9. Network model for the middle-aged group. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations).

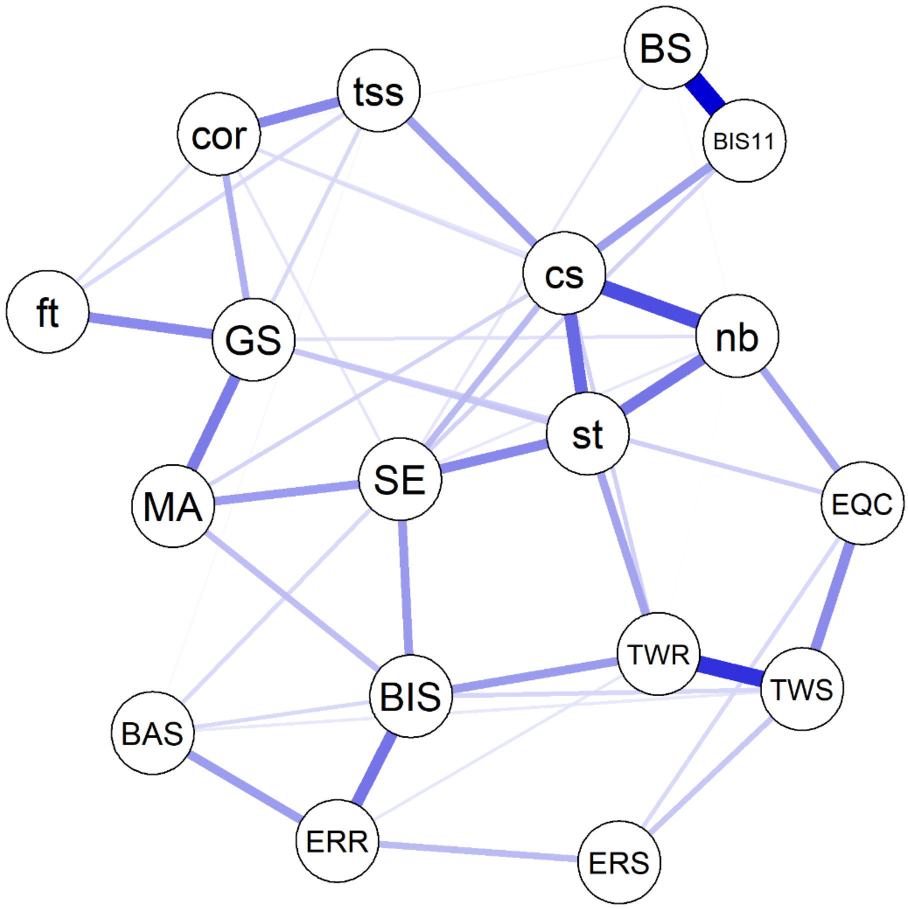

Figure A10. Network model for the older-aged group. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations).

9.5 Study 3: Relations of Executive Control Functions, Self-Regulation, and Affect: A Machine Learning and Network Modelling Approach.

Relations of Executive Control Functions, Self-Regulation, and Affect:
A Machine Learning and Network Modelling Approach

Markus Neubeck[1], Verena E. Johann[1, 2], Julia Karbach[1], and Tanja Könen[1]

[1]University of Kaiserslautern-Landau, Germany

[2]Johannes Gutenberg University Mainz, Germany

Author note:

Correspondence concerning this article should be addressed to Markus Neubeck, Department of Psychology, University of Kaiserslautern-Landau, Fortstraße 7, 76829 Landau, Germany. Email: markus.neubeck@rptu.de

We declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

We declare that all used procedures comply with the Declaration of Helsinki, ethical standards of the German Psychological Society, and EU General Data Protection Regulation as required by the local ethics committee at the Department of Psychology (RPTU Kaiserslautern-Landau).

Abstract

Executive control functions (EF) and self-regulation (SR) are wide-ranging psychological constructs supporting the regulation of cognition and affect (e.g., Bridget et al., 2013). Despite their theoretical overlap, behavioral tasks and self-report measures of EF and SR are often unrelated (e.g., Eisenberg et al., 2019; Neubeck et al., 2022). In order to explore the presumably complex interplay of EF, SR, and affect, and individual differences in these relations, we employed a new approach including machine learning and network modelling. *N* = 315 participants (14-80 years) completed self-report measures and behavioral tasks that assessed EF, SR, as well as positive and negative affect on two measurement occasions (one month apart). Using X-means and deep learning algorithms, we identified two groups with differential EF performances as well as differential SR and affective experiences. Grouping was predicted with logistic regression by age and personality (conscientiousness, neuroticism, and agreeableness). We further applied network model analysis to investigate the connections between EF, SR, and affect within the two groups and identified well-connected key variables. SR variables like behavioral inhibition as well as positive affect demonstrated the highest centrality in both groups. These findings were robust and present across both measurement occasions. They contribute to our understanding of individual differences in EF, SR, and affect.

Key Words: *Executive Control Functions, Self-Regulation, Affect, Network Analysis, Machine Learning*

Relations of Executive Control Functions, Self-Regulation, and Affect: A Machine Learning and Network Modelling Approach

Introduction

The present study aimed to explore the connections between executive control functions (EF), self-regulation (SR), and affect. EF and SR enable individuals to direct their thoughts, feelings, and behaviors in order to pursue desired objectives (Schmeichel & Tang, 2014). For example, they allow generating and monitoring action plans to pursue goals and to adapt them to changing environmental demands (Johann & Karbach, 2022). Affect allows evaluating which goals are worth pursuing to satisfy needs (Dixon & Dweck, 2022). However, the relations between these three domains are still not fully understood. Therefore, the current study utilizes an exploratory approach based on machine learning for clustering and network analysis to summarize and structure potential relations among EF, SR, and affect.

Executive control functions, self-regulation, and affect

EF are involved in controlling cognitive processing in complex tasks. They include the three core functions of working memory, inhibition, and shifting (Miyake et al., 2000; Bull & Scerif, 2001; Hermida et al., 2015). Working memory enables the storage and manipulation of information needed for other cognitive processes (Baddeley, 1992). Inhibition involves the deliberate suppression of a prepotent, automatic, or dominant response and the regulation of disruptive and conflicting information (Miyake et al., 2000). Shifting involves switching between distinct tasks, operations, or mental sets (Monsell, 1996).

SR is a wide-ranging term that describes the process of setting and achieving goals (Inzlicht et al., 2021). These goals may include behaviors, thoughts, emotions, task performances, attentional processes, regulating impulses, or appetites (Vohs & Baumeister, 2016). Thus, there is significant conceptual of overlap between SR and EF when it comes to controlling attentional resources.

Affect includes both emotions and mood, with the former being directed and phasic (i.e., having an onset and dissipating) and the latter being continually present (Lischetzke & Könen, 2022). Affect can be distinguished into a positive and a negative component (e.g., Russel & Caroll, 1999; Diener & Emmons, 1984; Warr et al., 1983). Positive affect includes feelings such as joy, happiness, excitement, and optimism. It is associated with higher well-being, increased motivation, and overall adaptive functioning. Negative affect includes feelings of sadness, guilt, anger, and worry. It can reduce motivation, limit the ability to engage in enjoyable activities, and is associated with symptoms of psychopathology (e.g., depression and anxiety).

EF and SR both impact affect in that they allow individuals to manage their thoughts, feelings, and behavior in order to reach desired outcomes (see Schmeichel & Tang, 2014, for a review). The ability to plan, organize, and strategize supports the regulation of emotions and the control of impulsive reactions. Moreover, with higher levels of SR, individuals are able to identify triggers for emotionally charged reactions and develop strategies to manage them. SR deficits are thus considered as transdiagnostic dimension for internalizing and externalizing psychopathology (Santens et al., 2020). Bridgett and colleagues (2013) discovered that better effortful control and working-memory updating abilities were uniquely correlated with lower dispositional negative affect. On the other hand, poor inhibition was distinctly tied to an increased expression of negative affect. Another study (Shields et al., 2016) demonstrated EF impairments when participants were in an anxious mood but not when they were in an angry mood (compared to neutral mood).

Traditionally, neurocognitive research has employed performance-based behavioral measures to assess EF while SR has been typically assessed by self-report questionnaires. Despite their theoretical overlap, empirical evidence suggests that correlations between performance on EF tasks and SR self-report measures can be elusive: Duckworth and Kern (2011, p. 259) investigated the convergent validity of EF and SR in a meta-analysis and found "moderate convergence as well as substantial heterogeneity in the observed correlations". In line with this conclusion, recent evidence also found little to no systematic relations between EF and SR measures (e.g., Eisenberg et al. 2019; Nęcka et al., 2018; Saunders et al., 2018). Our own research suggests that only some SR and EF measures, such as Grit Scale, Brief Self Control Scale, or Card Sorting, are well connected in the SR and EF construct space and can therefore be considered key variables in their network (Neubeck et al., 2022).

Most of these studies focused on the relations between SR, EF, or affect based on correlational methods assuming linear relations. However, we presume a complex interplay of these variables which might differ depending on interindividual differences on other cognitive or non-cognitive factors such as personality or age. At least some facets of personality such as conscientiousness seem to be related to self-regulation (Jensen-Campbell et al., 2002) as well as EF (Johann & Karbach, 2022). Moreover, Pavani and colleagues (2017) investigated the relations between affect, affect regulation strategies, and personality. They found that the networks between affect and affect regulation strategies - which are also related to SR and EF (Neubeck et al., 2022) - varied according to levels of extraversion and neuroticism.

Identifying and describing these complex relations is challenging with traditional psychological methods. Despite the theoretical overlap between SR and EF, single studies and meta-analyses found little to no relations between the constructs (Duckworth & Kern, 2011). This finding might be explained by an actual lack of similarity between the constructs or by a limited capacity of traditional analysis methods to identify complex relations between these constructs that are modulated by other variables. We therefore used a combination of a machine learning and network modelling approach in order to disentangle the relations between SR, EF, and affect.

The present study

The aim of this study was to determine whether the networks of EF, SR, and affect differ across distinct clusters of individuals. Interindividual differences in these relations are a plausible explanation for the relatively small relations of these theoretically well-connected variables in previous studies. Our first step was therefore to use a data-driven approach to identify clusters of individuals by means of unsupervised machine learning. As a second step, network models were fitted for each group to systematically examine the relations between EF, SR, and affect across a range of behavioral tasks and self-report measures. We selected a broad range of measures to cover different facets of EF (working memory, inhibition, and shifting), SR (e.g., sensation seeking, mindfulness, grit), and affect (positive and negative). Drawing on previous evidence (Allom et al., 2016; Duckworth & Kern, 2011; Eisenberg et al., 2019; Nęcka et al., 2018) and theoretical models (Bailey & Jones, 2019; Hofmann et al., 2012), we expected to find stronger connections of measures within than between domains (EF, SR, and affect). However, the exploratory nature of unsupervised machine learning and network modeling does not support confirmatory hypothesis testing. We thus exploratively compared the results of the models trained and fitted with data from a first measurement occasion to a second measurement occasion (one month later).

Method

Participants

The sample consisted of 315 participants aged between 14 and 80 years (*M* = 38.52 years, *SD* = 18.69; 58.1% female). They were recruited online; 16.2% were school students, 21.0% university students, 50.5% employees, and 13.3% were retired. They had the following education level: *without basic school graduation*: 8.9%, *basic school graduation*: 6.0%, *finished vocational training*: 27.0%, *high school graduation*: 13.0%; *bachelor's degree*: 12.1%; *master's degree*: 22.9%; *PhD*: 2.5% (other: 3.8%, *no information*: 1.5%) Participants were included if they were fluent in German and reported no diagnosed mental or physical conditions impairing cognitive performance or self-regulation.

Procedure

Participants were recruited online and registered by answering an online demographic questionnaire. From 1067 registered individuals, 625 subjects were invited to participate in the study. They were randomly selected if they fulfilled the inclusion criteria with the restriction that age groups were represented equally well. Of 506 individuals who started the study, 167 aborted the study (about 33% dropout), and six did not provide a valid answer for their age and were therefore excluded from the analysis. 18 did not take part in the second measurement occasion resulting in a final sample of 315 participants.

One measurement occasion of our study comprised two online sessions (total testing time: about 120 minutes). We used nine questionnaires to assess 12 different facets of self-regulation as well as six different tasks measuring EF. All questionnaires and tasks were administered online and completed on computers or laptops (no tablets or smartphones). The first session consisted of three EF tasks, three SR questionnaires, an affect questionnaire plus further control variables (e.g., personality questionnaire). The second session consisted of three EF tasks and six SR questionnaires. The order of the EF tasks was balanced by the domain of EF (day one: Corsi Block Backwards, Flanker Task, Task Switching; day two:

Wisconsin Card Sorting Task, Stroop Test, N-Back Task). For each session, the order of SR and EF measures was counterbalanced across participants (i.e., 50% started with the SR measures). All participants provided written informed consent – for minors, parents provided informed consent as well. Participants completed the same EF tasks, SR questionnaires, and the affect questionnaire on the second measurement occasion. They were compensated with 10€ or course credit per measurement occasion.

Power analyses for network models are not trivial as precise estimates of sensitivity, specificity, and correlations depend on the expected network structure (Epskamp & Fried, 2018). Simulation studies suggest that when estimating a lasso-regularized network, high specificity can generally be achieved, while sensitivity and correlations are dependent on sample size (Epskamp, 2016; Foygel & Drton, 2010; van Borkulo et al., 2014). To evaluate if the planned network models had sufficient power, we calculated simulations with 5000 iterations using the refitted networks for the two groups as the true network (see Figure A1, A2, A3, and A4). For $N = 100$ cases, the mean correlation between the true and estimated networks was .76 and .71 for the two groups, mean sensitivity .61 and .58, and mean specificity .94 and .96 at measurement occasion one. For measurement occasion two, the mean correlation between the true and estimated networks was .75 and .76 for the two groups, mean sensitivity .73 and .62, and mean specificity .84 and .74. As such, we concluded that for the given network models, the two groups derived by X-means clustering with $N > 100$ participants each fulfilled the necessary power considerations.

Measures

Self-Regulation Questionnaires

The Self-Regulation Questionnaires administered included the Barratt Impulsiveness Scale (Preuss et al., 2003; Patton et al., 1995), Behavioral Inhibition System and Behavioral Approach System Questionnaire (Strobel et al., 2001; Carver & White, 1994), Brief Self-Control Scale (Bertrams & Dickhäuser, 2009; Tangney et al., 2004), Emotion Regulation

Questionnaire (Abler & Kessler, 2009; Gross & John, 2003), Grit Scale (Schmidt et al., 2017; Duckworth & Quinn, 2009), Three-Factor Eating Questionnaire (Löffler et al., 2015; Karlsson et al., 2000), Mindful Attention and Awareness Scale (Michalak et al., 2008; Brown & Ryan, 2003), and Sensation Seeking Scale Form V (Beauducel et al. 2003; Zuckerman, 1971) and Theories of Willpower Questionnaire (Job et al., 2010). All questionnaires were adapted German versions, and some comprised two subscales. The items were rated on a scale from 1-4 or 1-6, depending on the questionnaire, and mean scores were calculated with good to acceptable internal consistencies (Cronbach's alpha range: .76 - .86). For details please see Neubeck et al. (2022; open access).

EF Tasks

All tasks were provided by Cognition Lab (BeriSoft, Inc.; https://cognitionlab.com/; 07.06.2023). Verbal-visual WM was measured using the N-Back Task (Gevins & Cutillo, 1993). The score was adjusted for skewness by calculating ln(1+1-aprime). Visuospatial WM was measured using the Corsi Block Backwards Task (Kessels et al., 2008). The score was adjusted for skewness by calculating ln(maximum correct sequence length). Shifting was measured using Task Switching (Rogers & Monsell, 1995) and Wisconsin Card Sorting Task (Berg, 1948). The score for the Task Switching was specific switch costs (switch – stay), and the score for the Wisconsin Card Sorting Task was adjusted for skewness by calculating ln(percentage of perseveration errors + 0.5). Inhibition was measured using the Flanker Task (Eriksen & Eriksen, 1974) and Stroop Task (Stroop, 1935). The score for the Flanker Task was adjusted for skewness by calculating ln(inverse efficiency score + 300), and the score for the Stroop Task was adjusted for skewness by calculating ln(inverse efficiency score + 200). For details please see Neubeck et al. (2022; open access).

