Re-conceptualizing Executive Functions: A Taxometric and Network Approach

by

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Abstract

Executive function is a neuropsychological construct that describe a collection of cognitive processes that aid in complex, goal-directed behaviours. In two manuscripts, the underlying assumption of dimensionality in latent variable methods is examined and an alternative conceptual model is discussed. The first manuscript uses two large demographically matched samples to assess the latent structure of two commonly studied executive functions, inhibition and set shifting, using taxometric methods. This study demonstrated latent dimensionality for inhibition and set shifting in both performance-based and behavioural rating measures, providing empirical support for the widespread usage of latent variable methods in typically developing populations across the lifespan. The second manuscript uses the same samples as the first to provide an alternative to latent variable methods when modelling executive functions. Network models were produced using the same data and results are discussed in the context of improvements in theory and clinical utility. Taken together, these manuscripts provide additional impetus for the importance of having strong theoretical reasons for performing specific analyses in executive function research.

Keywords: executive functions, taxometrics, network models

Table of Contents

List of Tables

List of Figures

Chapter 2

Chapter 3

List of Figures (Continued)

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Dedication

To my grandparents, Susan and Stephen, who left the comforts of home to start over in a new place so that their children and grandchildren could have a better life. To my parents, Chi-Ann and Alex, who took those opportunities and more to instill a sense of endless curiosity about the world and the importance of learning from everyone I can. To my partner, Alyssa, for your love and boundless support, both practical and emotional. Without you all, this dissertation would have held little value, you were the reasons why I made it to the finish line.

Chapter 1: Re-conceptualizing Executive Functions: A Taxometric and Network Approach

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Re-conceptualizing Executive Functions: A Taxometric and Network Approach

The concept of executive functions or executive functioning emerged in the early 20th century where clinical cases of frontal lobe lesion patients presenting with diverse presentations of neurocognitive deficits were classified as suffering from frontal lobe syndromes (Stuss & Benson, 1984). These behavioural profiles were initially tied to damage to particular neurological structures and led to one of three general dysexecutive syndromes (Schoenberg & Scott, 2011). More specifically, damage to dorsolateral regions of the prefrontal cortex was associated with poor problem solving and organizational ability, perseveration, and working memory deficits (i.e., a dysexecutive syndrome). Damage to orbitofrontal regions was associated with disinhibition, poor impulse control, distractibility, and emotional dysregulation (i.e., a pseudopsychopathic syndrome); whereas damage to medial frontal regions was associated with apathy, lack of insight or awareness, restricted emotional range, and memory issues (i.e., an apathetic syndrome).

As developments in the understanding of this construct grew, scientific inquiry moved towards examining executive functions in neurologically intact populations and delved into the emergence of executive functions in humans. Today, executive functions are broadly defined as a neuropsychological construct describing a collection of cognitive processes thought to underlie complex, goal-directed planning, action, self-monitoring, and self-regulation (Baggetta & Alexander, 2016). These cognitive processes are thought to be predominantly associated with prefrontal regions of the brain, though not exclusively so as these regions are also embedded within whole-brain networks that govern complex human behaviour (Stuss, 2011). Perhaps due to the involvement of nearly all cortical regions in producing executive behaviours, contemporary descriptions of executive functioning have attempted to explain virtually all forms of complex human behaviour, which unsurprisingly has led to a general lack of consensus surrounding basic definitions (Hass et al., 2014; Jurado & Rosselli, 2007; Maricle & Avirett, 2012) and weak or nonexistent associations between different measures (Toplak et al., 2013). As such, a brief overview of some of the most influential taxonomies of executive functioning may be illuminating in this regard.

Prominent Models of Executive Functioning

Hierarchical Model of Cortical Functioning: While originally derived as a general model for neuropsychological functioning and not specifically a model of executive functioning, Alexander Luria, the father of neuropsychology, posited the existence of three distinct but hierarchically organized units of brain function that worked in conjunction to produce human thought and behaviour (Luria, 1973). Unit 1 is composed of brainstem and midbrain structures that regulate attention and physiological arousal. Unit 2 is composed of the temporal, parietal, and occipital lobes and is responsible for processing and managing incoming sensory information. Unit 3 is composed of the prefrontal lobes and is responsible for planning, producing, and monitoring complicated behaviours. There is a further delineation of primary, secondary, and tertiary zones within Units 2 and 3 that work in tandem. It is in Unit 3 where higher-order cognitive processes like executive functions find their home (Goldstein et al., 2015) and this model remains one of the few neuropsychological models that ties together both functional abilities and neurological structures.

Supervisory Attention System: The supervisory attention system was posited as a model to describe the role of attention in behaviour and is comprised of the following two components: a contention scheduling module and a supervisory attention system (Norman & Shallice, 1986). A key distinction within this model is the separation of automatic actions or schemata and those that require deliberate focus, which are governed by the contention scheduling component and the supervisory attention system, respectively. In effect, the supervisory attention system is only truly engaged in novel or complex situations to guide a person through whatever actions need to be applied.

Central Executive: Another early model of executive functioning was the multicomponent model of working memory used to describe how individuals processed, held, and subsequently stored information (Baddeley & Hitch, 1974). This model was originally comprised of three components: a phonological loop, a visuo-spatial sketchpad, and a central executive. A fourth component, an episodic buffer was added in subsequent iterations of this model (Baddeley, 2000). Importantly, within this model, while the central executive did not contain any memory storage capacity, it acted as the conductor or coordinator between each of the other components. While this model was strongly criticized for the depiction of the central executive as a homunculus (Parkin, 1998), a criticism that Baddeley (2007) himself has acknowledged, it set the stage for future models of executive function that recognized the important role that working memory plays in complex, goal-directed behaviour.

Extended Phenotype: In his work with children diagnosed with ADHD, Barkley (1997) proposed a model of executive functions that held behavioural inhibition (i.e., self-control) as fundamental to the functioning of other executive functions that manifest as an individual's functioning in their social environment as a sort of extended phenotype of self-regulation. He posited that behavioural inhibition is the common and required component of four major executive functions: Nonverbal working memory, verbal working memory, self-regulation of emotion, and reconstitution (i.e., generativity or flexibility; Barkley, 2001). While his conception of inhibition being a precursor to other executive functions is fairly unique, delineating the lower-order cognitive processes that lead to complex executive behaviours is commonly used to describe the relationship between lower-order and higher-order executive functions.

Tripartite Model: In an attempt to address the issue of measurement impurity in the study of executive functioning, Miyake and colleagues (2000) demonstrated that it was possible to extract a unitary executive functioning construct from a set of neuropsychological tasks assessing inhibition, updating working memory, and shifting attention via confirmatory factor analysis, a first for the study of executive functions that had up to that point predominantly used correlational studies and exploratory factor analytic approaches. Despite the assertion from Miyake and others that there were likely more than those three executive functions, due to its relative simplicity and use of latent variable methodologies, this conceptualization has quickly become the most cited model of executive functioning to date with well over 12000 citations at the time of writing. While a number of variations of this model have been proposed with the most replicable model being a nested two-factor model composed to updating, shifting, and a common executive factor (Miyake & Friedman, 2012), there remains concern that these models of executive function do not replicate as strongly as might be expected for something that is so well-cited (Karr et al., 2018)

Hot and Cool Executive Functioning: Most models of executive functioning tend to provide an account of computational processes that are relatively devoid of emotional content. Recognizing that performance on executive function tasks can vary in the context of emotional stimuli, Zelazo & Muller (2002) proposed that there were two basic types of executive function: hot and cool. Hot executive functions speak to the coordination of cognitive and emotional processes (e.g., not yelling at someone in public when bumped into), whereas cool executive functions are the more traditional computational processes (e.g., retaining and manipulating information in the mind).

Executive function and related constructs

As noted previously, it has been consistently pointed out by many that executive functions are poorly defined (Baggetta & Alexander, 2016; Zelazo & Müller, 2010) and the lack of conceptual clarity has produced numerous permutations of different executive function models. Further complicating the issue is the existence of conceptually similar and well-documented constructs in other areas of psychology, namely intelligence, self-regulation, self-control, and cognitive control.

Executive function versus intelligence: With such a wide array of associated brain regions and integrated neurological systems, it is perhaps inevitable there have been comparisons made with the most widely known psychological construct, intelligence or psychometric *g* (Spearman, 1927). Intelligence is broadly defined as the ability to understand complex ideas and use previous knowledge and experiences to solve problems and adapt to the environment (Duggan & Garcia-Barrera, 2015).