Affect: PANAS (Breyer & Bluemke, 2016; Watson et al., 1988)

We used the German adaption of the Positive and Negative Affect Schedule (PANAS) (Breyer & Bluemke, 2016) to measure positive and negative affect of participants. It includes two subscales, positive affect and negative affect, consisting of ten items, such as “active” or “distressed”, respectively. Participants were instructed to indicate to which extent they had been feeling lately these affect states on a five-point Likert scale (from 1 = not at all to 5 = extremely). The items of both scales, which comprised ten items each, were aggregated by calculating mean scores with higher values representing higher positive or negative affect.

Personality: NEO-FFI (Borkenau & Ostendorf, 2008; Costa & McCrae, 1989)

We used the German adaption of the NEO Five-Factor Inventory (NEO-FFI) to measure the five main dimensions of personality: Neuroticism, extraversion, openness, agreeableness, and conscientiousness. Therefore, the questionnaire consisted of five corresponding subscales with 12 items each and 60 in total. Participants had to indicate to which extend statements like “I am not easily disturbed” described themselves on a five-point Likert scale (from 1 = strong disagreement to 5 = strong agreement). The items of the five scales were aggregated by calculating means cores. Higher numbers meant that the corresponding personality trait was more pronounced.

Data Analyses

X-Means

X-means (Pelleg & Moore, 2000) is an extension of K-means clustering (Hartigan 1975; Hartigan & Wong, 1979). K-means clustering is an unsupervised learning algorithm that attempts to find distinct clusters of data points in a data set. The algorithm works by randomly assigning each data point to a cluster, then computing the mean of all data points in that cluster to use as a centroid. The algorithm then reassigns each data point to the cluster whose centroid is closest to that data point. This process is repeated until the cluster assignments do not change anymore or the maximum number of iterations is reached. The algorithm uses sum of squared error (SSE) as an optimization method to measure the similarity between the data points within each cluster. The goal is to minimize the SSE by finding the optimal centroids for each cluster. The SSE is calculated by adding the squared distances between each data point and its assigned cluster centroid. The algorithm then iteratively adjusts the cluster centroids to minimize the total SSE and stops when the SSE stops decreasing, or the maximum number of iterations is reached. The resulting clusters are then used to identify distinct groups of data points in the dataset. We used an extended version of this algorithm (X-means) that does not require a specific value for the number of clusters but can find up to a certain number of clusters (Pelleg & Moore, 2000). We set the algorithm to identify up to five possible clusters.

Plausibility Checks: Deep Learning and Logistic Regression

Due to the high dimensionality of the data in the X-means algorithm, results are difficult to visualize. Therefore, we trained a fairly simple "deep" feedforward neural network as an autoencoder, which is comparable to principle component analysis (e.g., Kramer, 1991). The neural network consisted of an input and an output layer (the number of nodes is equivalent to the SR, EF, and affect variables in the data set) with three hidden layers (respectively 10, 2, and 10 nodes), which is reasonably sufficient for the relatively small dataset. The two-node layer in the middle acts as a "bottleneck" layer, while the inputs are equivalent to the outputs. During the unsupervised training process, the network is presented with the dataset (multiple times), and during each iteration, the network slightly adjusts its weights through backpropagation (e.g., Hecht-Nielsen, 1992) in a way that the inputs predict the outputs. With two nodes in the middle, information needs to be reduced, and this leads to the network learning a compact representation of the data, reducing 20 to two dimensions. After training, the values for this middle layer can be extracted as deep features for each data point or computed for data previously unknown to the model, like measurement occasion two. These values can then be plotted using the group assignments from the X-means algorithms to compare whether the two different algorithms find similar results. As a further plausibility check, we used control variables like age, gender, and personality in logistic regression to predict the group assignments found with X-means.

Network Models

We estimated regularized auto correlation network models of SR, EF, and affect using the statistic software R (version 4.0.4; R Core Team, 2021) with the package bootnet, following the approach outlined by its authors (Epskamp et al., 2018; Epskamp & Fried, 2018). Instead of the extended Bayesian information criterion (EBIC; Foygel & Drton, 2010), we used the ordinary Bayesian information criterion (BIC) for model selection due to the relatively small size of our networks. EBIC was initially developed for the case of moderate sample sizes combined with a large number of covariates, as seen in genome-wide association studies (Chen & Chen, 2008). To adjust for non-normality in the data, we selected the option for Gaussianization in the model estimation to relax the assumption of normality. Additionally, we used bootstrapping to assess network stability (Epskamp et al., 2018) for edge weights and centrality indices. Differences between the groups were tested with the *NetworkComparisonTest* developed by van Borkulo et al. (2017). In addition, we calculated graphical difference networks between the two groups on both measurement occasions, following Southworth et al. (2009). This was accomplished by subtracting the weights of one group from the corresponding weights of the other group.

Results

Descriptive Statistics

Please see Table 1 and 2 for descriptive statistics for all groups (found by cluster analysis; please see next section) at the two measurement occasions. Correlations between the EF, SR, and affect measures are presented in Table A1 and A2 for both groups at measurement occasion one and in Table A3 and A4 at measurement occasion two.

Clustering and Plausibility

Training the unsupervised X-means algorithm on the data from measurement occasion one, we found that our data were best represented by two clusters dividing our sample into two groups with 161 and 154 observations. The grouping mechanism was reasonably robust, with 85% of the participants being in the same group when predicting the group with the X-means model with the data from measurement occasion two. This resulted in two groups with 180 and 135 observations. Changes occurred in both directions, with 34 participants changing from group one to two and 15 from group two to one over time.

In the next step, we visualized the grouping by combining the grouping labels from X-means with unsupervised deep learning through a neural network, where we found that both the neural network and the X-means algorithm unveiled quite similar solutions for clusters in the data (Figure 1), which supports the plausibility of the derived groups.

As a further plausibility check, we performed logistic regression to predict grouping with the control variables age, gender, and personality. The two logistic regression models showed an excellent model fit for measurement occasion one with McFadden's pseudo-R^2 = .48 and a good model fit for measurement occasion two with McFadden's pseudo-R^2 = .37 (pseudo-R^2 > .2 corresponds to good fit; pseudo-R^2 > .4 corresponds to excellent fit; McFadden, 1979). We found that age, conscientiousness, agreeableness, and neuroticism were significant predictors of grouping at both measurement occasions (Tables 3 and 4). Taken together, at both occasions, clustering resulted in a first group which is significantly older, more conscientious, more agreeable and less neurotic.

Network Analysis

We estimated network models (Figures 2-5) for both groups at both measurement occasions and tested for network structure invariance. The differences between the network structures for groups one and two at measurement occasion one ($M = 0.25$, $p = 0.24$) as well as between groups one and two at measurement occasion two ($M = 0.26$, $p = 0.15$) were not significant. Furthermore, tests for invariance of global strength showed no significant differences (measurement occasion one: $S = 1.11$, $p = 0.50$; measurement occasion two: $S = 1.94$, $p = 0.35$). Therefore, as the overall connection strength and overall level of connectivity are comparable across two groups, specific differences between networks are likely of content-related nature, rather than measurement artifacts. To explore these differences, we calculated difference networks, using the difference of corresponding edge weights in the respective groups' network models (Figures 6 and 7).

In both groups and on both measurement occasions, connections were stronger within the domains of EF and SR than between them. Positive affect was well connected with SR but not with EF measures (Figures 2-5). Regarding centrality, for group one (older, more conscientious, more agreeable, and less neurotic) Behavioral Approach System, positive affect, and Behavioral Inhibition System were the variables with the highest node strength[3] for both measurement occasions. For group two (younger, less conscientious, less agreeable, and more neurotic), results are a little more inconsistent, as for measurement occasions one Behavioral Inhibition System, Behavioral Approach System, negative affect had the highest node strength (closely followed by positive affect), while on measurement occasion two Behavioral Approach System, Brief Self Control Scale, and Card Sorting Task showed the

[3] Node strength quantifies the direct connections to other nodes.

highest node strength. Difference tests conducted for the centrality index node strength confirmed that for these variables with the highest node strengths in all groups, their node strength was significantly larger than for most other variables (Figures A8-A11). However, Epskamp et al. (2018) discussed the issue of multiple testing as an unresolved problem in the field of psychological network estimation, which has to be taken into account when performing difference tests.

In group one (older, more conscientious, more agreeable, and less neurotic), the connection between Behavioral Approach System and positive affect was significantly stronger than most other connections on both measurement occasions, followed by the connection n-back Task and Card Sorting Task (Figures A12 and A14). For group two (younger, less conscientious, less agreeable, and more neurotic), subscales of Theories of Willpower followed by n-back Task and Stroop Task were the strongest connections at measurement occasion one (Figure A13), while this was the case for the connections of Barratt Impulsiveness Scale and Brief Self Control Scale, followed by n-back Task and Card Sorting Task, for measurement occasion two (Figure A15). Difference networks reflected this pattern changes, too (Figures 6 and 7).

In the last step, we examined the stability of the observed network structures and the centrality index node strength. We generated bootstrapped confidence intervals for the edge weights of all the networks (Figure A6), which typically showed no overlap between the confidence intervals of strong and weak edge weights, though there was an overlap between those of middle-sized edge weights. When the sample size was reduced, the bootstrapped centrality index node strength remained relatively consistent across all networks (Figure A7).

Discussion

Taken together, the unsupervised X-means algorithm was used to divide the data from measurement occasions one and two into two clusters, with 85% of participants being in the same group across both occasions. Visualizing the grouping with a deep learning neural network lead to a similar solution to that of X-means algorithms. Logistic regression showed that age, conscientiousness, agreeableness, and neuroticism were significant predictors of the grouping.

The results of the network models showed that there were no significant differences in overall connection strength and overall level of connectivity between the two groups at both measurement occasions. However, the difference networks showed that the connections were stronger within the domains of EF and SR than between them and that positive affect was well connected with SR but not with EF measures. The centrality analysis showed that for group one (older, more conscientious, more agreeable, and less neurotic), the Behavioral Approach System, positive affect, and Behavioral Inhibition System had the highest node strength for both measurement occasions, while for group two (younger, less conscientious, less agreeable, and more neurotic), the highest node strength varied across occasions except for Behavioral Approach System, which was consistently central. Further simulation analyses showed that the observed network structures and centrality index node strengths are stable, with no overlap between confidence intervals of strong and weak edge weights and relatively consistent centrality index node strengths across all networks when the sample size was reduced. Notably, the Behavioral Approach System captures goal-striving and approach to rewards (e.g., "When I want something, I usually go all-out to get it."; Strobel et al., 2001), which is not only central, but also strongly connected to positive affect in both groups at both occasions. From a theoretical point of view, this is in line with the *Broaden-and-Build Theory of Positive Emotions* (e.g., Fredrickson, 2001), which describes positive feedback-loops between experiencing positive emotions and building a thought–action repertoire as a personal resource to achieve goals (and thus experience more positive emotions). Positive affect had a high node strength (in the top 5 in the two groups at both measurement occasions; see Figure A5) and was well connected to many SR measures. Therefore, it seemed to be more relevant for better SR, or better SR could lead to a more positive affect. From a theoretical perspective, this also is in line with the *Mood-Behavior-Model* (Gendolla, 2000; Gendolla & Brinkmann, 2005), which postulates that moods can have a significant effect on a person's choice of goals and the deployment of resources, which are central for self-regulation. Furthermore, affect is connected to individual differences in traits connected to self-regulation, such as self-esteem, neuroticism, extraversion, dispositional anxiety, dispositional optimism, and depression (Gendolla & Brinkmann, 2005; Mischel & Shoda, 1995). As negative affect was not crucial in the networks with SR and EF (in terms of centrality), our results are in contrast to a study (Bridget et al., 2013) suggesting that better working-memory updating and effortful control were uniquely linked to lower dispositional negative affect, while low/poor inhibition was uniquely associated with an increased expression of negative affect. However, we might have found stronger connections with EF if we had used hot EF tasks (i.e. reward or affective-related tasks) (Salehinejad et al., 2021). Another explanation might be that further differentiation between aspects of negative affect might be necessary, as Shields et al. (2016) found that anxiety had an effect on EF but not anger. As Inzlicht and colleagues (2021) point out, the literature has not adequately explored the role of emotion in self-regulation yet; it has been implied but rarely explicitly discussed. An exception to this is found in trait models (like described above), where individual tendencies towards higher appetitive behavior are thought to lead to stronger desire for actions, which might come with the risk of undermining long-term goals.

For the personality traits agreeableness and neuroticism (but not for conscientiousness), our results are in line with a study (Robinson, 2007) that reviewed the link between extraversion, neuroticism, and agreeableness to different cognitive processing operations. It was suggested that extraversion and neuroticism are related to affective memory structures that favor positive and negative affect, respectively. Agreeableness is more closely linked to affect and emotion control following hostile thoughts. Regarding the division of the two groups, results are consistent with theoretical assumptions and previous indicating that age is a major grouping factor. It is also in line with our previous research, where we found different structures of EF and SR for different age groups (Neubeck et al., 2022).

Regarding the connections between SR and EF, our findings are in line with studies that found connections between SR and EF to be weak (Duckworth & Kern, 2011; Saunders et al., 2018; Nęcka et al., 2018; Eisenberg et al., 2019). They also showcase that depending on the variable(s) used for grouping, network models can show different patterns, and this question of connections between SR and EF can be answered differently for the same sample, as we found stronger connections in an older age group between both domains, when focusing on aging as the only grouping variable (Neubeck et al., 2022).

Taken together, there were similarities but also differences regarding SR, EF, and affect and their relations in the two groups. They did not differ regarding the relations between EF and SR or between EF and affect. However, there were differences regarding the relations within the domains of SR and EF.

Group 1 was significantly older, more conscientious, more agreeable, and less neurotic. Moreover, when considering the means of the two groups, this group had slightly higher positive affect and lower negative affect, higher values on Resisting Temptations, Reappraisal, and Grit and lower values on Suppression, and Behavioral Inhibition System pointing to better regulation strategies regarding affect, emotions, and actions. This result fits the findings of other studies showing that older adults report higher levels of well-being and being better at controlling their emotions relative to younger adults (Gross et al., 1997). Moreover, they deploy more attention to positive than to negative information resulting in a mood repairing effect (Isaacowitz et al., 2008; Urry & Gross, 2010). In contrast, Group 2 might be characterized by younger age, lower conscientiousness and agreeableness, but higher neuroticism. Moreover, this group reports higher levels of negative affect and this variable also has a high centrality within the network between SR, EF, and affect. However, the centrality and relations seem to be less stable. In sum, these results indicate that it may have been difficult to identify relations between SR, EF, and affect in previous research (e.g., Eisenberg et al. 2019; Nęcka et al., 2018; Saunders et al., 2018) because they vary as a function of other factors (e.g., personality and age).

A limitation of performance-based EF measures is their lower reliability compared to SR questionnaires (Enkavi et al., 2019), as well as affect questionnaires. This could lead to an underestimation of the existing connections between the domains of EF, SR, and affect, as the different measurement types (self-report for SR and affect vs. performance tasks for EF) favor stronger connections between domains than within them.

From a methodological point of view, X-means clustering has the shortcoming of sometimes converging towards local optima instead of global ones (Pelleg & Moore, 2000), and clustering results can be difficult to validate (Huang, 1998). Therefore, we took the recommended steps (Huang, 1998) to investigate the clustering with visualization and combination with the deep learning algorithm as another data-driven approach and added a theory-derived prediction of the grouping label by control variables like age and personality. Despite being powerful tools for analyses of complex connections of many variables, machine learning algorithms like X-means or deep learning neural networks have the well-known issue of being a black box in terms of processing data. Therefore, they require a valid data basis as inputs and a sound theoretical understanding of the variables entering the models, as well as a combination with other methods.

Additionally, the network approach has its specific limitations. It does not allow for causal conclusions due to its explorative nature, and the centrality indices should be interpreted with caution since the approach is still in development (Bringmann et al., 2019).

Furthermore, the stability of the centrality measures may be questionable, which we addressed by employing bootstrapping (see Figure A7). Therefore, we did not report closeness and betweenness as these metrics require the "presence of flow and shortest paths" (Bringmann et al., 2019, p. 892). Instead, we reported only node strength. Lastly, multiple testing is an issue that is yet to be resolved when using difference tests for network models (Epskamp et al., 2018). Furthermore, we have to take into account that network model analysis is mainly used for exploration. The option to validate the model results with a second measurement occasion is a strength of our longitudinal study design.

Investigating the interplay between EF, SR, and affect with the help of key variables is necessary to form a stronger theoretical framework and bridge the gap between different disciplines. Understanding the relationship between SR and EF could help explain the discrepancies in how these concepts have been studied and how they are connected to affect. Additionally, these variables provide promising targets for interventions designed to induce near (e.g., similar cognitive tasks or emotional situations) and far transfer effects (e.g., related tasks or activities and affect in daily life). Further confirmatory research with longitudinal designs is thus needed to explore the key variables and their effect on EF, SR, and affect.