By definition, executive functions govern what might be considered “intelligent” behaviour and there have been a number of researchers that have posited that intelligence and executive functions are one and the same, with constructs like fluid reasoning (Decker et al., 2007; Salthouse & Davis, 2006), fluid intelligence (Duncan, 2013; Duncan et al., 1995), fluid cognition (Blair, 2006) and metacognition (Ardila, 2018; Roebers, 2017) being presented as constructs that capture elements of both intelligence and executive function. Other researchers have proposed that executive functions are the cognitive processes that form the basis of intelligence (Sternberg, 1985, 1999) with a number of studies that support this idea with aspects of executive function, specifically shifting and updating, showing unique contributions to intelligence (Chen et al., 2019; K. Lee et al., 2009; Yeniad et al., 2013). Additionally, as found in twin studies, there is a strong genetic overlap between the two (Engelhardt et al., 2016). Indeed, executive function is usually highly correlated with intelligence in both youth (Arffa, 2007; Brydges et al., 2012; Rahbari & Vaillancourt, 2015) and adults (Buczyłowska et al., 2020).

At the same time, there is evidence that we can differentiate between the two. While "cool" executive functions (e.g., metacognitive aspects) have strongly correlated with measures of intelligence, "hot" or affectively charged executive functions have not (Ardila, 2018). In a similar vein, individuals with ADHD, which is considered to primarily be a disorder in executive function, demonstrate similar scores on IQ tests as their neurotypical peers (Crinella & Yu, 1999). Furthermore, it is possible to have a double dissociation between the two constructs in neuropsychological cases of frontal damage (Blair, 2006; Crinella & Yu, 1999)

From a neuroanatomical perspective, psychometric *g* and executive function share a number of underlying brain systems with activation in the same frontal-parietal networks being implicated in complex cognitive tasks (Barbey et al., 2012; Blair, 2006; Jung & Haier, 2007; Roca et al., 2010). While there are shared neurological systems implicated in both cognitive processes, there are also a number of brain regions that appear to be distinctly related to each. For example, psychometric *g* tends to be associated with the left inferior occipital gyrus and right parietal lobe whereas the anterior frontal pole is more related to executive function (Barbey et al., 2012; Roca et al., 2010).

Given the number of similarities between the two constructs and their underlying neural mechanisms, perhaps the most theoretically parsimonious way to distinguish between intelligence and executive function is to view them as the outcome of differential task demands

(Duggan & Garcia-Barrera, 2015). In other words, intelligence emerges when the complexity of task demands is high, whereas executive function emerges when the task demands involve an element of novelty or uniqueness.

Executive function versus self-regulation: Self-regulation can be defined as goal-directed behaviour, within a minimum temporal range (Hofmann et al., 2012) and is seen as an ongoing, dynamic, and adaptive process (Nigg, 2017). By this definition, it may seem like executive functioning and self-regulation are nearly identical; however, there are a few key differences in how these two constructs are conceptualized: 1) Compared to executive functions, self-regulation is an even broader psychological construct that captures non-volitional (i.e., bottom-up) processes such as priming, habit formation, and operant conditioning (Bridgett et al., 2015; Nigg, 2017); 2) while executive functions may be the underlying cognitive basis for top-down self-regulation, they are also recruited for other behaviours (e.g., mental arithmetic) that are not inherently self-regulatory in nature (Nigg, 2017); and 3) self-regulation can involve more extrinsic regulatory controls like social norms and interpersonal relationships, while executive functioning does not (Hofmann et al., 2012; Nigg, 2017).

Executive function versus self-control: Self-control has been defined as a narrower set of processes involved in overriding pre-potent responses or impulses (Duckworth & Steinberg, 2015; Hofmann et al., 2012). In other words, self-control is the behavioural component of inhibitory processes that speak specifically to instances where one must actively prevent a response for short-term reinforcement in order to reach long-term goals (Duckworth & Steinberg, 2015). Like executive functioning, self-control involves volitional control of behaviour towards a specific goal but is only analogous to inhibition and does not necessarily involve other functions like verbal fluency or updating working memory.

Executive function versus cognitive control: Cognitive control is a construct originating from cognitive neuroscience and is defined as a set of processes that underlie the ability to flexibly shape, initiate, and constrain thoughts or actions in the context of specific goals (i.e., working memory, response inhibition, response selection, and task-set switching; Niendam et al., 2012). This is perhaps the most difficult construct to distinguish from executive functioning. Indeed, there are a number of researchers that have used the two terms interchangeably (Benedek et al., 2014; Friedman & Miyake, 2017; Friedman & Robbins, 2022; Lenartowicz et al., 2010; Menon & D'Esposito, 2022) with the main distinction between executive functioning and cognitive control is in their scope of analysis. Cognitive control predominantly involves lower-order executive functions but does not involve higher-order aspects like planning or problem representation (Nigg, 2017).

While having differing viewpoints on the nature of a specific neuropsychological phenomenon is part of the scientific process, there is a potential risk that executive function researchers and others may be collectively committing jingle and jangle fallacies (Block, 1995). Indeed, executive function research is not alone in this respect as many areas of psychological research have been subject to these concerns, including but not limited to research in personality (Higgs & Lichtenstein, 2010), emotion (Weidman et al., 2017), self-efficacy (Larsen et al., 2013), motivation (Lee et al., 2020), and cognitive abilities at large (Stanek & Ones, 2017). In order to navigate this complicated web of interrelated constructs and models, it may be useful to revisit the foundational tenets of psychological research, and by extension, executive function research.

On the nature of executive functions: Theory and measurement

How you view the true nature of a psychological phenomenon changes how you examine and intervene upon it, and latent variable methodologies have formed the basis of modern psychological research with theoretical constructs like general intelligence (Spearman, 1904) and personality (Stanek & Ones, 2017) being the most well-known phenomenon examined using this methodology. Prior to the use of latent variable methodologies, psychological research was influenced by classical test theory. Classical test theory, states that any observed score on a test or task designed to measure a psychological phenomenon can be described as composed of two components: a true score plus random and normally distributed measurement error (Crocker & Algina, 1986). While intuitively this seems appealing and parsimonious, this approach led to a number of epistemological difficulties where researchers were effectively unable to generalize their findings to other measures and address the problem of measurement error (Borsboom, 2005). In response to the limitations of classical test theory, latent variable methods have largely stepped into the forefront of psychological research and this has applied to the study of executive functions as well.

Executive functions as latent constructs: Generally, when referencing latent constructs, one is making the claim that there is an unobservable common variable or latent construct (e.g., intelligence) and between-subject differences in this common variable directly cause the between-subject variation on a given set of items or tasks (e.g., Sue obtained better scores on the Wechsler Adult Intelligence Scale than Joe because she is more intelligent). This reference to a common latent variable has implications for how researchers explain causal relationships. In other words, a latent intelligence construct theoretically can be measured using other tests designed to assess intelligence like the Woodcock-Johnson Tests of Cognitive Abilities or the Stanford-Binet Intelligence Scales (i.e., As she is more intelligent, Sue should obtain better scores than Joe on both of these tests as well). This line of reasoning would apply as well if Sue were to have better inhibition or shifting than Joe on measures of executive functioning. While most, if not all, psychological constructs are considered to be reflective (Borsboom, 2005), ensuring that one knows how they are conceptualizing a construct forms an important theoretical link in how they understand the causal relationships when they observe changes or differences in measures.

Executive functions as reflective latent constructs: Reflective models depict a direct relationship between latent construct and manifest variables that is top-down. In other words, the values observed in the measures used are a direct result (or reflection) of the unobserved latent entity. For example, between-subject differences in performance on an inhibition task like the Go No-Go would be considered to be caused by between-subject differences in latent inhibitory control but the reverse would not be true. From this viewpoint, it would be incoherent to say that changing performance on the Go No-Go cause changes in latent inhibitory control. A prime example of this conceptualization would be the tripartite model of executive functions and its many variations (Miyake et al., 2000; Miyake & Friedman, 2012).