Conclusion

We used a data-driven approach with machine learning algorithms X-means and deep learning for clustering EF, SR, and affect and found two groups that were mostly robust across two measurement occasions. Furthermore, these groups were predicted by age and some facets of personality, adding to the theoretical plausibility of these clusters. We identified key variables in these clusters by means of network models and found that connections were stronger within the domains of EF and SR than between them and that positive affect was well connected with SR but not with EF measures. Further research is needed to gain a better understanding of the exact processes that may be causing the different network structures revealed by this exploratory approach.

Table 1

Descriptive statistics for the two groups at measurement occasion one

	Group 1 (*n* = 154)		Group 2 (*n* = 161)	
	M	*SD*	*M*	*SD*
Gender (female in %)	61		58	
Executive Control Functions				
Corsi Block Backwards Task	1.42	0.75	1.59	0.61
n-back Task	0.16	0.13	0.18	0.22
Flanker Task	5.86	0.14	5.87	0.14
Stroop Task	6.12	0.46	6.08	0.45
Task Switching	190.99	102.14	173.30	95.10
Wisconsin Card Sorting Test	0.53	0.25	0.60	0.08
Self-Regulation Measures				
BIS	2.73	0.51	3.13	0.49
BAS	3.08	0.36	3.03	0.30
BIS11	1.93	0.22	2.17	0.24
Brief Self-Control	2.70	0.29	3.11	0.31
ERQ Reappraisal	4.87	1.15	4.22	1.10
ERQ Suppression	3.56	1.33	3.99	1.31
Eating Cognitive Control	2.22	0.65	2.08	0.66
Grit Scale	3.74	0.45	3.08	0.49
MAAS	2.52	0.58	3.15	0.61
Sensation Seeking	0.40	0.17	0.47	0.15
TW Strenuous Mental Activity	3.06	0.83	2.64	0.77
TW Resisting Temptations	4.27	0.75	3.58	0.74
Affect				
Positive Affect	3.51	0.59	2.95	0.58
Negative Affect	1.73	0.50	2.36	0.71
Age (years)	44.44	18.69	32.82	16.88
Personality				
Openness	3.36	0.51	3.32	0.51
Conscientiousness	4.14	0.41	3.55	0.52
Extraversion	3.38	0.54	3.13	0.59
Agreeableness	3.91	0.45	3.69	0.50
Neuroticism	2.30	0.63	3.09	0.69

Note. Some scores are recoded for readability as they initially express costs. BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; ERQ = Emotion Regulation; MAAS = Mindful Attention and Awareness Scale; TW = Theories of Willpower. Gender is coded with male = 0 and female = 1.

Table 2

Descriptive statistics for the two groups at measurement occasion two

	Group 1 (n = 135)		Group 2 (n = 180)	
	M	*SD*	*M*	*SD*
Gender (female in %)	58		60	
Executive Control Functions				
Corsi Block Backwards Task	1.55	0.58	1.70	0.53
n-back Task	0.15	0.20	0.15	0.20
Flanker Task	5.87	0.14	5.87	0.16
Stroop Task	6.00	0.45	6.02	0.47
Task Switching	181.25	100.72	144.43	97.04
Wisconsin Card Sorting Test	0.58	0.21	0.62	0.13
Self-Regulation Measures				
BIS	2.64	0.49	3.16	0.50
BAS	3.01	0.36	3.00	0.31
BIS11	1.93	0.21	2.18	0.25
Brief Self-Control	2.69	0.25	3.11	0.35
ERQ Reappraisal	4.87	1.02	4.33	1.17
ERQ Suppression	3.55	1.23	4.04	1.17
Eating Cognitive Control	2.16	0.65	2.06	0.67
Grit Scale	3.72	0.42	3.12	0.48
MAAS	2.55	0.55	3.29	0.62
Sensation Seeking	0.41	0.16	0.47	0.17
TW Strenuous Mental Activity	3.08	0.78	2.72	0.74
TW Resisting Temptations	4.25	0.71	3.60	0.77
Affect				
Positive Affect	3.44	0.61	2.89	0.60
Negative Affect	1.69	0.43	2.33	0.72
Age (years)	46.10	18.95	32.75	16.33
Personality				
Openness	3.38	0.52	3.32	0.51
Conscientiousness	4.12	0.41	3.63	0.56
Extraversion	3.41	0.52	3.14	0.59
Agreeableness	3.90	0.47	3.72	0.49
Neuroticism	2.26	0.61	3.03	0.70

Note. Some scores are recoded for readability as they initially express costs. BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; ERQ = Emotion Regulation; MAAS = Mindful Attention and Awareness Scale; TW = Theories of Willpower. Gender is coded with male = 0 and female = 1.

Table 3

Estimates for logistic regression of grouping at measurement occasion one.

Estimate	Std.	Error	z	*p*-value
(Intercept)	-8.25	2.69	-3.07	**.002**
Gender	1.11	0.42	2.66	**.008**
Age	0.04	0.01	3.59	< **.001**
Openness	-0.39	0.33	-1.19	.236
Conscientiousness	2.62	0.42	6.29	< **.001**
Extraversion	-0.87	0.37	-2.37	**.018**
Agreeableness	1.69	0.44	3.86	< **.001**
Neuroticism	-2.29	0.36	-6.32	< **.001**

Note. Group one was coded as 1 and group two as 0. Gender was coded with 0 = male and 1 = female. Age was not recoded in any form with higher values corresponding to higher age in years. The items of the five personality scales were aggregated by calculating mean cores. Higher numbers meant that the corresponding personality trait was more pronounced. Significant *p*-values (α =.05) are depicted in bold font type.

Table 4

Estimates for logistic regression of grouping at measurement occasion two.

Estimate	Std.	Error	z	*p*-value
(Intercept)	-8.62	2.56	-3.37	**.001**
Gender	0.42	0.37	1.14	.253
Age	0.03	0.01	3.87	< **.001**
Openness	0.04	0.31	0.12	0.907
Conscientiousness	1.99	0.37	5.42	< **.001**
Extraversion	-0.02	0.33	-0.05	0.957
Agreeableness	0.84	0.38	2.22	**.026**
Neuroticism	-1.61	0.30	-5.40	< **.001**

Note. Gender was coded with 0 = male and 1 = female. Age was not recoded in any form with higher values corresponding to higher age in years. The items of the five personality scales were aggregated by calculating mean cores. Higher numbers meant that the corresponding personality trait was more pronounced. Significant *p*-values (α =.05) are depicted in bold font type.

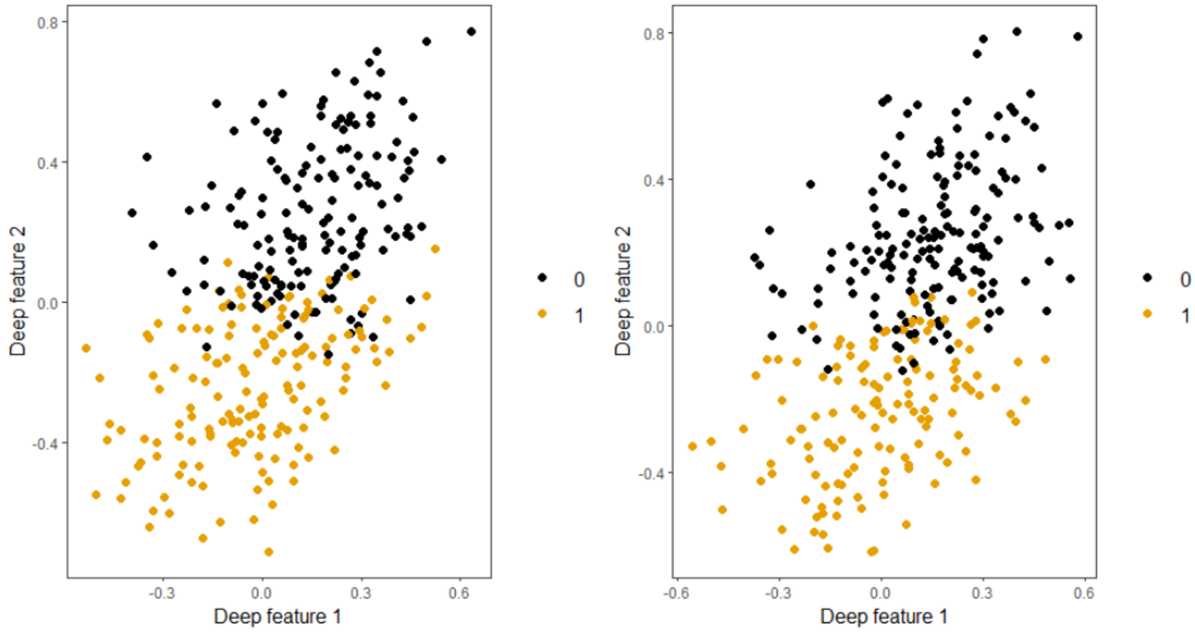

Figure 1. Extracted deep features from neural network using k-means cluster labels for colour coding. Groups are coded with 1 = group one (black) and 0 = group two (orange). Measurement occasion one is depicted on the left side and two at the right side.

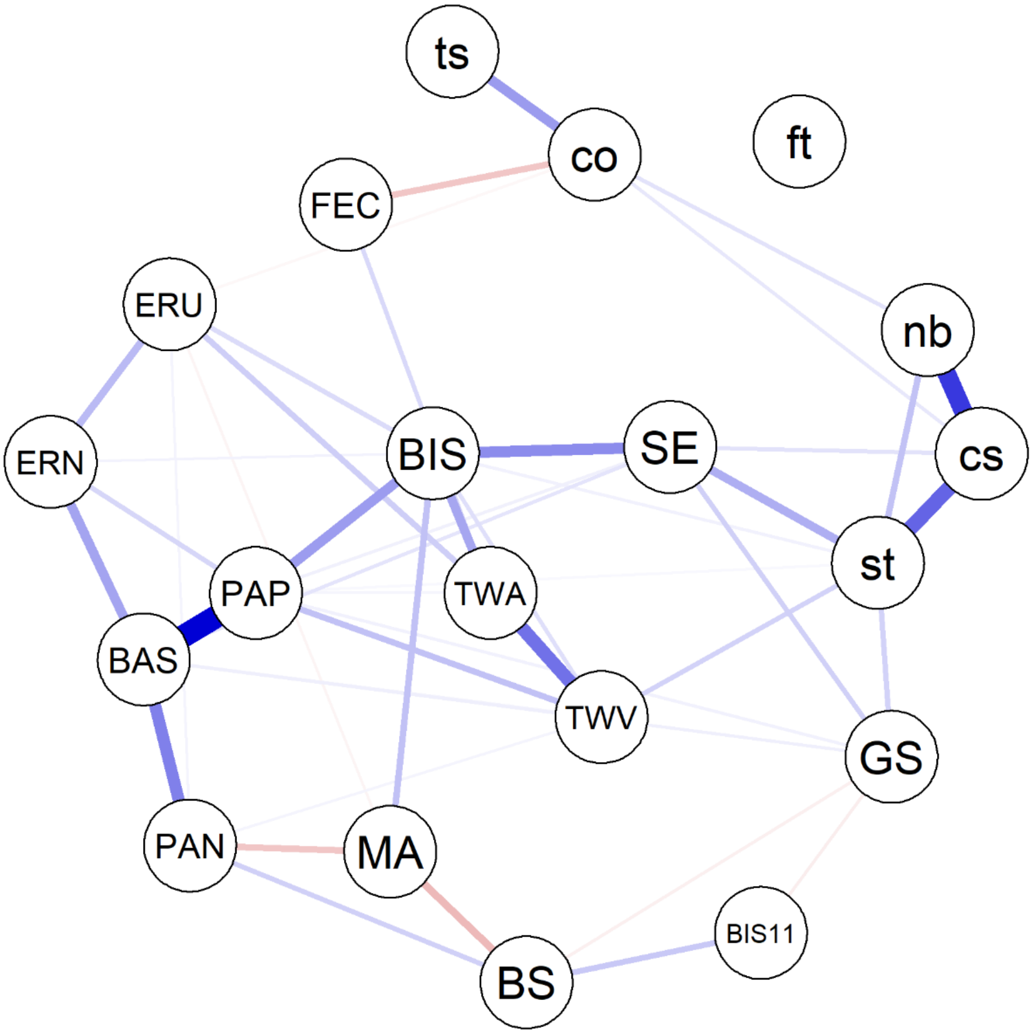

Figure 2. Network model for group one of measurement occasion one. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation and affect measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

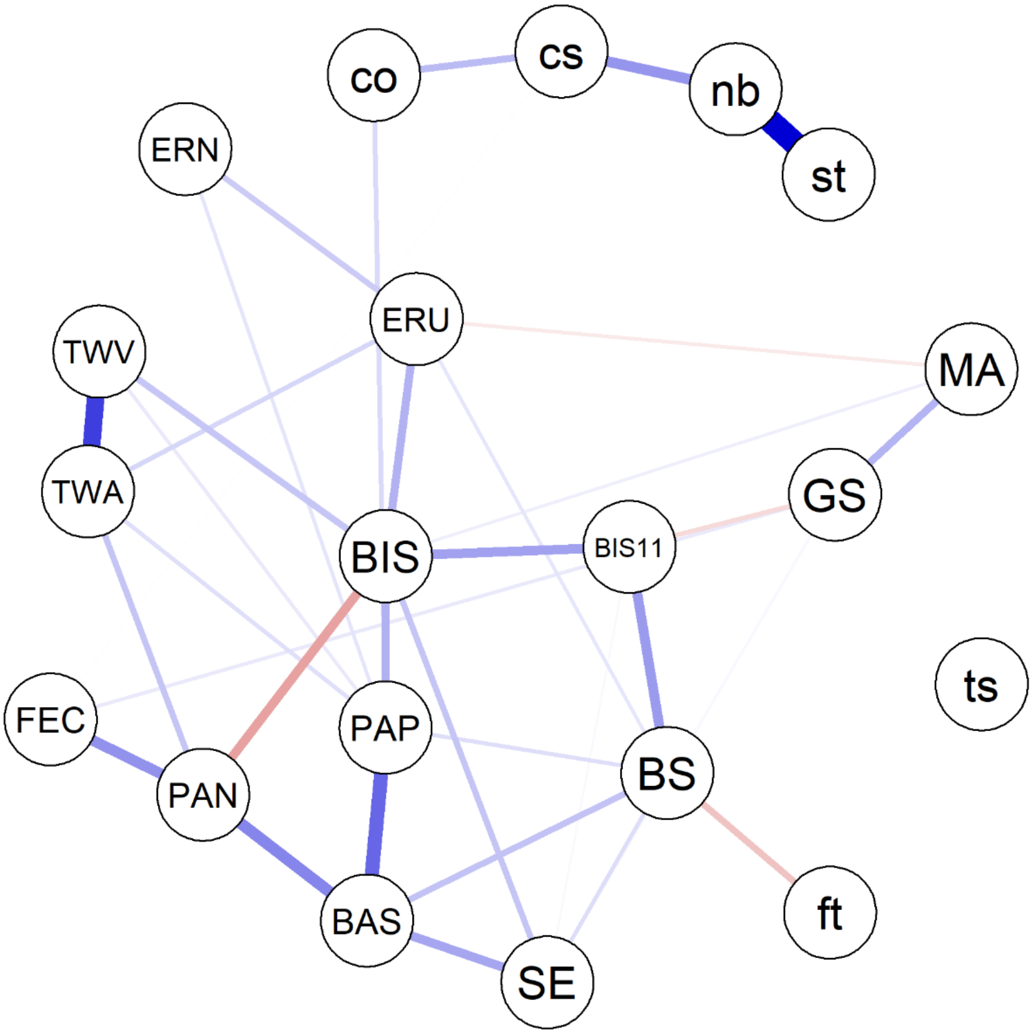

Figure 3. Network model for group two of measurement occasion one. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation and affect measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

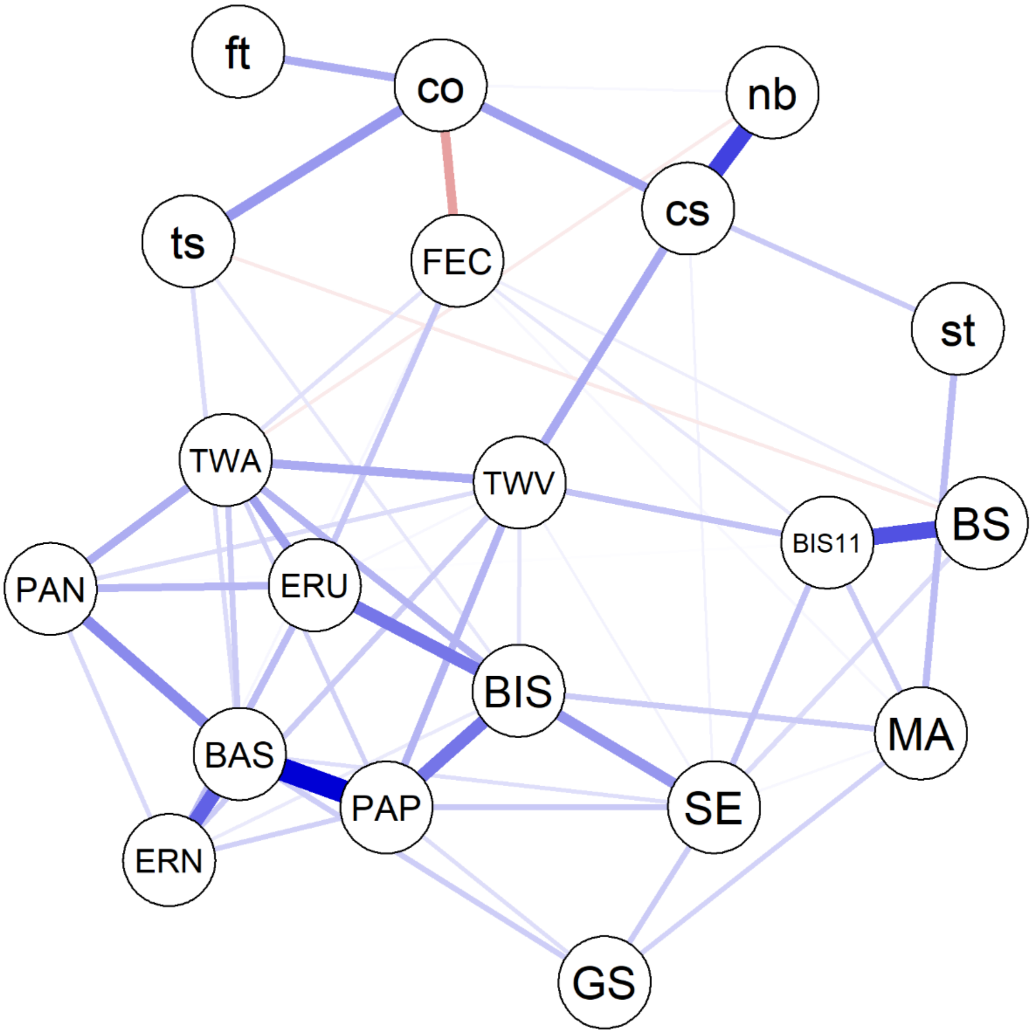

Figure 4. Network model for group one of measurement occasion two. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation and affect measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

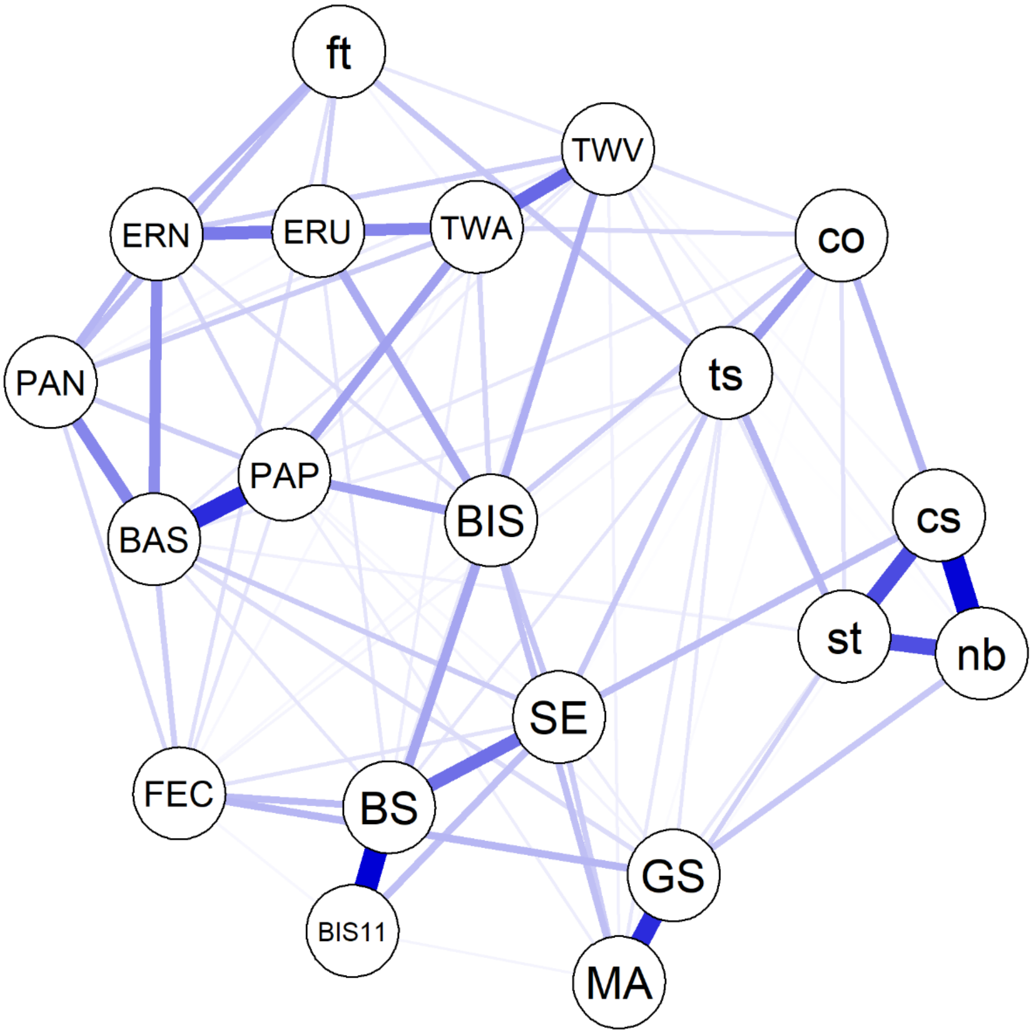

Figure 5. Network model for group two of measurement occasion two. Darker blue corresponds to stronger positive connection strengths (red indicates negative connections). Executive control functions are written in lower case letters and self-regulation and affect measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

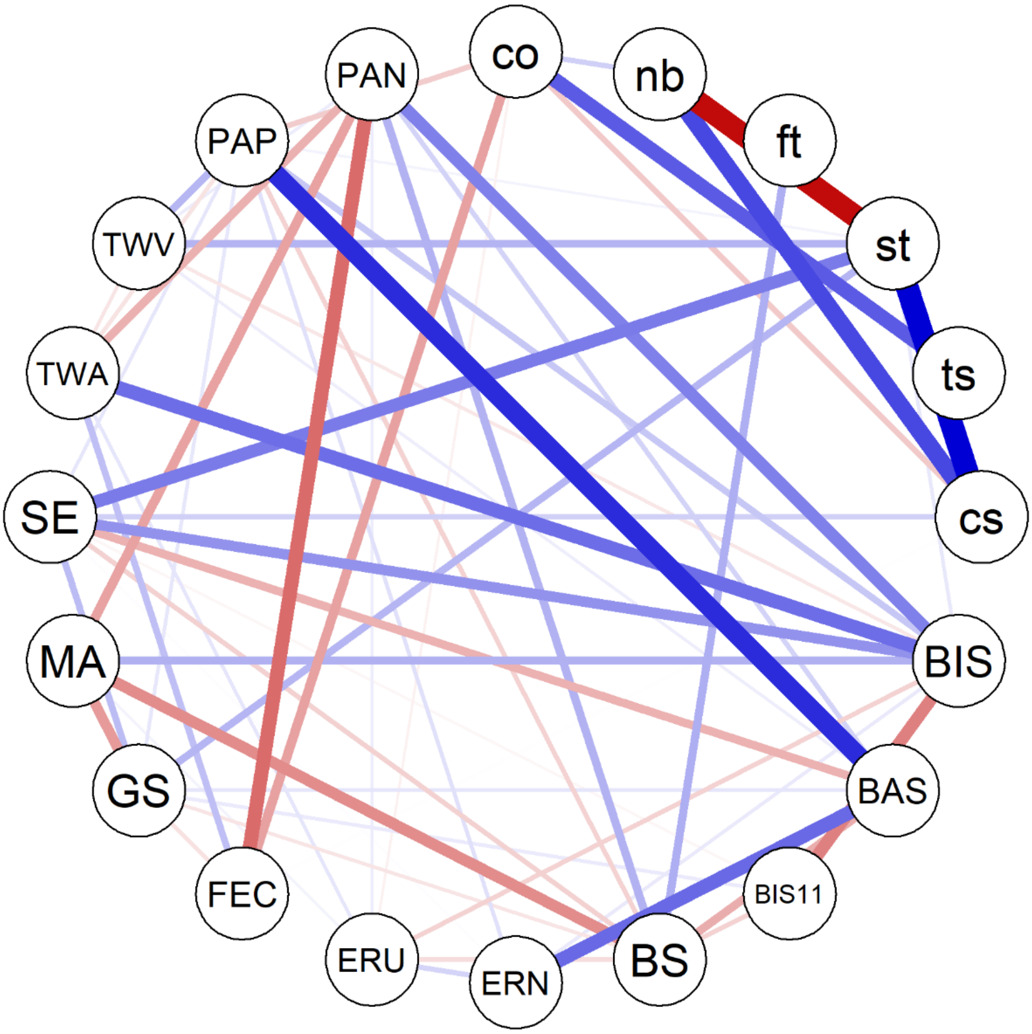

Figure 6. Difference between networks for the two groups at measurement occasion one. Red corresponds to a decrease in connection strength from group two to one. Blue corresponds to an increase in connection strength from group two to one. Executive control functions are written in lower case letters and self-regulation and affect measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

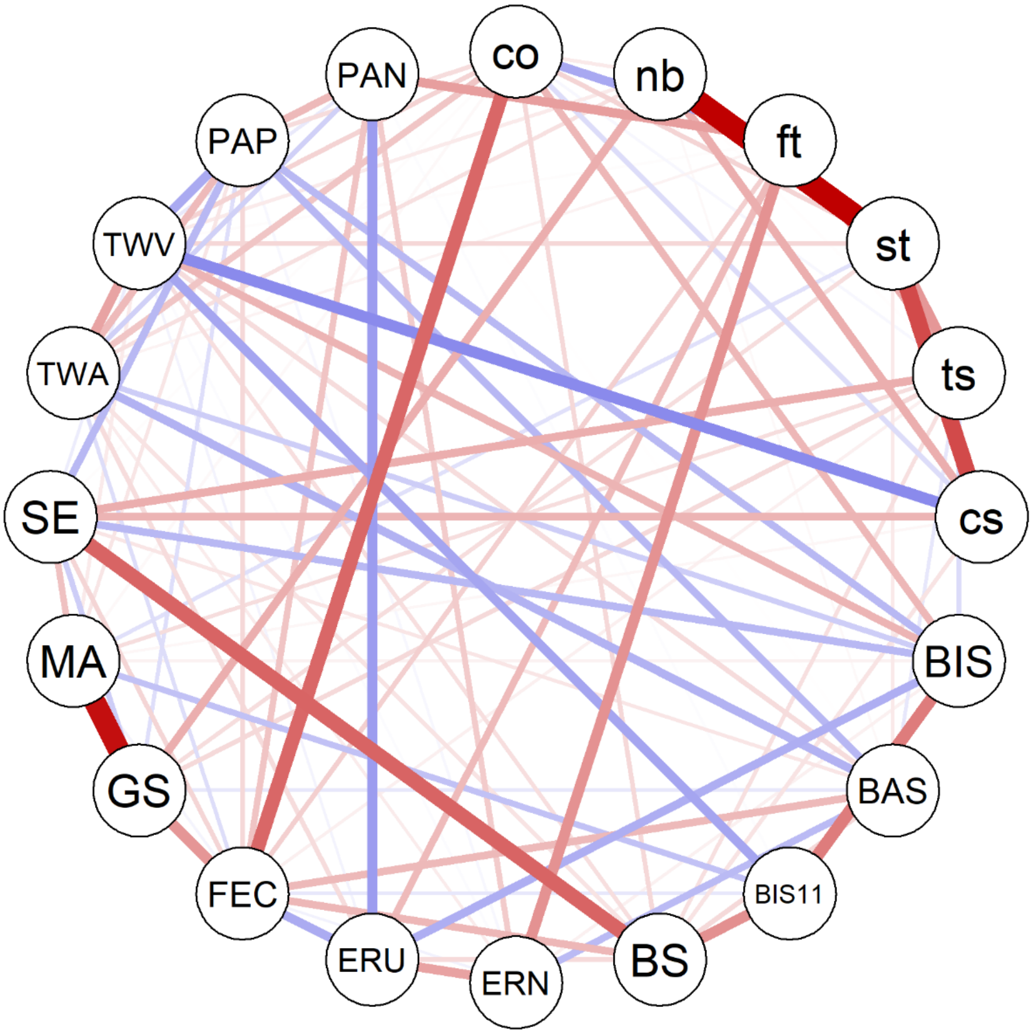

Figure 7. Difference between networks for the two groups at measurement occasion two. Red corresponds to a decrease in connection strength from group two to one. Blue corresponds to an increase in connection strength from group two to one. Executive control functions are written in lower case letters and self-regulation and affect measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

Open Practices Statement

The data and appendix are available at OSF: https://osf.io/9k5rg/?view_only=7387d83e7b6b4d79b0ecf29d26080bce. References for all scales and tasks are included, but they are established instruments and subject to the copyright of authors, publishing companies, and a software company. This paper is based on exploratory analyses of a non-experimental longitudinal data set, which were not preregistered.

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9.6 Supplementary Material for Study 3

Table A1
Correlations of executive control functions and self-regulation measures for group one at measurement occasion one

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. cor																			
2. nb	0.31																		
3. ft	0.01	-0.03																	
4. st	0.18	0.29	-0.17																
5. tss	0.27	0.05	0.05	0.14															
6. cs	0.29	0.58	-0.18	0.31	-0.03														
7. BIS	0.02	0.04	0.02	0.17	0.09	-0.04													
8. BAS	0.04	-0.02	0.07	0.10	0.12	0.05	0.04												
9. BIS11	-0.06	-0.08	0.08	-0.04	-0.08	-0.04	0.10	0.11											
10. BS	0.09	-0.12	0.01	-0.07	-0.01	-0.17	0.00	0.04	0.18										
11. ERN	-0.02	-0.02	-0.12	0.03	0.01	-0.03	0.08	0.23	0.07	0.12									
12. ERU	-0.07	-0.04	-0.07	-0.04	-0.05	-0.04	0.12	-0.07	-0.14	0.00	0.15								
13. FEC	-0.21	-0.14	-0.01	-0.16	-0.22	-0.06	-0.09	-0.05	0.10	0.00	-0.04	0.09							
14. GS	0.10	0.04	0.00	0.24	0.13	0.16	0.09	0.20	-0.23	-0.23	0.12	0.02	-0.04						
15. MA	0.00	0.02	-0.09	0.14	0.12	0.04	0.24	-0.14	-0.13	-0.33	-0.12	-0.20	-0.16	0.01					
16. SE	0.13	0.16	0.00	0.33	0.19	0.14	0.42	0.26	0.07	0.06	0.18	0.02	-0.06	0.20	0.06				
17. TWS	0.05	-0.13	0.00	0.05	-0.01	-0.05	0.23	0.01	-0.06	-0.02	-0.12	0.12	0.17	-0.04	-0.01	0.09			
18. TWR	0.01	0.05	-0.04	0.25	0.02	0.14	0.16	0.12	0.03	0.01	0.01	-0.14	0.07	0.00	0.06	0.19	0.30		
19. PAP	-0.01	0.11	-0.01	0.25	-0.04	0.13	0.25	0.54	0.08	0.05	0.19	-0.03	-0.09	0.21	0.00	0.28	0.12	0.20	
20. PAN	0.12	-0.10	0.21	-0.06	-0.01	-0.12	-0.27	0.31	0.00	0.21	-0.02	0.06	-0.13	0.00	-0.28	-0.05	0.03	0.10	0.09

Note. Executive control functions are labelled in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect. Significant correlations are presented in bold typeface ($p < .05$).