On latent dimensions and categories

Within the realm of latent variable methodologies, a researcher must also conceptualize their construct as having a dimensional latent structure or a categorical one and this distinction goes beyond mere semantics. Observing and explaining differences within dimensional constructs are fundamentally different than within categorical constructs (i.e., differences in quantity versus differences in quality). Determining the latent structure of a construct also carries a great deal of importance as knowledge of latent structures has implications for theory, assessment, treatment, and dictates the next steps in statistical analysis (i.e., dimensional constructs can be examined with factor models and categorical constructs can be examined with mixture models; Ruscio et al., 2006; Sakaluk, 2019). This discussion can even go beyond the simple binary of continuous versus categorical and can been framed as a continuum of latent structure (Masyn et al., 2010) with different statistical methods corresponding to each variation on latent structure.

“Kinds” of executive function

As is the nature of psychological research, most of what is measured is invisible and largely construct-based with latent variable methodologies such as factor analysis being the most commonly used. However, factor analysis is only one of many ways to conceptualize and examine something like executive function. As discussed previously, each of these different methods contains a set of assumptions and implications for theory and practice. Deciding which method to use is highly dependent on the theorized nature of the phenomenon of interest and there is a theoretical decision-making process that is not always explicitly known or made clear in psychological research. Psychological research begins with choosing a set of assumptions about the nature of reality or the phenomenon being studied. Broadly speaking, there are four common perspectives to explain the nature of psychological phenomenon: natural kinds, social kinds, practical kinds, and complex kinds (Fried, 2017).

Executive function as a natural kind: Natural kinds refer to phenomenon or entities that exist independent of any type of evaluation. If executive functions are viewed as a natural kind of psychological phenomenon, this would imply that they are a real set of cognitive processes waiting to be discovered. Neuropsychology as a whole would likely subscribe to this notion since executive functions or their absence were initially discovered via neuropsychological case studies of localized brain damage to the frontal lobes. In all neuropsychological interpretations of behaviour, cognitive abilities and their component processes are considered to be produced by their underlying neurological systems, which presumably exist as an independent entity.

Executive function as a social kind: Social kinds refer to the idea that psychological phenomena are socially constructed, they are produced by or through our social interactions. In other words, we as researchers collectively define what executive functioning is. If executive function is viewed as a social kind of psychological phenomenon, this might in some way explain how there seem to be so many distinct conceptualizations of what is supposed to be the same construct and why there has been much difficulty in unifying the field. In a sense, researchers would all be playing a neuropsychological variant of the beetle-in-a-box thought experiment (Wittgenstein, 1953).

Executive function as a practical kind: Practical kinds refer to the perspective that it does not necessarily matter whether something is naturally existing or socially constructed but whether the object of study is useful in some way. Viewing executive functions as practical kinds implies that while they may or may not exist independently from our perceptions of it, the construct itself is useful in applications or predictions for human or social development. Indeed, executive functioning could be considered a very practical construct as it is consistently associated with a large number of important life outcomes and as a result, has often been the target of clinical assessment and intervention. In the case of those who operate under this perspective, they are more likely to be somewhat agnostic about the true nature of executive functions.

Executive function as a complex kind: Complex kinds refer to the idea that psychological phenomenon or entities emerge as a function of interactions between symptom clusters or cognitive processes. In other words, executive functioning is an emergent property of its cooccurring component processes. The aggregation of lower-order cognitive processes like inhibition, updating working memory, and shifting attention serve to produce behaviour that one might understand to be executive. Furthermore, each of these processes has an impact on the other and vice-versa in a dynamical fashion. Under this conceptualization, executive functioning gains a sense of “executive-ness” when and only when its component processes are in action. It may be that instead of a latent executive construct, the mutual relationships and interactions between cognitive processes produce what could account for much of the common variance without needing to make allusions to an unseen construct (e.g., exerting inhibitory control may require someone to shift their attention away from an upsetting stimulus, which then would decrease the burden on inhibitory control processes).

Interestingly, these theoretical conversations have been largely sidestepped in executive functioning literature and the dominant perspective driving research today is the one implicitly elucidated by Miyake and colleagues (2000), namely that executive functions are best viewed as latent constructs that are dimensional, best explored using common factor methods, and fall under the purview of natural phenomenon. However, the overwhelming fixation on a single conceptualization and methodology to research such a multifaceted construct like executive functioning is, in many ways, unfortunate.

Indeed, it may be a fruitful exercise to examine new ways to examine executive functioning in order to provide novel insights into this phenomenon. For example, if one were inclined to operate within the latent variable framework for executive function research, it might behoove the researcher to commit to deeply delving into the theoretical foundations of this phenomenon. Indeed, calls for improving theory in psychological research at large have been made over the years with some proposals ranging from major revisions to how psychological research is conducted (Hanfstingl, 2019), to the complete abandonment of the construct paradigm (Schmittmann et al., 2013). In either case, both sides strongly advocate for increased theoretical legwork on the part of would-be researchers. While the directions one could go are nearly endless, for those who might be skeptical about the utility of alternative procedures in executive function research, it may be prudent to provide two examples of how this could be accomplished.

For those who are more inclined to stay within the tradition of latent reflective construct methodologies, one avenue of pursuit could be to examine one of the most basic assumptions underlying the factor analytic method, namely latent dimensionality. Fortunately, there are statistical procedures available to these researchers in providing empirical support for latent dimensions or categories called taxometric methods or taxometrics (Ruscio et al., 2006). Taxometrics are based on latent variable methodologies and involve producing unique statistical fingerprints via iterative computations that indicate the underlying latent structure of the data (Ruscio et al., 2013) and researchers can use taxometric results to further refine their theoretical conceptualization of their constructs and apply the appropriate statistical analyses to their data. To date, there have been no studies examining the latent structure of executive functions using taxometric methods.

Conversely, for those who are more inclined to dispose of the idea of latent reflective constructs or constructs in general, there are also methods in which provide alternate explanations for the emergence of complicated cognitive and psychological phenomenon, without the explicit need to call for constructs. Network models of psychological phenomenon are recent innovation in psychological research that adhere to the complex kinds perspective on psychological entities (Fried, 2017). Contrary to latent constructs, causal networks dispose of the need for an unobservable latent entity and instead draw direct relationships between the variables being assessed (Borsboom et al., 2016; Borsboom & Cramer, 2013; Cramer et al., 2010). As their name implies, causal networks suggest a chain of causation that can emanate to and from each observed variable, forming a dynamic system (van der Maas et al., 2006) and the psychological phenomena being studied is an emergent property of this system, distinct but not reducible to its components (Guyon et al., 2017). In the most basic sense, networks are composed of nodes and edges (Borsboom & Cramer, 2013) with nodes representing variables and edges representing the relationship between two variables. Conceptually speaking, nodes and edges can be virtually anything but in the context of psychology, tend to be symptoms, thoughts, or behaviours. It should be noted that while some foundational latent variable models (e.g., Rasch models) can be viewed as statistically equivalent to some causal networks (e.g., sparse network models), this does not imply they are interchangeable as the use of each entails fundamental differences in how one comes to understand relationships between the different parts of the model (van Bork et al., 2018). Despite the relatively sparse body of research showing executive functions modeled as networks, there remains a strong theoretical reason to consider their use. By definition, executive functions are constantly operating together and in conjunction with one another (Roebers, 2017) and researchers consistently reference actual neurological and functional networks of interconnected brain regions and cognitive processes that act in concert to produce complex behaviour (Duggan & Garcia-Barrera, 2015). These dynamic relationships are not easily captured by latent variable methods but do align well with network perspectives.

Program of Research

The current dissertation involves two manuscripts that focus on 1) determining the latent structure of executive functioning and 2) highlighting an alternative theoretical framework and methodology to approach executive functioning research and both draw from the standardization data of the Delis-Kaplan Executive Function System and the Behaviour Assessment System for Children – 3rd Edition. The first study is titled, *Latent structure in executive functioning: A taxometric approach* and the second is titled *Executive functioning networks: An alternative to latent constructs*. In other words, the first study aims to revisit one of the fundamental tenets of contemporary executive function research and demonstrate the importance of checking basic theoretical assumptions. The second study will show the utility of theoretical parsimony in executive function research by providing an alternative method to examine this phenomenon that hews more closely to what occurs in clinical and historical settings. While they do not even approach the full scope of alternative methods of inquiry into executive function, these two studies can serve as an example of what can be possible, if researchers are willing to take a risk with testing new theories and trying out new models.

Chapter 2: Latent Structure in Executive Functioning: A Taxometric Approach

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Abstract

Executive function is a neuropsychological construct that describe a collection of cognitive processes that aid in complex, goal-directed behaviours. There is a plethora of proposed functions observed to emerge at various points of human development but neuropsychological measurement of executive function remains difficult due to methodological differences and conceptual ambiguity. Latent variable methodologies have aided in greatly improving the field's understanding of executive functions but the statistical assumptions surrounding latent structure have not been independently verified (i.e., latent dimensionality). Using taxometric methods and the large, demographically representative, standardization samples of the D-KEFS and BASC-3, the current study provides empirical evidence for this basic assumption and discusses the implications for how executive function research, assessment, and intervention should be conducted in the future.

Keywords: executive functioning, taxometrics, D-KEFS, BASC-3

Latent structure in executive functioning: A taxometric approach

Executive function, broadly defined, is a neuropsychological construct describing a collection of cognitive processes thought to underlie complex, goal-directed planning, action, self-monitoring, and self-regulation (Baggetta & Alexander, 2016). Executive functioning is composed of lower-order and higher-order processes where the designation of lower-order is indicative of more basic cognitive process (e.g., inhibition or shifting attention) and higher-order being indicative of a behaviour produced by a series of lower-order processes working together (Camilleri et al., 2021). In terms of specific functions, executive functions have included a number of lower-order processes such as inhibition (Barkley, 1997; Miyake et al., 2000; Munakata et al., 2011; Tiego et al., 2018), working memory (A. Baddeley, 2007; Miyake et al., 2000), attentional control (Norman & Shallice, 1986; Tiego et al., 2018), and verbal fluency (Aita et al., 2019; Lezak et al., 2004), as well as higher-order processes and behaviours such as problem solving (Garcia-Barrera et al., 2011; Zelazo & Müller, 2010), goal-setting (Anderson, 2002), decision-making (Lezak et al., 2004), and emotion regulation (Barkley, 1997).

Executive functioning across the lifespan

Most models of executive functioning express the construct as it appears in adults and while fully developed executive functions are interesting in their own right, executive functions do not suddenly materialize fully maturated from a vacuum and like many cognitive processes, executive function demonstrates an inverted U-shape in terms of its developmental trajectory (Dempster, 1992; Jurado & Rosselli, 2007; Zelazo et al., 2004). Some executive functions like attentional control, have been observed to emerge fairly early, around the first year of life; while others, like information processing, cognitive flexibility, and goal-setting develop shortly afterwards in early childhood (Anderson, 2002) and as children develop and grow, their executive abilities grow commensurately. Early developmental trajectories are remarkably stable as differences in executive functioning observed in children continue to hold into late adolescence (Friedman et al., 2011; Miyake & Friedman, 2012). Interestingly, researchers often have difficulty in parsing out different executive functions in children (Brydges et al., 2012; Huizinga et al., 2006; Karr et al., 2018), which is usually seen as a reflection of the developmental immaturity in the young brain (Casey et al., 2000; McKenna et al., 2017). Once in adulthood, barring injury or other insult to brain systems, individual differences in executive functioning remains fairly stable; however, executive functioning is subject to age-related declines (Gustavson et al., 2018; Mayr, 2001; Salthouse et al., 2003) and executive processes are observed to de-differentiate around this time as well (Gerstorf et al., 2008).

Measuring executive functioning

Measuring executive functioning is primarily achieved through two methodologies: performance-based tasks and behavioural report measures (McCoy, 2019). Neuropsychology as a field of study has predominantly used performance-based cognitive tasks (e.g., Stroop Task) to examine executive functions and as technology improved, has incorporated the use of computers as well (e.g., Go No-Go). Consistent with the theorized hierarchical structure of executive functioning (Camelleri et al., 2021), performance-based tasks can be categorized into two types, those that assess lower-order cognitive processes (e.g., Go No-Go, N-back, and Local-Global) and those that assess higher-order or more complex executive functions where multiple lower-order processes are necessarily involved in task completion (e.g., Tower of London, Wisconsin Card Sort Task, Iowa Gambling Task).

While these tasks can be sensitive to localized prefrontal lesions (e.g., Wisconsin Card Sorting Task; Barceló & Knight, 2002), performance-based tasks have been criticized as being overly restrictive and not representing real-world behaviour (Toplak et al., 2013). As such, there has been a movement to supplement traditional neuropsychological tasks with measures that are considered to be more ecologically valid (McCoy, 2019). Two such measures are the Behaviour Rating Inventory of Executive Functions (BRIEF; Gioia et al., 2000) and the Behaviour Assessment System for Children Executive Function Screener (BASC-EF; Garcia-Barrera et al., 2011; Reynolds & Kamphaus, 2015), which are self-report or informant-report questionnaires that provide a Likert-like scale in which subjects are asked to rate themselves or others on real-life behaviours that are thought to involve executive functioning.

While these types of ecologically valid measures have shown themselves to be predictive of real-world outcomes, there remains a concerning observation that behavioural rating scales of executive functioning either do not correlate or weakly correlate with their performance-based counterparts, even when purportedly measuring the same construct (Barkley, 2001; Toplak et al., 2013). Worse still, correlations are weak to modest even between performance-based tasks, though this is often attributed to measurement impurity (Friedman & Miyake, 2017; Willoughby, 2014), which raises questions about the validity of this all-encompassing construct.

Generally speaking, there are two main explanations for this phenomenon of weaker than expected correlations between levels of measurement. The first explanation is methodological in that most performance-based tasks are designed specifically to produce reliable experimental effects (e.g., high within-subject variability and low between-subject variability; Dang et al., 2020) and are subject to significant error variance making it mathematically difficult to produce high correlations. The second explanation is based on how differing response processes may be elicited by each type of measurement, where performance-based tasks tend to elicit maximal performance in a highly structured environment on metrics like reaction time or accuracy using novel stimuli and self-report elicits subjective judgments about typical performance across a variety of unstructured areas (Dang et al., 2020; Toplak et al., 2013). While this provides an explanation for why dissociation between levels of measurement occurs, the suggestion that there are different response processes does not fit well with the interpretation that the same construct is being assessed. If anything, this would be an explicit admission that different constructs are being measured.

Modeling executive functioning

Prior to the use of latent variable methodologies, psychological research was (and to an extent still is) largely influenced by classical test theory. Classical test theory states that any observed score on a test or task designed to measure a psychological phenomenon can be described as composed of two components: a true score plus random and normally distributed measurement error (Crocker & Algina, 1986). While intuitively this seems appealing and parsimonious, this approach led to a number of epistemological difficulties where researchers were effectively unable to generalize their findings to other measures and address the problem of measurement error (Borsboom, 2005). In response to the inadequacies of classical test theory, latent variable methods have largely stepped into the forefront of psychological research and this has applied to the study of executive functions as well. Since the publication twenty years ago of the influential work of Miyake and colleagues (2000) on the unity and diversity of executive functions, the study of executive functioning has largely (but not exclusively) focused on latent variable methodologies with the moderately correlated constructs of inhibition, updating working memory, and shifting attention receiving the most scientific interest (Karr et al., 2018).

Within the realm of latent variable methodologies, a researcher must also conceptualize their construct as having a dimensional latent structure or a categorical one and this distinction goes beyond mere semantics. For example, while many commonly studied psychological constructs like personality or general psychopathology have been shown to be dimensional (Haslam et al., 2020), there remain instances where a categorical latent structure has been observed, including in autism (Frazier et al., 2010; Ingram et al., 2008; James et al., 2016), addictions (Goedeker & Tiffany, 2008; James et al., 2014; Walters et al., 2009), suicide risk (Rufino et al., 2018; Witte et al., 2017), and pedophilia (McPhail et al., 2018; A. F. Schmidt et al., 2013). Observing and explaining differences within dimensional constructs are fundamentally different than within categorical constructs (i.e., differences in quantity versus differences in quality). Determining the latent structure of a construct also carries a great deal of importance as knowledge of latent structures has implications for theory, assessment, treatment, and dictates the next steps in statistical analysis (Ruscio et al., 2006; Sakaluk, 2019). Interestingly, these theoretical conversations have been largely sidestepped in executive functioning literature and the dominant perspective driving research today is the one elucidated by Miyake et al. (2000), namely that executive functions are best described as latent constructs that are dimensional and best explored using common factor methods.