Table A2

Correlations of executive control functions and self-regulation measures for group two at measurement occasion one

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. cor																			
2. nb	0.06																		
3. ft	-0.01	-0.06																	
4. st	0.06	0.33	-0.02																
5. tss	0.09	-0.06	0.02	0.11															
6. cs	0.27	0.39	0.08	0.19	0.12														
7. BIS	0.15	0.01	0.02	-0.07	-0.13	0.05													
8. BAS	0.10	-0.10	-0.09	0.05	0.05	-0.16	-0.14												
9. BIS11	-0.07	-0.15	0.03	-0.24	-0.13	-0.17	0.22	0.04											
10. BS	0.08	0.02	-0.19	-0.09	-0.07	-0.16	0.04	0.19	0.22										
11. ERN	0.00	0.10	0.07	-0.02	0.09	0.15	0.06	0.01	-0.06	0.04									
12. ERU	-0.01	0.00	-0.18	-0.14	-0.04	-0.01	0.14	-0.10	0.06	0.10	0.13								
13. FEC	-0.09	-0.05	-0.06	-0.05	0.12	-0.19	-0.09	0.06	-0.20	0.05	-0.01	0.00							
14. GS	0.04	0.00	-0.01	0.10	0.01	0.03	-0.03	0.06	-0.37	-0.13	-0.10	-0.03	0.09						
15. MA	-0.03	-0.03	0.14	0.02	-0.03	0.05	0.22	-0.09	-0.21	-0.15	-0.07	-0.26	-0.09	0.23					
16. SE	0.21	-0.01	-0.04	0.05	-0.07	0.12	0.24	0.24	0.09	0.14	0.03	0.01	-0.04	0.06	-0.01				
17. TWS	-0.08	-0.10	0.08	-0.07	-0.13	0.02	-0.01	0.00	-0.02	-0.01	-0.10	0.12	0.08	0.10	0.05	-0.12			
18. TWR	0.02	-0.02	-0.01	0.03	-0.12	0.05	0.12	-0.07	-0.06	-0.03	-0.07	-0.10	0.08	0.02	0.15	-0.09	0.32		
19. PAP	0.25	-0.03	0.06	0.07	-0.02	0.02	0.14	0.28	0.01	0.15	0.08	-0.16	0.03	0.08	0.12	0.14	0.09	0.08	
20. PAN	-0.08	-0.05	-0.10	-0.11	0.05	-0.06	-0.49	0.21	-0.11	-0.03	-0.09	0.00	0.28	0.04	-0.23	-0.05	0.13	-0.04	-0.11

Note. Executive control functions are labelled in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect. Significant correlations are presented in bold typeface ($p < .05$).

Table A3

Correlations of executive control functions and self-regulation measures for group one at measurement occasion two

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. cor																			
2. nb	0.04																		
3. ft	0.32	0.10																	
4. st	0.07	0.08	0.22																
5. tss	0.17	-0.14	-0.11	0.11															
6. cs	0.45	0.16	0.10	-0.03	-0.02														
7. BIS	0.05	-0.10	-0.06	-0.02	0.13	0.11													
8. BAS	0.03	0.00	-0.06	0.03	0.22	0.07	0.10												
9. BIS11	-0.02	-0.13	0.03	-0.06	0.02	-0.03	0.07	-0.09											
10. BS	0.11	-0.11	0.14	-0.03	-0.07	0.01	-0.02	0.05	0.26										
11. ERN	-0.07	0.03	-0.12	0.03	0.13	0.05	0.08	0.31	-0.02	0.07									
12. ERU	-0.04	-0.08	-0.12	-0.04	0.01	-0.09	0.20	0.00	-0.22	-0.08	0.13								
13. FEC	-0.28	0.01	-0.02	-0.05	-0.20	-0.23	-0.12	-0.18	0.02	0.00	0.09	0.19							
14. GS	0.08	-0.01	0.06	0.09	0.16	0.17	0.10	0.20	-0.26	-0.07	0.05	-0.01	-0.15						
15. MA	0.03	0.00	0.03	0.15	-0.09	-0.01	0.20	-0.24	0.05	-0.12	0.00	-0.14	-0.04	0.03					
16. SE	0.08	0.03	0.10	0.03	0.14	0.03	0.36	0.25	0.09	0.07	0.03	-0.05	-0.07	0.10	0.00				
17. TWS	-0.10	-0.15	-0.03	-0.07	0.05	-0.06	0.14	0.12	-0.05	0.01	-0.16	0.10	0.09	0.06	-0.09	0.05			
18. TWR	0.10	0.07	-0.05	-0.05	0.12	0.21	0.05	-0.04	0.17	-0.08	0.07	-0.06	0.00	-0.01	-0.12	0.11	0.13		
19. PAP	0.13	-0.03	-0.05	-0.17	0.15	0.22	0.30	0.54	-0.02	0.11	0.18	0.01	-0.22	0.20	-0.16	0.26	0.13	0.15	
20. PAN	0.03	-0.20	0.00	-0.22	-0.04	-0.02	-0.25	0.16	0.04	0.10	0.06	0.10	-0.14	0.00	-0.38	-0.14	0.07	0.01	0.05

Note. Executive control functions are labelled in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect. Significant correlations are presented in bold typeface ($p < .05$).

Table A4
Correlations of executive control functions and self-regulation measures for group two at measurement occasion two

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. cor																			
2. nb	0.07																		
3. ft	0.05	-0.02																	
4. st	0.13	0.20	0.05																
5. tss	0.13	0.15	0.01	0.26															
6. cs	0.20	0.28	0.46	0.34	0.20														
7. BIS	0.07	-0.16	-0.08	-0.03	-0.05	-0.07													
8. BAS	-0.07	-0.06	0.06	0.11	0.17	0.01	-0.11												
9. BIS11	-0.12	-0.06	-0.08	-0.19	-0.14	-0.11	0.25	-0.04											
10. BS	0.05	-0.11	-0.14	-0.14	-0.01	0.02	0.06	0.08	0.38										
11. ERN	-0.06	0.09	0.10	0.00	0.02	0.05	0.04	0.15	0.06	0.07									
12. ERU	-0.05	-0.06	0.00	0.00	-0.03	-0.11	0.13	-0.07	0.04	0.11	0.16								
13. FEC	0.05	-0.08	0.07	-0.09	0.00	-0.07	-0.06	0.15	-0.09	0.01	0.04	0.00							
14. GS	-0.06	0.05	-0.11	0.11	0.05	-0.02	0.02	0.15	-0.34	-0.37	-0.05	0.04	-0.02						
15. MA	0.03	-0.03	0.02	0.12	0.07	0.08	0.16	0.06	-0.12	-0.33	-0.08	-0.21	-0.18	0.25					
16. SE	0.04	-0.01	-0.04	0.00	0.17	0.16	0.26	0.19	0.12	0.19	0.00	0.05	-0.07	-0.05	-0.03				
17. TWS	0.08	0.01	0.03	-0.07	-0.12	-0.12	0.04	-0.12	-0.03	0.12	0.02	0.12	0.05	-0.05	-0.13	-0.11			
18. TWR	0.10	0.07	0.04	0.04	0.01	0.09	0.07	0.02	0.01	0.11	0.04	-0.14	0.01	-0.04	0.04	0.00	0.18		
19. PAP	-0.03	-0.04	0.03	-0.19	-0.17	-0.03	0.10	0.39	0.01	0.06	0.07	-0.13	0.10	0.10	0.08	0.17	0.11	0.02	
20. PAN	-0.14	-0.04	0.01	-0.26	-0.18	-0.18	-0.33	0.19	0.03	0.05	0.10	-0.06	0.18	-0.01	-0.22	-0.05	0.06	-0.01	0.11

Note. Executive control functions are labelled in lower case letters and self-regulation measures in capital letters. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect. Significant correlations are presented in bold typeface ($p < .05$).

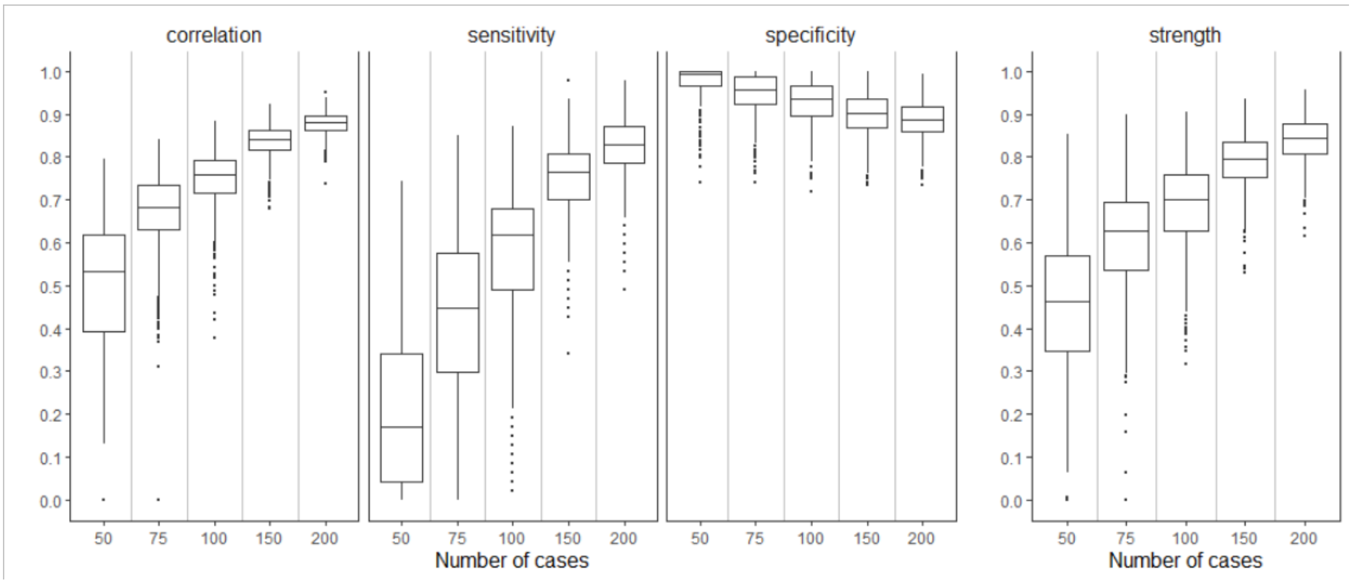


Figure A1. Simulation results using the estimated refitted networks for group one at measurement occasion one as true network structure. Sensitivity, specificity, and correlation between true and estimated networks can be evaluated in the left side and the correlation between true and estimated centrality index node strength on the right side.

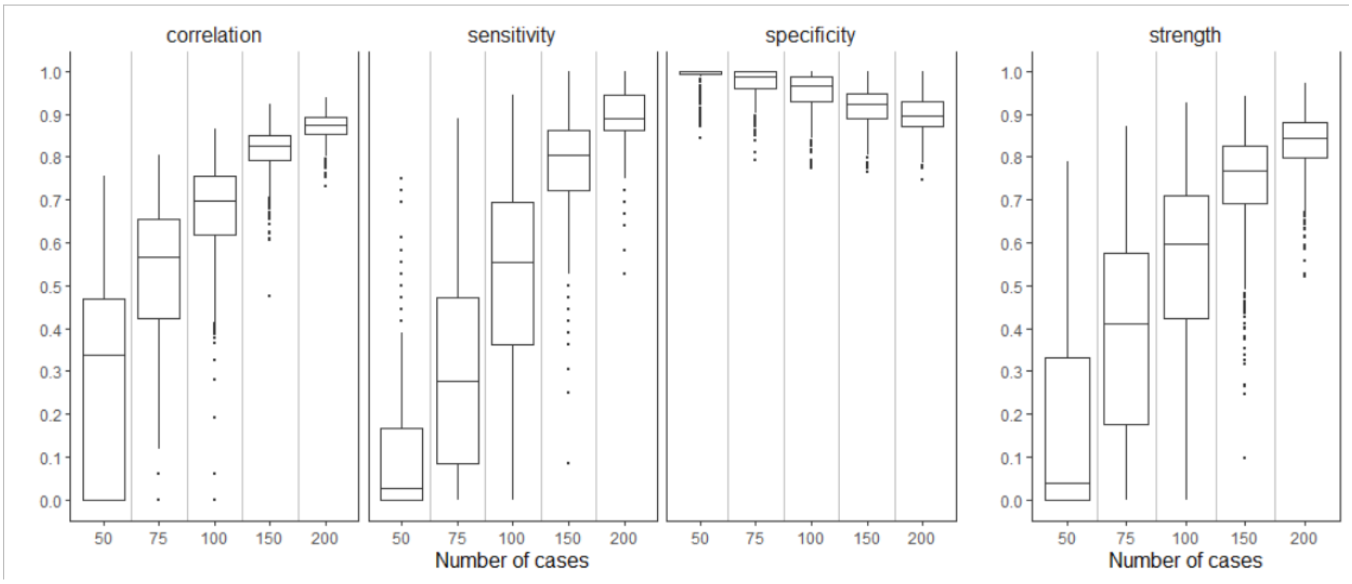


Figure A2. Simulation results using the estimated refitted networks group two at measurement occasion one as true network structure. Sensitivity, specificity, and correlation between true and estimated networks can be evaluated in the left side and the correlation between true and estimated centrality index node strength on the right side.

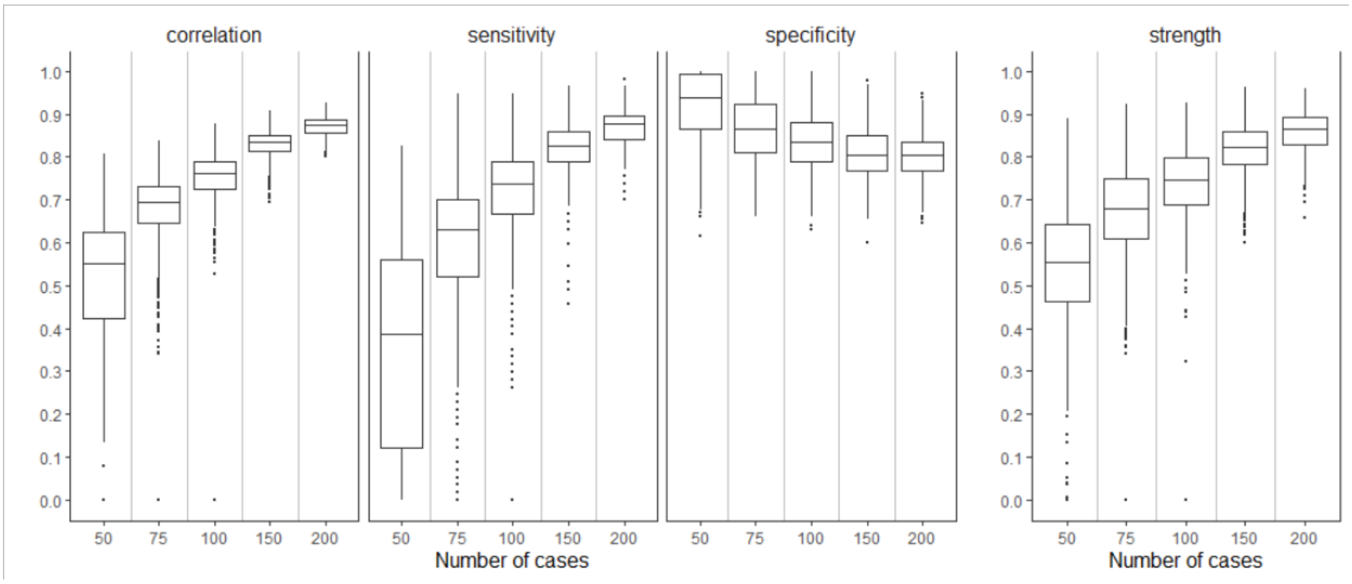


Figure A3. Simulation results using the estimated refitted networks for group one at measurement occasion two as true network structure. Sensitivity, specificity, and correlation between true and estimated networks can be evaluated in the left side and the correlation between true and estimated centrality index node strength on the right side.