How we conceptualize psychological phenomenon changes how we come to study it. This has significant implications for statistical analysis as certain latent variable methodologies presume a specific latent structure and there are consequences for the inappropriate use of latent variable methods, such as severe bias being introduced into the models (Rhemtulla et al., 2020) and by extension, incorrect conclusions. As there are two general ways to conceptualize latent structure, there are two types of measurement models that can be used: common factor and mixture models. Common factor models assume latent dimensionality and include the use of methods such as confirmatory and exploratory factor analysis, or Rasch models (Borsboom, 2005); whereas mixture models assume categorical structure and include the use of methods such as latent class analysis, clustering, and random effects modeling (Lindsay, 1995). In other words, common factor models assume at least one latent dimensional construct that generates differences in the observed scores on manifest variables. Mixture models on the other hand, assume there exist at least two different subgroupings within a given population that can be described by differences in at least one latent categorical variable.

This also changes how we would assess and intervene on them as well. For instance, the explanation, assessment, and treatment for a well-documented psychological phenomenon like executive dysfunction would drastically differ based on the identification of a dimensional or categorical latent structure (Borsboom, 2005; Sakaluk, 2019). If a specific executive function (or dysfunction) is deemed to be dimensional, from a theoretical standpoint this suggests inter-individual disparities in performance are due to quantitative differences (i.e., differences in amount), which are generally due to multifactorial or incremental influences that have a cumulative effect on a person's executive functioning (e.g., a combination of multiple genes, early life experiences, and lifestyle factors). Assessing dimensional executive functions might require more complicated or elaborate procedures that tap into the various facets of the construct (e.g., using multiple measures or multiple assessment periods). Intervening or improving on dimensional executive functions might also require treatments that incrementally address the complexity of causal forces that have led to this state. Conversely, if an executive function is deemed to be categorical, this would suggest that observed inter-individual differences in executive function are qualitative in nature (i.e., difference in kind) and are due to singularly impactful experiences or characteristics (e.g., brain injury or developmental disability). Assessment of categorical executive functions is relatively efficient as it only requires the measure to discriminate between those who have executive dysfunction and those who do not. However, intervening on categorical executive functions may prove to be more difficult as treatments must be particularly specialized to address the unique and powerful contribution of the causal variable.

Using data to inform theory: Taxometrics

Without a doubt, theory in psychological research is important and forms the foundation of how we understand psychological phenomenon; however, there is also value in providing empirical data to help inform and shape these theories, which in turn will influence future instances of experimentation. While one could solely use theory to determine what methods and statistical models they might apply to a given set of data, there are statistical procedures like taxometric analysis that can assist in the decision-making process.

Taxometric analysis falls under latent variable methodologies and is subject to the same basic underlying philosophical assumption as its statistical family, namely that the construct being measured exists independent of the measurements used. Like other latent variable methods, there are a number of statistical procedures that generate indices for the "fit" of a specific construct or model. In this particular case, these indices specify whether or not the latent structure of a construct resembles or fit a dimensional or categorical structure. Before running the analysis, a researcher must first consider the following criterion: sample size, indicator (measurement) quality, and specifying base rates (Sakaluk, 2019).

Sample size considerations: Taxometric analysis is computationally intensive and as such, requires a minimum sample size of 300 participants (Meehl, 1995). Failing to provide adequate sample size leads to difficulties in identifying latent structure and increases the likelihood ambiguous results will emerge. It is important to note that this number is a suggestion as small absolute base rates of categorical groups will require much larger samples (Sakaluk, 2019).

Indicator quality considerations: For taxometric analyses to be adequately conducted, the quality of indicator variables need to be considered. The properties of a desirable indicator (e.g., items or variables) of latent structure are ones with continuous scales of measurement (i.e., 4 or more possible responses), non-redundant breadth of content (e.g., 3-5 indicators), and good discriminability (Ruscio et al., 2006; Sakaluk, 2019). This often means that using multimethod forms of assessment are preferred as this reduces the issue of shared method variance between indicators (Meehl, 1995).

Base rate considerations: In terms of specifying base rates, this was historically a highly subjective process, as base rates are often not known in a given population. Surprisingly, there is evidence that it is possible for experts to provide reasonable guesses as to what they may be (Meehl & Yonce, 1996). However, there are newer, less subjective ways of determining base rates that involve calculating multiple taxometric procedures repeatedly over an array of incrementally varying base rates and assessing fit based on average values and overall agreement and this has become less of a pressing issue in preparing for a taxometric analysis (Ruscio et al., 2018).

Once sample size, indicator selection, and taxon base rates are adequately addressed, the next step is to conduct the taxometric analysis itself. One important characteristic of taxometric methods is that if the analyses were to indicate a taxonic (i.e., categorical) latent structure, it would not be able to specify how many taxon groups exist, only that there are at least two. The main product of taxometric analyses are comparison curve fit indices (CCFIs), which provide information about the latent structure of the construct. The three most common indices are as follows:

Mean Above Minus A Cut (MAMBAC): MAMBAC procedures calculate the difference between scores on indicator variables at different cut scores of other indicator variables (Meehl & Yonce, 1994). This process is repeated across all combinations of indicator variables and cut scores. If the differences are plotted, a clear peak in the graph is indicative of a categorical boundary that exists near the value of the peak. A lack of definitive peak indicates a dimensional latent structure.

Maximum Eigenvalue (MAXEIG): MAXEIG procedures select a single indicator variable and focus on the association between the other variables across overlapping intervals of the indicator variable (Waller & Meehl, 1998) and like MAMBAC, this process is repeated across all combinations of indicator variables. If plotted in a graph, a peak would also indicate a categorical boundary.

Latent Mode (L-Mode): L-Mode procedures involve determining to what extent are there multiple modes in the latent distribution of the construct, where the presence of the multiple modes is indicative of categorical boundaries. Unlike the other two procedures, L-Mode is only calculated once (Ruscio et al., 2013).

Despite a long and rich history in diverse areas of psychological research ranging from personality (Haslam, 2003; Haslam et al., 2012), attachment (Fraley et al., 2015), malingering (Frazier et al., 2007), psychopathy (Walters et al., 2015), and psychopathology in general (Haslam, 2007; Haslam et al., 2020; Ruscio et al., 2004), the impact of taxometric methodologies have yet to fully reach into the realm of neuropsychology. The current study aims to verify long-held assumptions around the latent structure of executive functioning and hopefully provide clarity around how to conceptualize this construct.

Methods

Sample

Two samples were obtained from the Delis-Kaplan Executive Function System (D-KEFS; Delis et al., 2001) and Behavior Assessment System for Children – 3rd Edition (BASC-3; Reynolds & Kamphaus, 2015) normative samples, respectively. The D-KEFS normative sample data collection procedure involved a standardized sampling of 1750 individuals with representation of sex, age, ethnicity, education, and geographic region in line with the 2000 U.S. Census (8-89 years old). The BASC-3 normative sample data collection procedure involved a standardized sampling of 3500 total individuals with representation of sex, age, ethnicity, socioeconomic status, and geographic region in line with the 2013 U.S. Census (12-18 years old). The BASC-3 sample can be further subdivided into the Parent Rating Scales (PRS; n = 3351) and Teacher Rating Scales (PRS; n =1946) with different forms for ages 2 to 5 (Preschool or P), 6 to 11 (Child or C), and 12 to 18 (Adolescent or A). Differences in total sample counts can be attributed to some children having only parent ratings, only teacher ratings, or both parent and teacher ratings. All data was provided by Pearson and was received as previously anonymized data.

Measures

While several different performance variables can be extracted from the D-KEFS, many are repetitive and overlap significantly with one another, or are contingent on other variables (e.g., ratio or contrast scores). Therefore, D-KEFS test scores from each individual task were included on the basis of a priori determinations of item quality, construct coverage, and decisions were made to avoid repetitive measurement.

Trail Making Test: A task that tests speed of processing, flexibility of thinking, and motor speed, via a paper and pencil visual-motor modality analogous to "connecting the dots". Lower completion times and error rates are indicative of better performance. Time to complete the switching condition and total errors on the switching condition were included as variables of interest.

Verbal Fluency Test: A task that assesses fluent verbal production to letter or category cues within a defined set of rules and requires a degree of cognitive flexibility and working memory. Greater number of words produced and fewer repetitions or rule-breaking words are indicative of better performance. Total category fluency, total phonemic fluency, and total switching fluency were included as variables of interest.

Design Fluency Test: A task that assesses fluent visual-motor production using an array of dots within a defined set of rules, requiring a degree of cognitive flexibility and working memory. Greater number of designs and fewer repetitions or rule-breaking designs are indicative of better performance. Total number of switching designs, total number of filled and empty designs, and total number of repetition errors were included as variables of interest.

Color-Word Interference Test: A task that assesses verbal inhibition, cognitive flexibility, and processing speed and is analogous to the classic Stroop Task. Greater number of correctly identified stimuli are indicative of better performance. Total performance on the third and fourth conditions were included as variables of interest.

Sorting Test: A task that assesses problem solving, concept formation, and cognitive flexibility where the participant is asked to sort a number of stimuli in as many unique ways as they can. A greater number of unique and correct sorts are indicative of better performance. Total number of correct sorts was included as the variable of interest.

Twenty Questions Test: A task that assesses problem solving and abstract reasoning where the participant is given a limited number of opportunities to ask yes/no questions in order to identify predetermined stimuli. Better performance is reflected by fewer questions used to correctly identify the stimuli. Total number of questions asked was included as a variable of interest.

Word Context Test: A task that assesses deductive reasoning based on the participants ability to identify the meaning of unfamiliar "words" based on their context. Better performance is reflected by fewer guesses required to correctly identify the meaning. Total words correctly guessed on the task was included as a variable of interest.

Tower Test: A task that assesses planning, reasoning, and impulse control using a set of concentric disks and pegs where the participant is asked to replicate specific configurations within a defined set of rules. Fewer number of moves required to complete the task and fewer number of errors or rule-breaking moves are indicative of better performance. Total number of completed towers and total number of errors were included as variables of interest.

Proverbs Test: A task that assesses abstract thinking and comprehension of increasingly metaphorical and uncommon proverbs. Better performance is reflected in more accurate and abstract descriptions of the true meaning of these proverbs. Total number of proverbs identified was included as the variable of interest.

BASC-3 items were drawn from a previously derived Executive Behaviour Screener consisting of four subscales (Garcia-Barrera et al., 2011; Wong et al., 2019). All items were scored on a 4-point Likert-like scale and some items were reverse coded so that all subscales with higher scores indicate greater impairment in the target domain.

Problem Solving: Consists of items designed to assess for a child's ability to make decisions and solve problems effectively in daily life, which is considered to be separate from the ability to solve abstract problems that might be found on an intelligence test. This subscale was not included in either of the Preschool Forms of the BASC-3 as the skills involved within this domain are considered to be more developmentally advanced and therefore are difficult to observe in this age range. For the PRS-A and PRS-C, the scale consisted of 9 items and 8 items, respectively. For the TRS-A and TRS-C, the scale consisted of 10 items and 9 items, respectively.

Attentional Control: Consists of items designed to assess for a child's ability to focus their attention and sustain it in the face of distractions. For the PRS-A and TRS-A, the scale consisted of 9 items. For the PRS-C and PRS-P, the scale consisted of 7 items, while the TRS-C consisted of 8 and the TRS-P consisted of 5.

Behavioural Control: Consists of items designed to assess for a child's ability to inhibit behaviours that may be considered impulsive or disruptive to others. For the PRS-A, the scale consisted of 7 items. For the PRS-C and PRS-P, the scale consisted of 6 items. For the TRS-A, TRS-C, and TRS-P, the scale consisted of 6, 7, and 5 items, respectively.

Emotional Control: Consists of items designed to assess for a child's ability to exert control over their emotions, particularly negative emotions, when they become elevated. For the PRS-A and PRS-C, the scale consisted of 4 items. For the PRS-P, it consisted of 7 items. For the TRS-A, TRS-C, and TRS-P, the scale consisted of 6, 7, and 8 items, respectively.

Data Analysis

The normative data for the D-KEFS was originally split into four distinct age ranges (8-11, 12-19, 20-59, and 60-89), based on observed and theorized developmental trajectories in extant developmental literature (Delis et al., 2001). All normative data were age-corrected and standardized for all D-KEFS variables (M = 10, SD = 3). Items that were positively worded were reverse scored for all forms of the BASC-3 so that increasing index scores reflected greater difficulty in the target domain. All taxometric analyses were conducted in R Version 4.0.4 (R Core Team, 2021) using the package RTaxometrics (Wang & Ruscio, 2017).

Indicator Selection

Following recommendations outlined by Sakaluk (2019), D-KEFS indicators were selected based on theoretical breadth of coverage for the constructs of inhibition and shifting. These selections were informed by previous work by Karr et al., (2018), where a three-factor model of executive functions was extracted which included inhibition and shifting factors. There were no variables indicative of updating working memory. When selecting indicators for Attentional and Behavioural Control as measured by the BASC-3, each form had to be considered separately as they do not necessarily share all of the same questions. To assist with the selection process, item information curves were separately visualized for each set of Attentional Control and Behavioural Control items for each form. Item information curves can be found in Appendix A, Supplemental Figures 1-12. Items showing the highest information values as well as showing ample coverage across different ability levels were selected.

Taxometrics

Three common taxometric procedures were used to examine the latent structure of two executive functions, inhibition and shifting, as measured by the D-KEFS as well as conceptually similar counterparts, behavioural control and attentional control, as measured by the BASC-3. To streamline the taxometric analysis and to alleviate possible struggles with interpretation of taxometric curves, CCFIs were computed using RTaxometrics (Ruscio & Wang, 2017). As this analysis is largely exploratory, there is no known base rate for an executive function (or dysfunction) taxon in the general population and calculating CCFIs largely sidesteps this issue. CCFIs values range from 0 to 1 and values under 0.5 indicate dimensional latent structure and values above 0.5 indicate categorical latent structure (Sakaluk, 2019). Furthermore, values between 0.45 and 0.55 are typically seen to indicate ambiguity.

Results

The detailed results can be seen in Tables 1-3 and Figures 1-20. Overall, for both the D-KEFS (Table 1) and BASC-3 (Table 2), the vast majority of CCFIs (70% or 51/60) across all age ranges and forms suggest a dimensional latent structure for all four components of executive function. Ambiguous results were found for 11.6% of the CCFIs (7/60) and 3.3% (2/60) indicated a categorical structure. Similarly, in terms of mean CCFIs, 90% of the mean CCFIs (18/20) indicate a dimensional structure and 10% indicate ambiguity (2/20).

When examining the D-KEFS and BASC-3 separately, we find a similar result. For the D-KEFS, 87.5% of the CCFIs indicate dimensionality (21/24), 4.2% indicate categorical latent structure (1/24), and 8.3% indicate ambiguity (2/24). Notably, MAMBAC values for Shifting in the ages 8-11 subsample indicate a latent category comprising of 51% of this group (Table 3). In terms of mean CCFIs, 87.5% indicate dimensional structure (7/8) and 12.5% indicate ambiguity (1/8).

For the BASC-3, 83.3% of the CCFIs indicate dimensionality (30/36), 2.8% indicate categorical latent structure (1/36), and 13.9% indicate ambiguity (5/36). While the L-Mode value indicated a latent categorical structure for PRS-P Behavioural Control, the estimated base rate was only 2.5% of the subsample, which matched the estimates produced by MAMBAC and

MAXEIG (Table 3). In terms of mean CCFIs, 91.7% indicate dimensionality (11/12) and 8.3% indicate ambiguity (1/12).

At the level of conceptually similar constructs, for Shifting and Attentional Control, 86.7% of CCFIs indicate dimensionality (26/30), 3.3% indicate categorical latent structure (1/30), and 10% indicate ambiguity (3/30). For Inhibition and Behavioural Control, 83.3% indicate dimensionality (25/30), 3.3% indicate categorical latent structure (1/30), and 13.3% indicate ambiguity (4/30).

Discussion

The present study used multiple measures and multiple demographically representative samples to examine the latent structure of executive functioning. To our knowledge, this is the first ever taxometric analysis of executive function. Broadly speaking, results overwhelmingly suggest a dimensional latent structure for the constructs of Shifting/Attentional Control and Inhibition/Behavioural Control. These results held true across measurement type (i.e., performance-based tasks versus rating scales and developmental stages (e.g., childhood, adolescence, adulthood, and older adulthood). Indeed, the results strongly support long-held (but never checked) assumptions of latent dimensionality in different executive functions and are consistent with the vast majority of psychological phenomenon (Haslam et al., 2020).