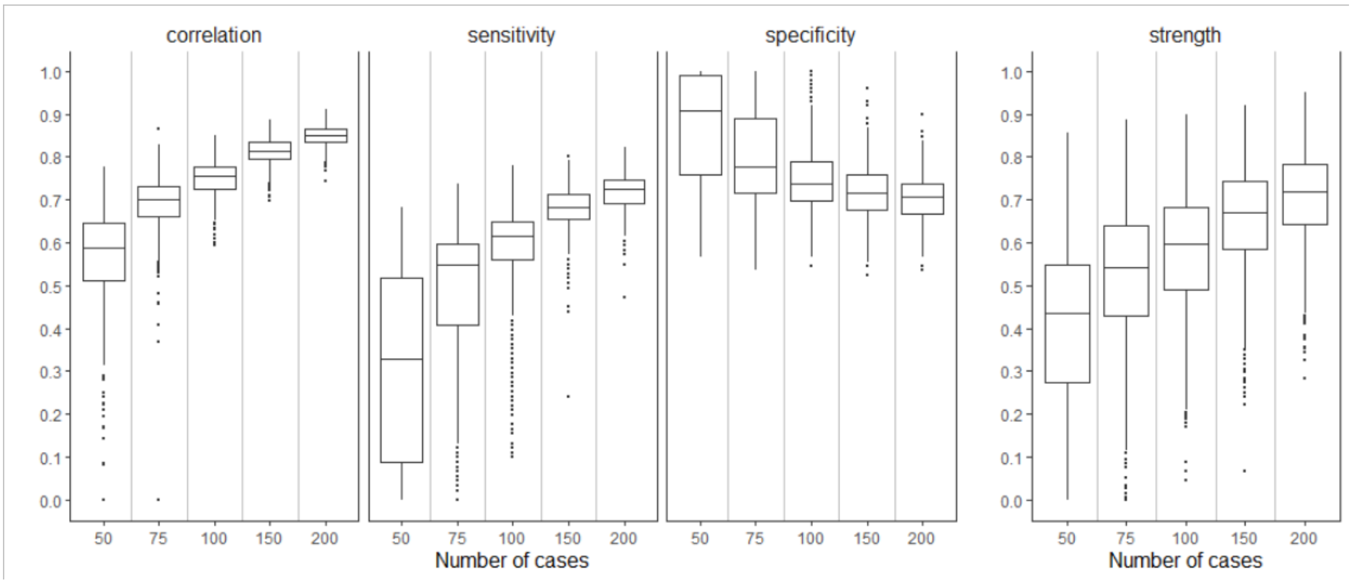
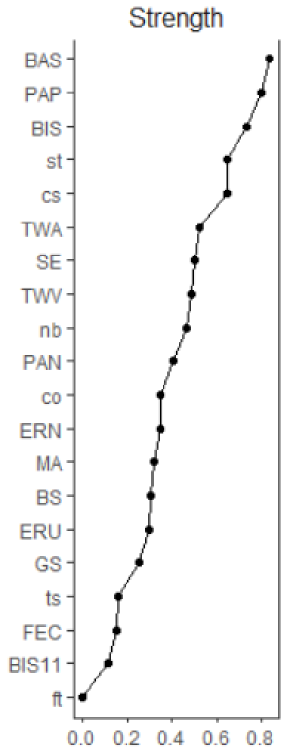


Figure A4. Simulation results using the estimated refitted networks group two at measurement occasion two as true network structure. Sensitivity, specificity, and correlation between true and estimated networks can be evaluated in the left side and the correlation between true and estimated centrality index node strength on the right side.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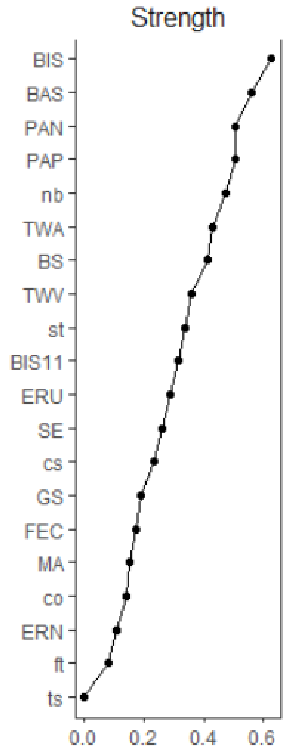
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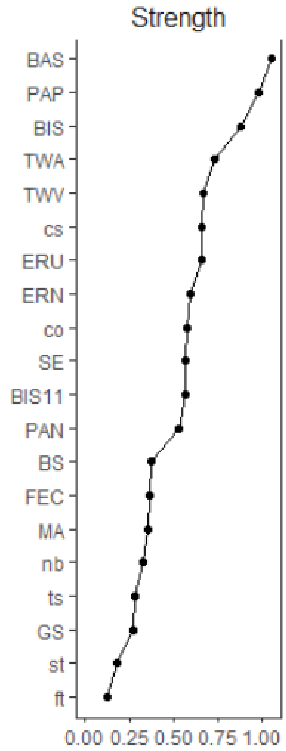
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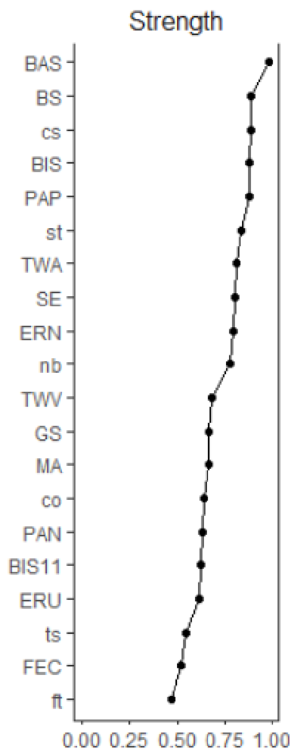
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Figure A5. Centrality index node strength as standardized z-scores (from left to right: measurement occasion one group one and group two after that measurement occasion two group one and group two). Node strength quantifies the direct connection to other nodes. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

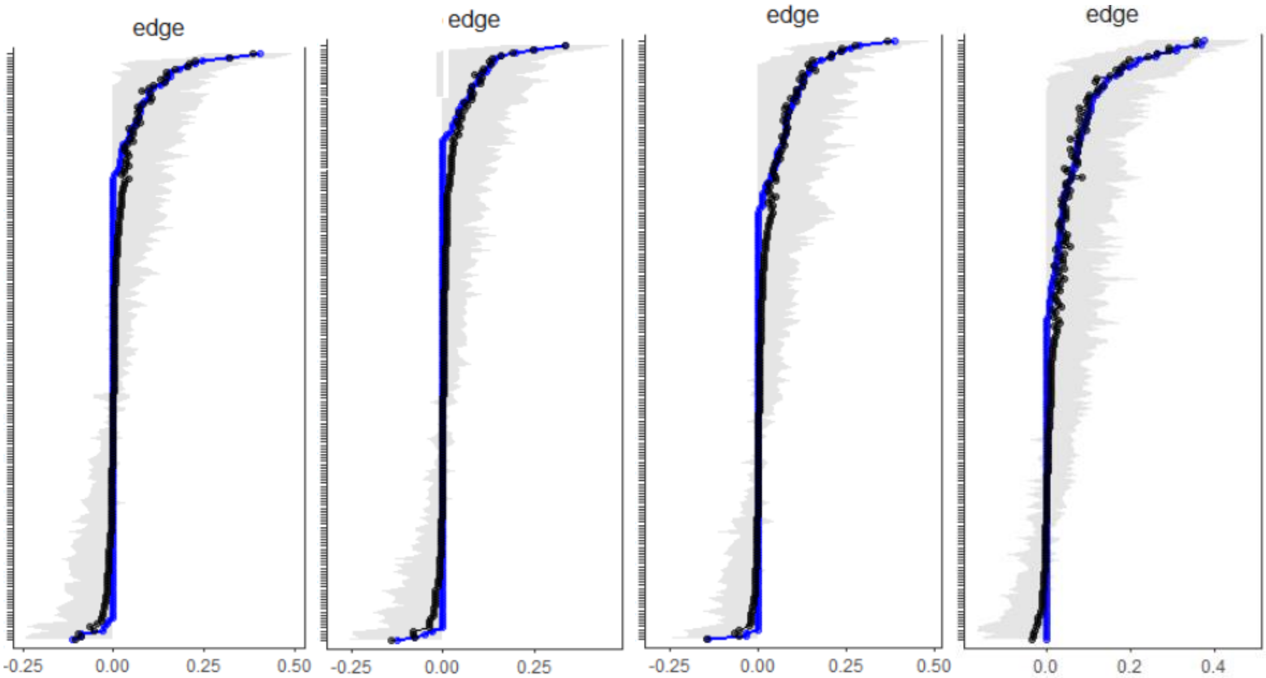

Figure A6. Bootstrapped confidence intervals for estimated edge-weights in the estimated networks (from left to right: measurement occasion one group one and group two after that measurement occasion two group one and group two). The blue line indicates the sample values and the grey area the bootstrapped 95% CIs. Horizontal lines represent network edges, ordered from highest edge-weight to the lowest edge-weight. Please note that edge weights in network models are regularized with a penalty by the graphical lasso algorithm and are therefore smaller than correlations or partial correlations. The y-axis labels have been removed to avoid cluttering.

Figure A7. Centrality stability for all networks as average correlations between the centrality indices of networks while reducing sample size in comparison with the original sample (top down: measurement occasion one group one and group two after that measurement occasion two group one and group two).. Lines correspond to the means and areas to the range between the 2.5th and the 97.5th quantile.

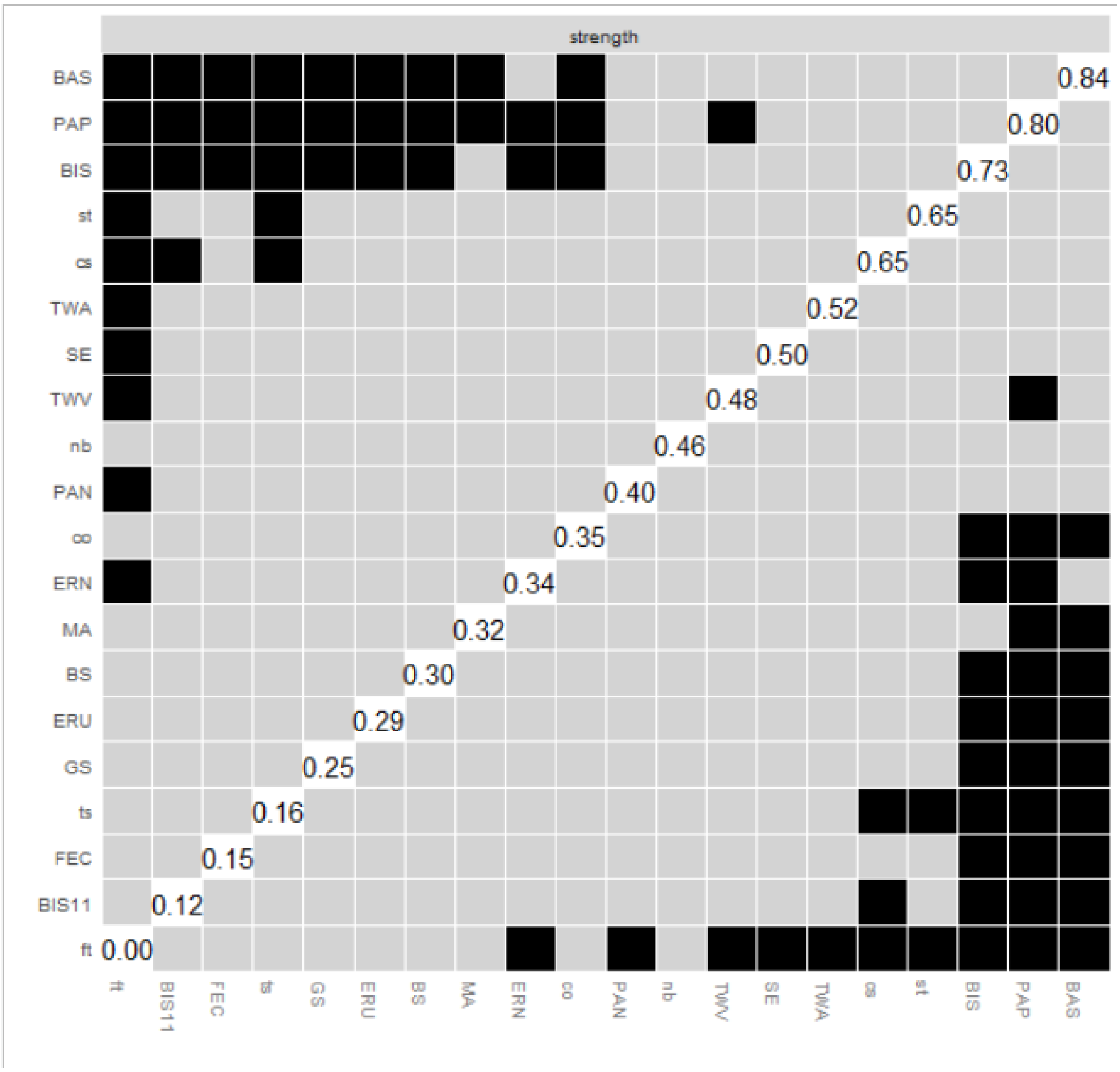

Figure A8. Bootstrapped difference test (α =.05) for centrality index node strength at measurement occasion one for group one. Black parcels mark node strengths that differ in a significant way from one another, whereas grey parcels do not differ significantly. The value of the node strength is in the white diagonal. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

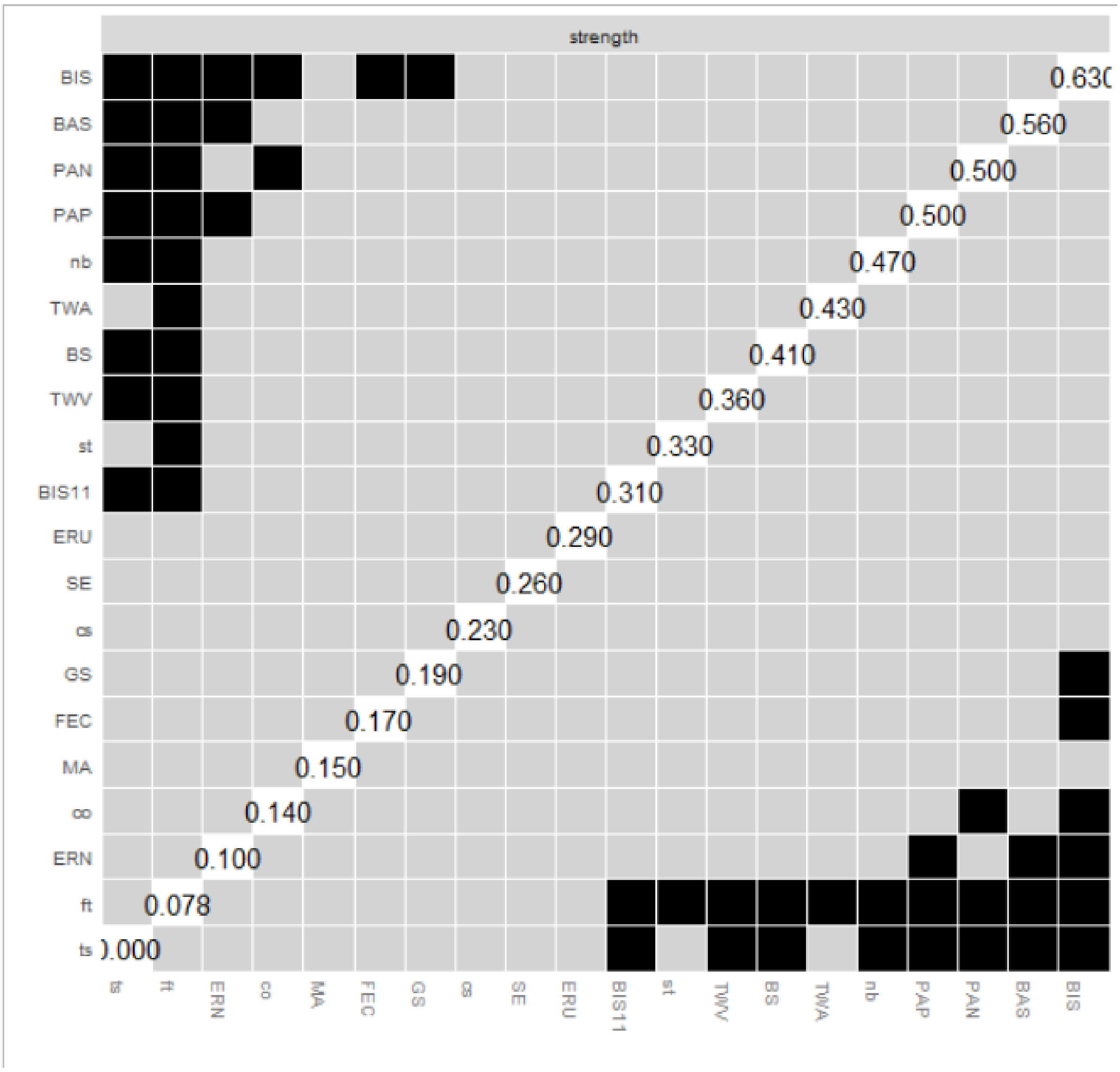

Figure A9. Bootstrapped difference test (α =.05) for centrality index node strength at measurement occasion one for group two. Black parcels mark node strengths that differ in a significant way from one another, whereas grey parcels do not differ significantly. The value of the node strength is in the white diagonal. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