From a conceptual standpoint, these results suggest our basic understanding of executive functions as a construct is sound, and the common usage of factor analytic methods is appropriate. This is particularly reassuring given previous evidence that different types of executive function measurement (i.e., performance-based vs. rating scales) that are supposed to measure the same construct (e.g., inhibition), tend not to correlate with one another (Toplak et al., 2013), which have generated a degree of skepticism regarding our understanding of the constructs themselves. Indeed, recent evidence has found that theoretically consistent relationships can be observed between different levels of executive function measurement using BASC-2 ratings and performance-based cognitive tests, when modelled using structural equation modeling (Zonneveld et al., preprint) though this remains an uncommon result. This raises the possibility of further insights to be gained regarding our understanding of executive functioning across measurement types when using more complex statistical models and adds to the literature supporting our current understanding of this construct.

Developmentally speaking, it is notable that the only pieces of evidence suggesting latent taxonicity in either sample occurred in the earliest age groups (MAMBAC for the D-KEFS ages 8-11 & L-Mode for the BASC-3 PRS-Preschool). While frontal lobe function and by extension, executive functions are considered to fully mature in young adulthood, there remain critical periods in which significant change in executive abilities occur in childhood (Best & Miller, 2010). Beyond infancy, where the greatest changes in neurological development tends to occur (Gilmore et al., 2018; Lenroot & Giedd, 2006; Ouyang et al., 2019) studies show major improvements in cognitive performance within early childhood (before age 5) for inhibition tasks (Best & Miller, 2010) and middle childhood (ages 7-11) for shifting tasks (Huizinga et al., 2006). These age ranges coincide with the two pieces of taxonic evidence in this study, suggesting that some of the taxometric indices may have detected a latent taxon. Specifically, the MAMBAC index for Shifting in the D-KEFS ages 8-11 sample suggested a latent taxon comprised of 51% of the age group. If it is the case that shifting is still developing in that age range, it may be that the sample can be divided into those who have developed a mature or more adult-like shifting ability and those who have not. That said, MAMBAC has rarely, if ever been used as a standalone metric for taxonicity (Beauchaine, 2007) and the other two indices strongly indicated a dimensional latent structure. Therefore, while further investigation within this age range may be fruitful, evidence remains predominantly in favour of a dimensional executive function and implications for identification of issues in assessment and treatment will be discussed below.

Implications for assessment & treatment

Generally speaking, when assessing for dimensional constructs, it is most useful to have more complex or multifaceted measures that can measure smaller or more subtle differences between individuals. This is already the case in most executive functioning research and clinical assessment tools, including the two used in this study. It is still informative for future researchers and test developers to keep this in mind as there might be a temptation to generate a measure with categorical cut-off scores, in a well-meaning effort to address time limitations in assessment or as a cost-saving measure. For example, one might be influenced by tests of executive function with extremely skewed distributions (e.g., WCST) where perfect performance is described as simply being "within normal limits" and make an attempt to emulate this categorization inappropriately instead of using commonly established terminology (Guilmette et al., 2020). As there is no current support for categorical latent structure in executive functions, researchers should continue to strive towards using and creating measures and labels of task performance that adhere to a dimensional understanding of the construct. Equally as important, in the context of improving executive functions, dimensional latent structure suggests a similarly multifactorial approach to treatment or intervention. In terms of contemporary interventions for executive function, many research studies tend to focus on a single method for improvement whether that be exercise-related (Schmidt et al., 2015; Staiano et al., 2012), skill-building (Klingberg et al., 2005; Mackey et al., 2011), or medication (Kempton et al., 1999; Semrud-Clikeman et al., 2008) and due to the plethora of restrictions and limitations placed on researchers, this may continue to be the case. However, from the perspective of constructing a program of intervention in clinical settings, it is imperative to create a multifaceted system that reflects the complexity of executive function and the many ways it can be improved. For example, while it may be true that incremental gains can be observed with one particular treatment modality (e.g., medication-based interventions for children; Hosenbocus & Chahal, 2012), in order to truly maximize the benefits of intervention, treatments should include a multitude of pathways towards improvement (i.e., addressing emotional, social, and physical needs; Diamond, 2012; Diamond & Ling, 2016). Interestingly, the BASC-3 samples included clinical subgroups which are predominantly composed of individuals diagnosed with ADHD (TRS = 167, PRS = 282; Reynolds & Kamphaus, 2015). ADHD is generally considered to be a disorder of executive functioning (Brown, 2009; Nigg, 2001; Toplak et al., 2005) and despite this conceptual distinction, the current statistical analysis does not support the existence of a latent taxon in any of the BASC-3 samples. This suggests that parent and teacher rated differences in attentional or behavioural control between individuals with ADHD and those without are quantitative in nature as opposed to qualitative (i.e., differences in amount as opposed to differences in kind). This is in line with our current understanding of ADHD as it emerges due to a multifactorial confluence of genetics and environment (Thapar et al., 2013), which tends to produce dimensional latent structure. More generally, this quantitative relationship should hold across any pair of individuals within a sample, specifically in terms of BASC-3 executive function ratings.

Conversely, the D-KEFS standardization exclusion criterion removed those with atypical development, learning or cognitive deficits (Delis et al., 2001) and it remains unknown whether a dimensional latent structure would have emerged if these groups were included. This leaves open the possibility of a latent taxon emerging in the context of clinical groups with known executive deficits, like traumatic brain injury (Cicerone et al., 2006; Levin & Hanten, 2005; Stuss & Benson, 1984) or dementia (Stopford et al., 2012; Voss & Bullock, 2004). Theoretically, latent taxons tend to emerge when the underlying causes of a phenomenon are significant. Events like brain injury or the disease processes involved in dementia may qualify as sufficient conditions for producing qualitative differences in executive functioning. Indeed, there are number of widely used and well-validated neuropsychological tools assessing various executive functions that conform with this understanding of qualitative differences in performance like the Wisconsin Card Sorting Task (Berg, 1948) or clock drawing tasks (e.g., CLOX; Royall et al., 1998). Even behavioural ratings like the Frontal Systems Behavior Scale (FrSBe; Grace & Malloy, 2001) provide clinical cut-offs for aberrant scores, though it is important to remember that the aforementioned measures were primarily designed for use in brain-injured populations and have highly skewed norms. Therefore, current conclusions involving the between-person differences in shifting or inhibition should be limited to non-clinical populations or typically developing populations. Furthermore, while all samples involved in this study are large and demographically representative of the USA at the time of data collection, they are cross-sectional in nature. This in turn limits the capacity to make any strong claims about the developmental trajectory of the latent structure of executive functions as the participants in each age grouping were not the same individuals, though it should be noted the latent structure was suggested to be dimensional across all samples and age groups, providing reasonable but not definitive support for the dimensionality of executive functions across the lifespan in typically developing populations.

The taxometric methodology used in this study proves to be an important tool in the expansive executive functioning literature and helps strengthen our underlying assumptions about this elusive construct. While current results are clear-cut, this is simply the first step in what should be a series of re-examinations of one of the most basic assumptions guiding executive function research. Further studies should include other common measures of executive functioning, age ranges in critical periods of development, and other clinical samples with known profiles executive deficits (e.g., brain injury or developmental disability; Babikian & Asarnow, 2009; Pennington & Ozonoff, 1996). Additionally, it would be beneficial to examine the latent structure of executive function across time in the same group of individuals.

Table 1. Comparison Curve Fit Indices for the D-KEFS Shifting and Inhibition Constructs

Age Range	MAMBAC	MAXEIG	L-Mode	Mean	Proportion[1]	Descriptor
Shifting						
8-11	0.631	0.239	0.360	0.400	1/3	Dimensional
12-19	0.407	0.286	0.361	0.336	0/3	Dimensional
20-59	0.438	0.378	0.400	0.396	0/3	Dimensional
60-89	0.288	0.350	0.432	0.357	0/3	Dimensional
Inhibition						
8-11	0.382	0.351	0.399	0.370	0/3	Dimensional
12-19	0.482	0.446	0.370	0.432	0/3	Dimensional
20-59	0.428	0.440	0.375	0.423	0/3	Dimensional
60-89	0.419	0.536	0.462	0.470	0/3	Ambiguous

Note: Values greater than 0.55 suggest a categorical latent structure whereas values less than 0.45 suggest a dimensional latent structure. Values between 0.45 and 0.55 are considered to be ambiguous. [1]Proportion denotes the number of CCFIs that indicate a categorical latent structure.