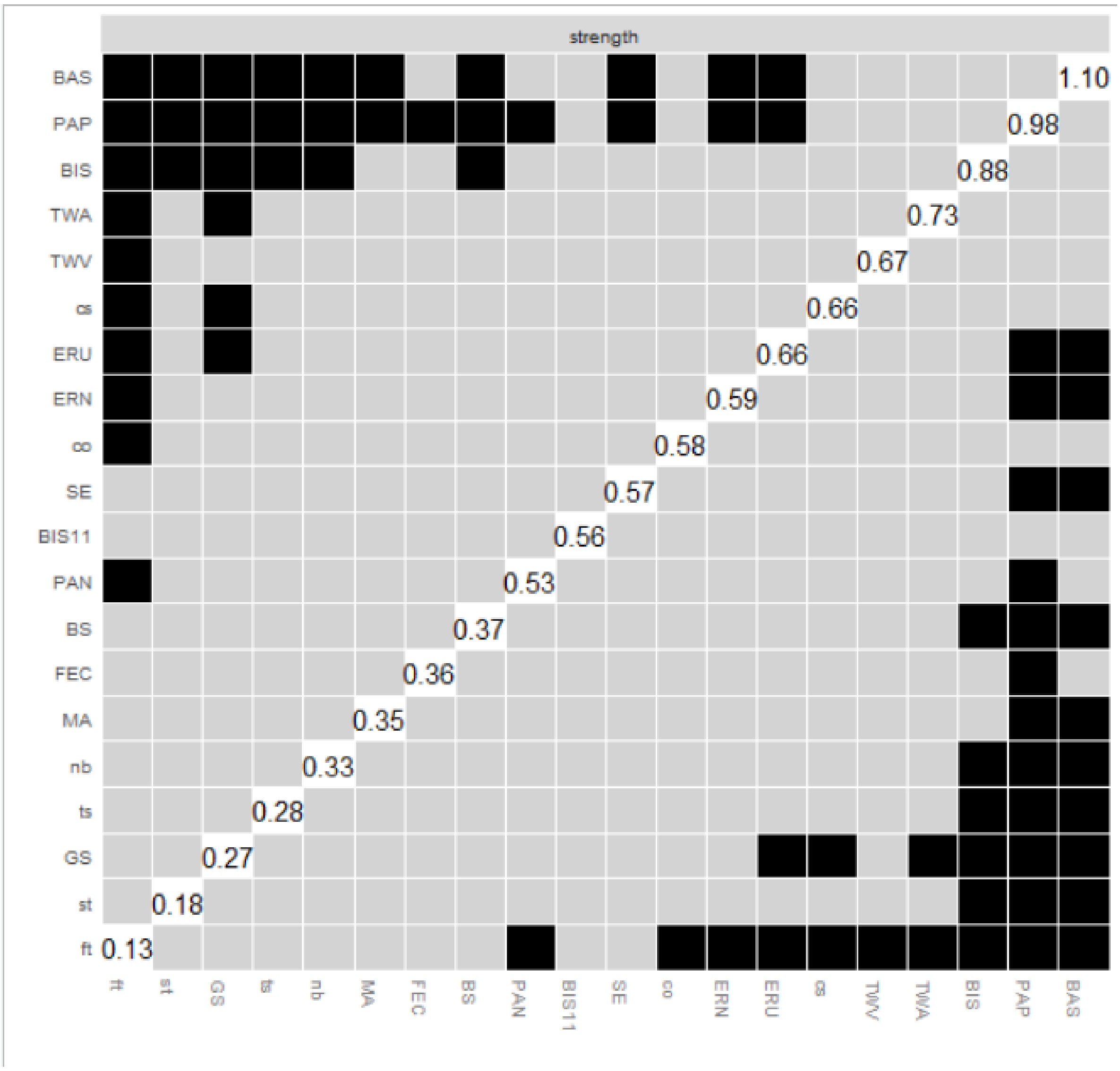

Figure A10. Bootstrapped difference test (α =.05) for centrality index node strength at measurement occasion two for group one. Black parcels mark node strengths that differ in a significant way from one another, whereas grey parcels do not differ significantly. The value of the node strength is in the white diagonal. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

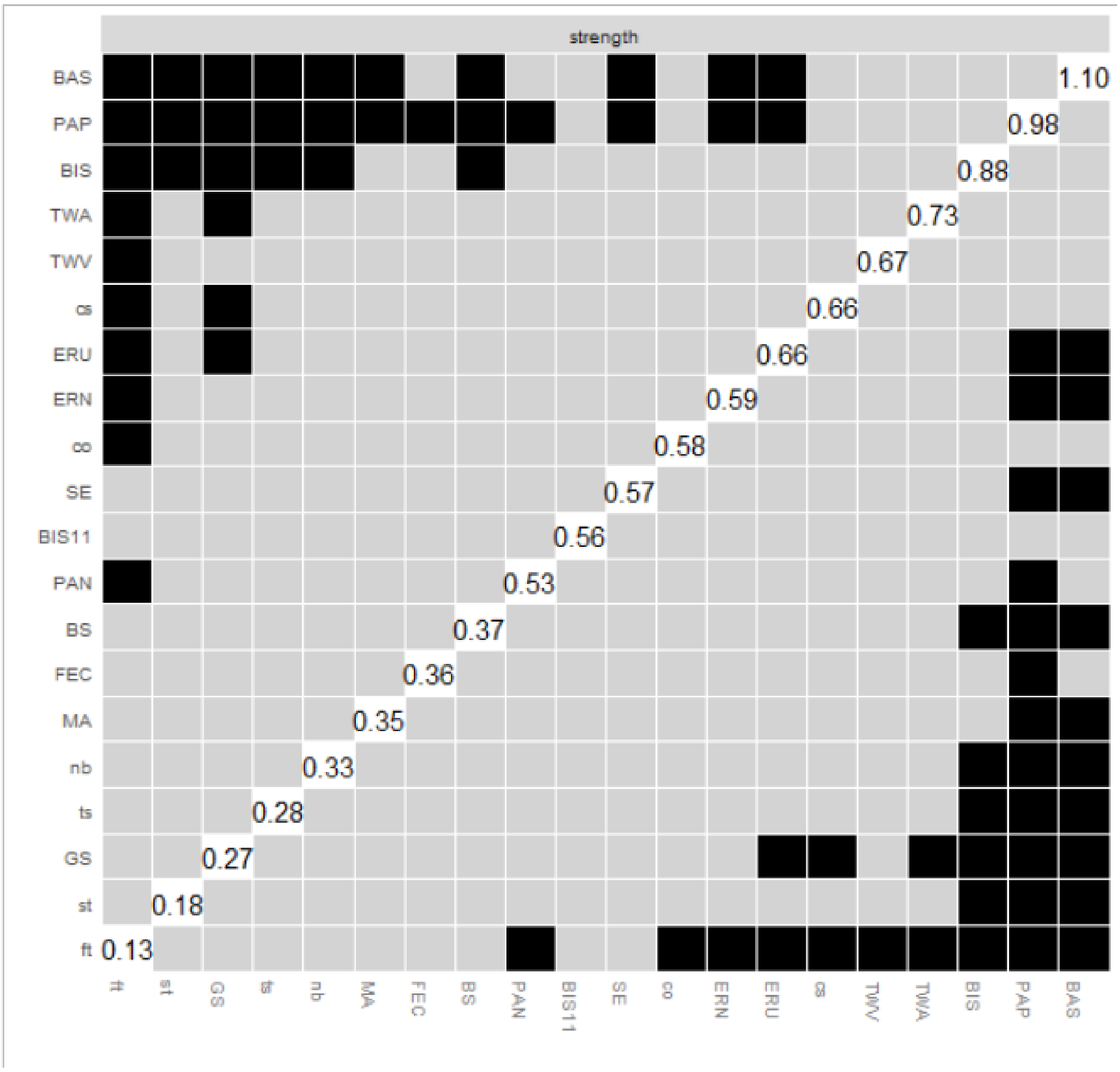

Figure A11. Bootstrapped difference test (α =.05) for centrality index node strength at measurement occasion two for group two. Black parcels mark node strengths that differ in a significant way from one another, whereas grey parcels do not differ significantly. The value of the node strength is in the white diagonal. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

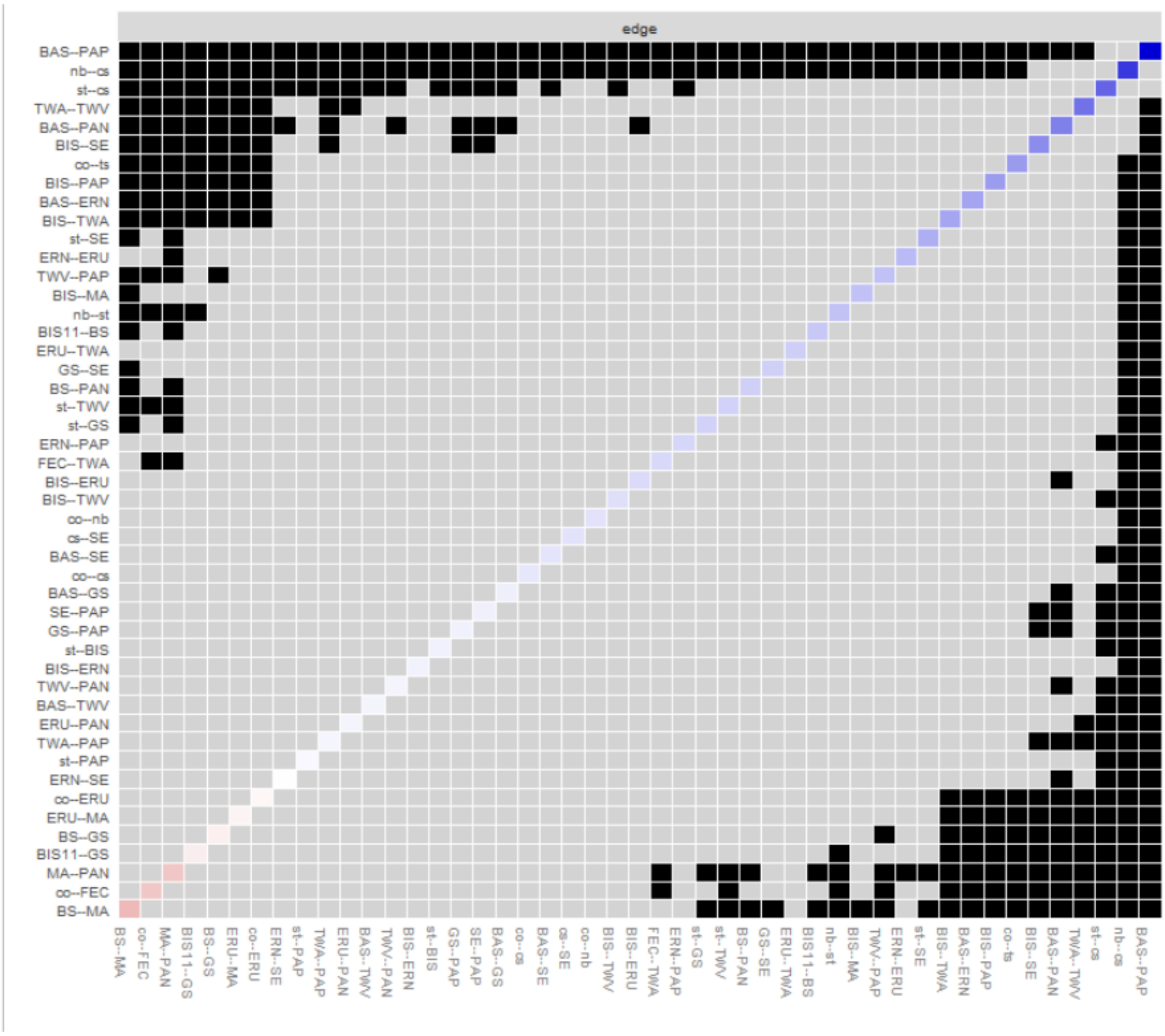

Figure A12. Bootstrapped difference test (α =.05) for all edge-weights at measurement occasion one for group one. Blue color coding corresponds to the color of edge-weights in the network plots. Black parcels indicate edge-weights that differ significantly from one another, whereas grey parcels do not differ significantly. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERR = Emotion Regulation (reappraisal); ERS = Emotion Regulation Scale (suppression); EQC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PA = Positive Affect; NA = Negative Affect.

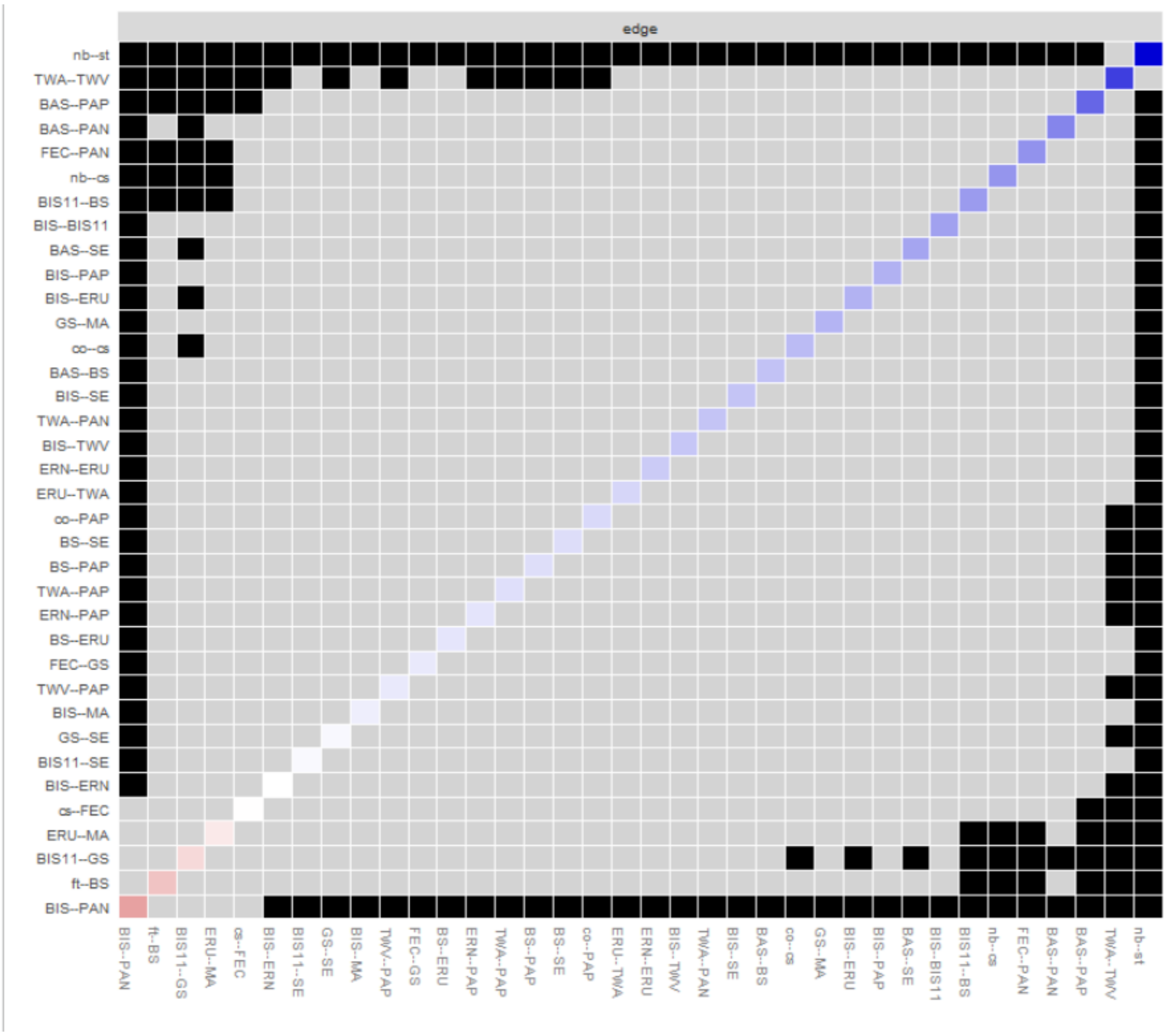

Figure A13. Bootstrapped difference test (α =.05) for all edge-weights at measurement occasion one for group two. Blue color coding corresponds to the color of edge-weights in the network plots. Black parcels indicate edge-weights that differ significantly from one another, whereas grey parcels do not differ significantly. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

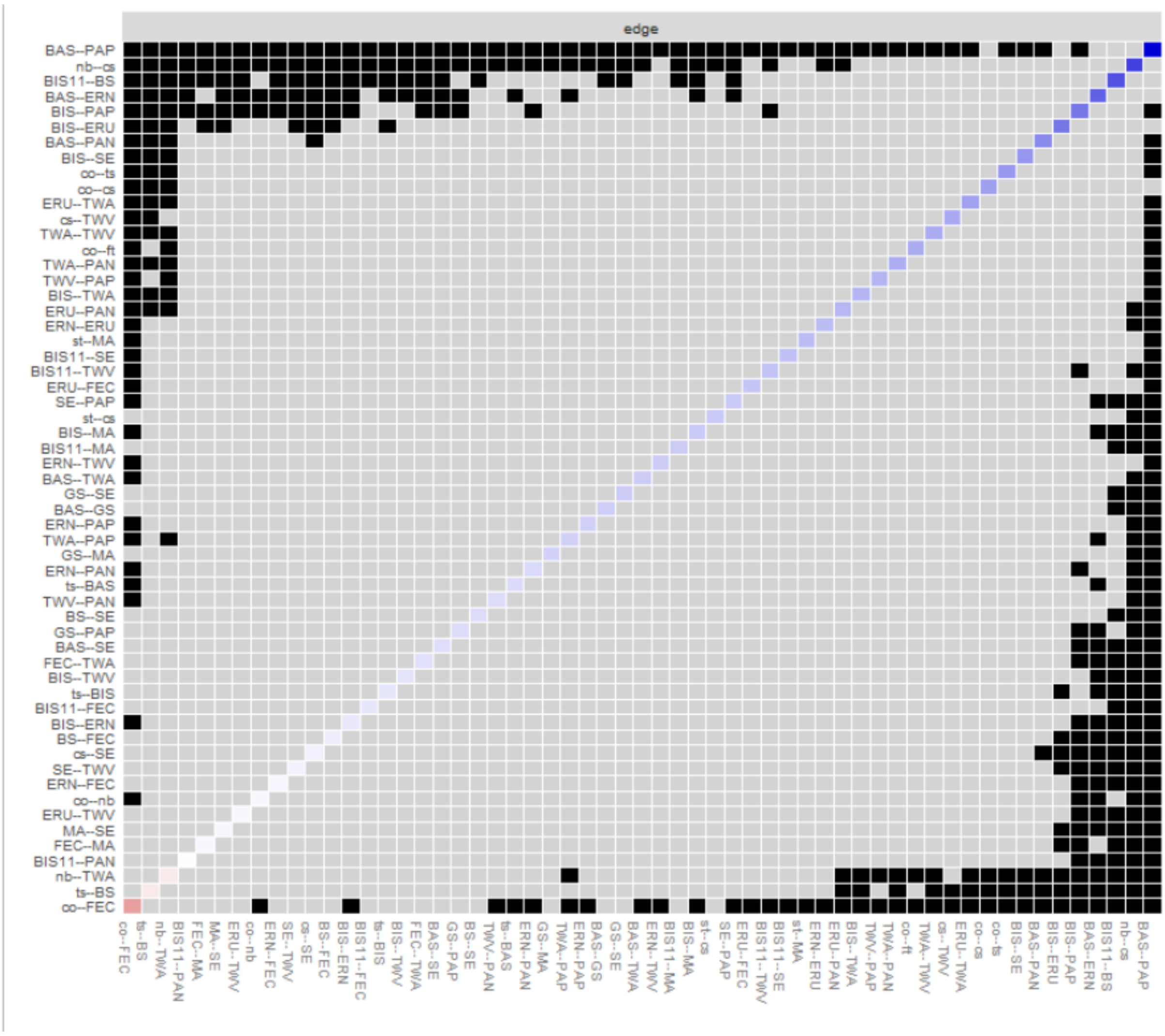

Figure A14. Bootstrapped difference test (α =.05) for all edge-weights at measurement occasion two for group one. Blue color coding corresponds to the color of edge-weights in the network plots. Black parcels indicate edge-weights that differ significantly from one another, whereas grey parcels do not differ significantly. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

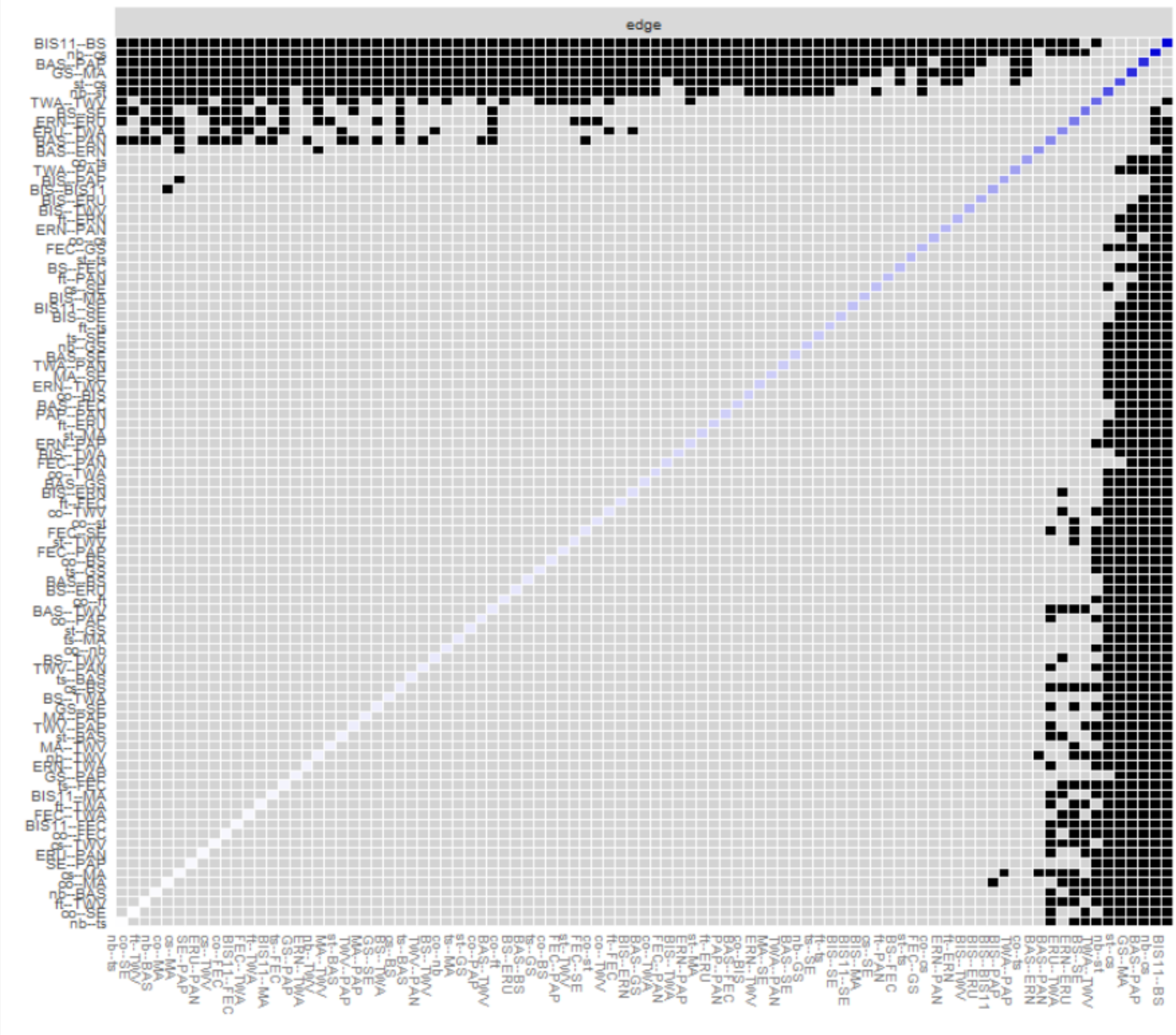

Figure A15. Bootstrapped difference test (α =.05) for all edge-weights at measurement occasion two for group two. Blue color coding corresponds to the color of edge-weights in the network plots. Black parcels indicate edge-weights that differ significantly from one another, whereas grey parcels do not differ significantly. cor = Corsi Span Backwards Task; nb = n-back Task; ft = Flanker Task; st = Stroop Task; tss = Task Switching; cs = Wisconsin Card Sorting Task; BIS = Behavioral Inhibition System; BAS = Behavioral Approach System; BIS11 = Barratt Impulsiveness Scale; BS = Brief Self Control Scale; ERN = Emotion Regulation (reappraisal); ERU = Emotion Regulation Scale (suppression); FEC = Three Factor Eating Questionnaire (cognitive control); GS = Grit Scale; MA = Mindful Attention and Awareness Scale; SE = Sensation Seeking Scale; TWS = Theories of Willpower (strenuous mental activity); TWR = Theories of Willpower (resisting temptations); PAP = Positive Affect; PAN = Negative Affect.

10 Appendix

10.1 General Statement & Author’s Contributions (in German)

Eidesstattliche Erklärung

Hiermit erkläre ich, Markus Neubeck, dass ich die Synopse der vorliegenden Dissertation eigenständig ohne die unzulässige Inanspruchnahme Dritter verfasst habe und keine anderen als die angegeben Hilfsmittel verwendet habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken habe ich als solche gekennzeichnet.

Für die drei im Rahmen dieser Dissertation verfassten Publikationen wurden folgende individuelle Beiträge von den einzelnen Autor*innen (definiert nach dem CRediT-System) erbracht:

Manuskript #1

Neubeck, M., Karbach, J., & Könen, T. (2022). Network models of cognitive abilities in younger and older adults. *Intelligence*, *90*, 101601.

<u>Individuelle Beiträge von den Autor*innen nach dem CRediT-System:</u>

MN: Conceptualization, Methodology, Data Curation, Formal analysis, Validation, Visualization, Writing - Original Draft

JK: Investigation, Project administration, Data Curation, Resources, Supervision, Writing - Review & Editing

TK: Conceptualization, Methodology, Validation, Supervision, Writing - Review & Editing

Manuskript #2

Neubeck, M., Johann, V. E., Karbach, J., & Können, T. (2022). Age-differences in network models of self-regulation and executive control functions. *Developmental Science, 25*(5), e13276.

Individuelle Beiträge von den Autor*innen nach dem CRediT-System:

MN: Conceptualization, Investigation, Project administration, Methodology, Data Curation, Formal analysis, Validation, Visualization, Writing - Original Draft

VEJ: Conceptualization, Investigation, Project administration, Writing - Review & Editing

JK: Conceptualization, Resources, Supervision, Writing - Review & Editing

TK: Conceptualization, Methodology, Validation, Supervision, Writing - Review & Editing

Manuskript #3

Neubeck, M., Johann, V. E., Karbach, J., & Könen, T. (2023). Relations of Executive Control Functions, Self-Regulation, and Affect: A Machine Learning and Network Modelling Approach. *Manuscript under review*.

Submitted: 13.06.2023 to Behavior Research Methods.

<u>Individuelle Beiträge von den Autor*innen nach dem CRediT-System:</u>

MN: Conceptualization, Investigation, Project administration, Methodology, Data Curation, Formal analysis, Validation, Visualization, Writing - Original Draft

VEJ: Conceptualization, Investigation, Project administration, Writing - Review & Editing

JK: Conceptualization, Resources, Supervision, Writing - Review & Editing

TK: Conceptualization, Methodology, Validation, Supervision, Writing - Review & Editing

Diese Arbeit habe ich weder Gänze noch in Teilen in gleicher noch in ähnlicher Form als Prüfungsarbeit für eine staatliche oder andere wissenschaftliche Prüfung eingereicht.

Landau, der 26.06.2023

Markus Neubeck

Markus Neubeck, M.A.

10.2 Acknowledgments (in German)

Zuerst möchte ich mich bei Tanja Könen für die in jeder Hinsicht hervorragende Betreuung meiner Dissertation bedanken sowie bei Frau Julia Glombiewski dafür, dass sie das Zweitgutachten für diese Arbeit übernimmt.

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Ohne ProbandInnen, die an den jeweiligen Forschungsvorhaben teilgenommen hätten, sowie Studierende und Hilfskräfte, die bei der Rekrutierung und Datenerhebung mitgewirkt hätten, wäre dieses Forschungsvorhaben nicht möglich gewesen – Dankeschön.

Auch die konstruktive Kritik der anonymen Reviewer, die bereits publizierten Beiträge begutachtet haben, hat maßgeblich zur Verbesserung dieser Arbeit beigetragen.

Danke auch an alle Kolleginnen und Kollegen aus meiner Arbeitsgruppe, die mir in vielerlei Dingen mit Rat und Tat zur Seite gestanden haben.

Zuletzt möchte ich mich auch bei allen Freunden und meiner Familie bedanken, die mich während dieser Zeit unterstützt haben.

10.3 Academic Curriculum Vitae (in German)

Angaben zur Person

Name: Neubeck, Markus

Studium sowie Schul- und Berufsbildung

10/2016 –03/2019	Masterstudium in Erziehungswissenschaften Goethe-Universität Frankfurt am Main Thema d. MA-Arbeit: „Die prognostische Performanz von Machine Learning im Vergleich mit klassischen statischen Verfahren bei der Analyse bildungswissenschaftlicher Daten.“ Abschlussnote: 1,3
10/2013 – 09/2016	Bachelorstudium in Erziehungswissenschaften Goethe-Universität Frankfurt am Main Thema d. BA-Arbeit: „Zur Überschätzung Computerbezogener Fähigkeiten: Kommt es darauf an, was man fragt?“ Abschlussnote: 1,0
09/2010 – 01/2013	Ausbildung zum Industriekaufmann Heraeus Holding GmbH
04/2010 – 09/2010	Berufliche Neuorientierung und Bewerbungsphase
10/2009 – 03/2010	Bachelorstudium in Informatik Technische Universität Darmstadt
09/2000 – 07/2009	Allgemeine Hochschulreife Kronberg-Gymnasium Aschaffenburg

Berufserfahrung

Seit 07/2019	Wissenschaftlicher Mitarbeiter Entwicklungspsychologie und Pädagogische Psychologie Universität Koblenz · Landau
10/2017 – 04/2018 sowie 10/2018 – 03/2019	Studentische Hilfskraft Entwicklungspsychologie und Pädagogische Psychologie Universität Koblenz · Landau
04/2016 – 09/2017	Studentische Hilfskraft Cognition and Development Lab (Pädagogische Psychologie) Goethe-Universität Frankfurt am Main
11/2014 – 03/2018	Studentische Hilfskraft Quantitative Methoden der Erziehungswissenschaft Goethe-Universität Frankfurt am Main
09/2013 – 11/2015	Aushilfe Personalmanagement Heraeus Holding GmbH
01/2013 – 08/2013	Sachbearbeiter Personalmanagement Heraeus Holding GmbH

Publikationen

Neubeck, M., Karbach, J., & Könen, T. (2022). Network models of cognitive abilities in younger and older adults. *Intelligence*, *90*, 101601.

Neubeck, M., Johann, V. E., Karbach, J., & Könen, T. (2022). Age-differences in network models of self-regulation and executive control functions. *Developmental Science*, 25(5), e13276.

Konferenzbeiträge

04/2023	Conference of the European Cognitive Aging Society (EUCAS), Leuven, Belgien Poster: Network models of cognitive abilities in younger and older adults.
08/2022	Conference of the European Society for Cognitive Psychology (ESCOP), Lille, Frankreich Vortrag: Age-differences in network models of self-regulation and executive control functions.

Auslandsaufenthalte

01/2012 – 03/2012	Praktikum während der Berufsausbildung Heraeus Kulzer Schweiz AG

Wettbewerbe

Sommersemester 2018	Smart Supply Chain Data Challenge: 2. Platz Procter & Gamble und Frankfurt Big Data Lab Goethe Universität Frankfurt

Engagement

09/2010 – 01/2013	Gruppensprecher der kaufmännischen Auszubildenden meines Lehrjahres

Frankfurt am Main, 26. Juni 2023