Table 2. Comparison Curve Fit Indices for the BASC-3 Attentional and Behavioural Control

Measure	MAMBAC	MAXEIG	L-Mode	Mean	Proportion[1]	Descriptor
BASC-3 AC						
PRS-P	0.159	0.355	0.443	0.313	0/3	Dimensional
PRS-C	0.337	0.223	0.262	0.275	0/3	Dimensional
PRS-A	0.282	0.327	0.458	0.354	0/3	Dimensional
TRS-P	0.408	0.249	0.502	0.395	0/3	Dimensional
TRS-C	0.457	0.404	0.448	0.435	0/3	Dimensional
TRS-A	0.219	0.288	0.256	0.261	0/3	Dimensional
BASC-3 BC						
PRS-P	0.429	0.490	0.587	0.502	1/3	Ambiguous
PRS-C	0.320	0.308	0.248	0.292	0/3	Dimensional
PRS-A	0.480	0.447	0.403	0.443	0/3	Dimensional
TRS-P	0.328	0.351	0.366	0.350	0/3	Dimensional
TRS-C	0.186	0.194	0.284	0.222	0/3	Dimensional
TRS-A	0.142	0.276	0.292	0.239	0/3	Dimensional

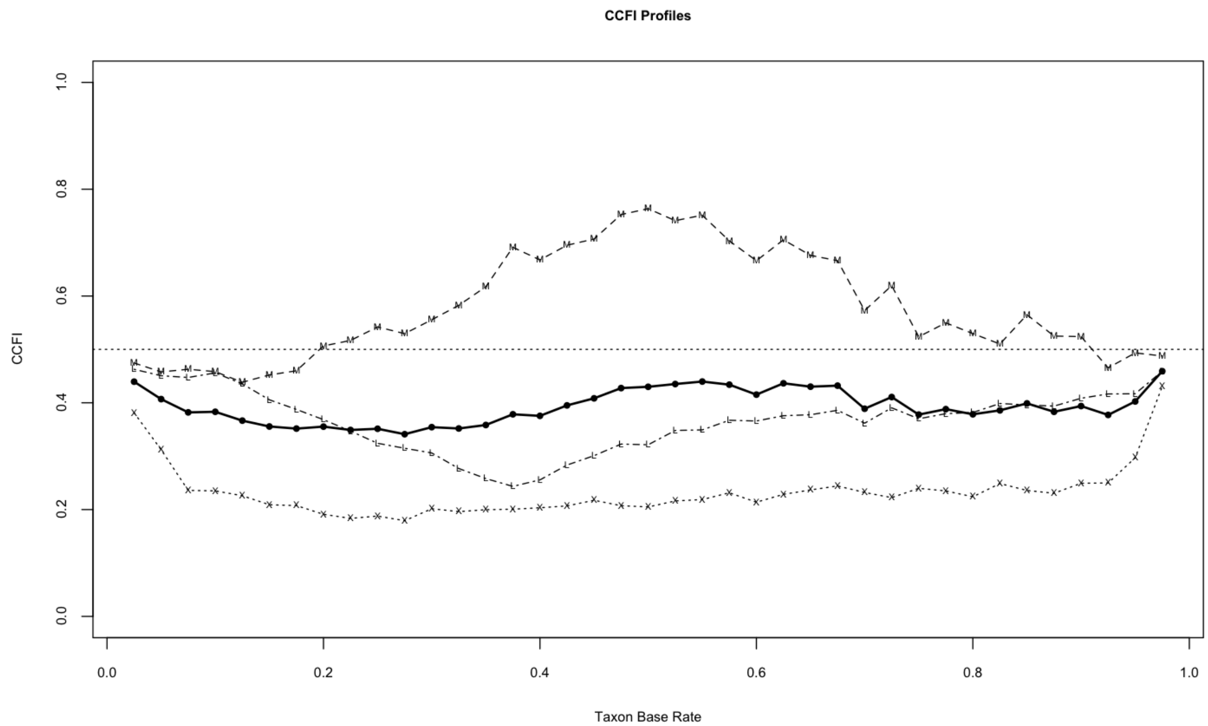
Note: AC = Attentional Control, BC = Behavioural Control. Values greater than 0.55 suggest a categorical latent structure whereas values less than 0.45 suggest a dimensional latent structure. Values between 0.45 and 0.55 are considered to be ambiguous. [1]Proportion denotes the number of CCFIs that indicate a categorical latent structure.

Table 3. CCFI Estimated Taxon Base Rates for the D-KEFS and BASC-3

	MAMBAC	MAXEIG	L-Mode		MAMBAC	MAXEIG	L-Mode
Shifting				Inhibition			
8-11	0.510*	0.975	0.064	8-11	0.025	0.975	0.070
12-19	0.489	0.025	0.975	12-19	0.675	0.025	0.071
20-59	0.515	0.975	0.975	20-59	0.975	0.460	0.025
60-89	0.975	0.975	0.975	60-89	0.975	0.607	0.975
AC				BC			
PRS-P	0.602	0.025	0.025	PRS-P	0.025	0.025	0.025*
PRS-C	0.058	0.025	0.025	PRS-C	0.025	0.025	0.025
PRS-A	0.386	0.025	0.025	PRS-A	0.025	0.025	0.025
TRS-P	0.426	0.025	0.025	TRS-P	0.055	0.025	0.025
TRS-C	0.103	0.084	0.025	TRS-C	0.088	0.025	0.054
TRS-A	0.299	0.084	0.025	TRS-A	0.071	0.025	0.025

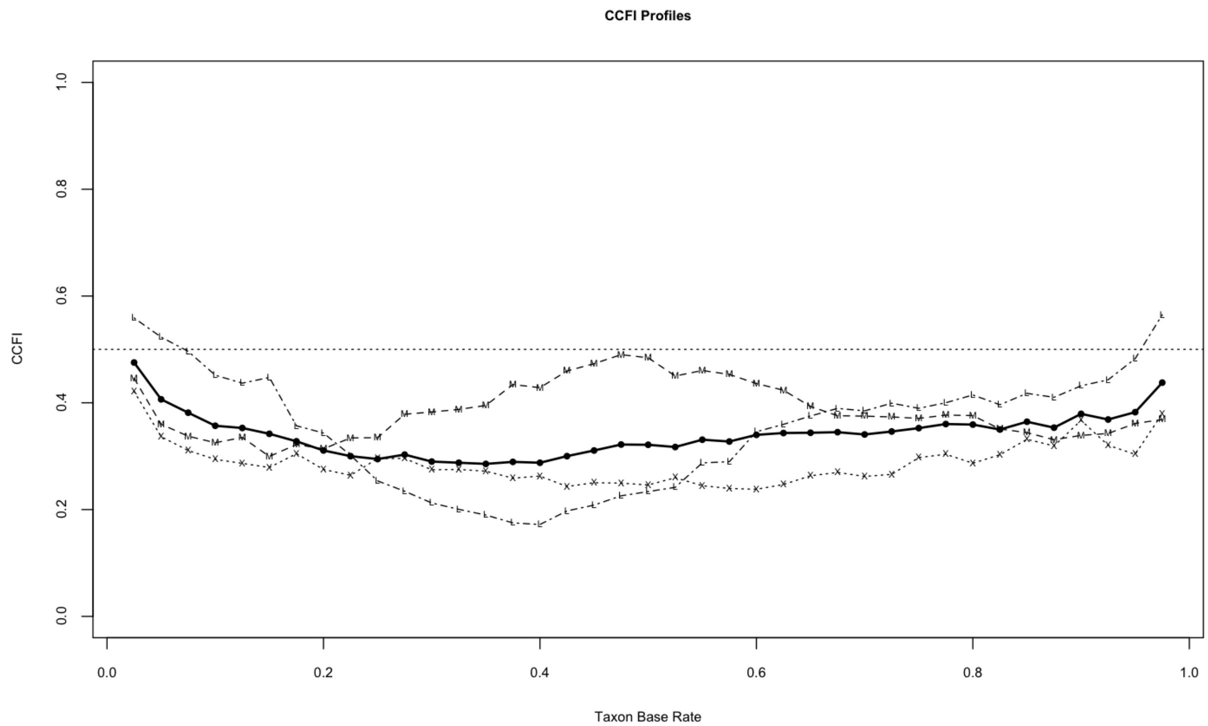
Note: AC = Attentional Control, BC = Behavioural Control. Values indicate the proportion of the sample that forms a latent taxon, ranging from 0.250 - 0.975. Taxon base rates can only be interpretable for CCFIs that indicate categorical latent structure. * = CCFI indicating categorical latent structure.

Figure 1. Comparison Curve Fit Indices (CCFIs) for D-KEFS Shifting (Ages 8-11)



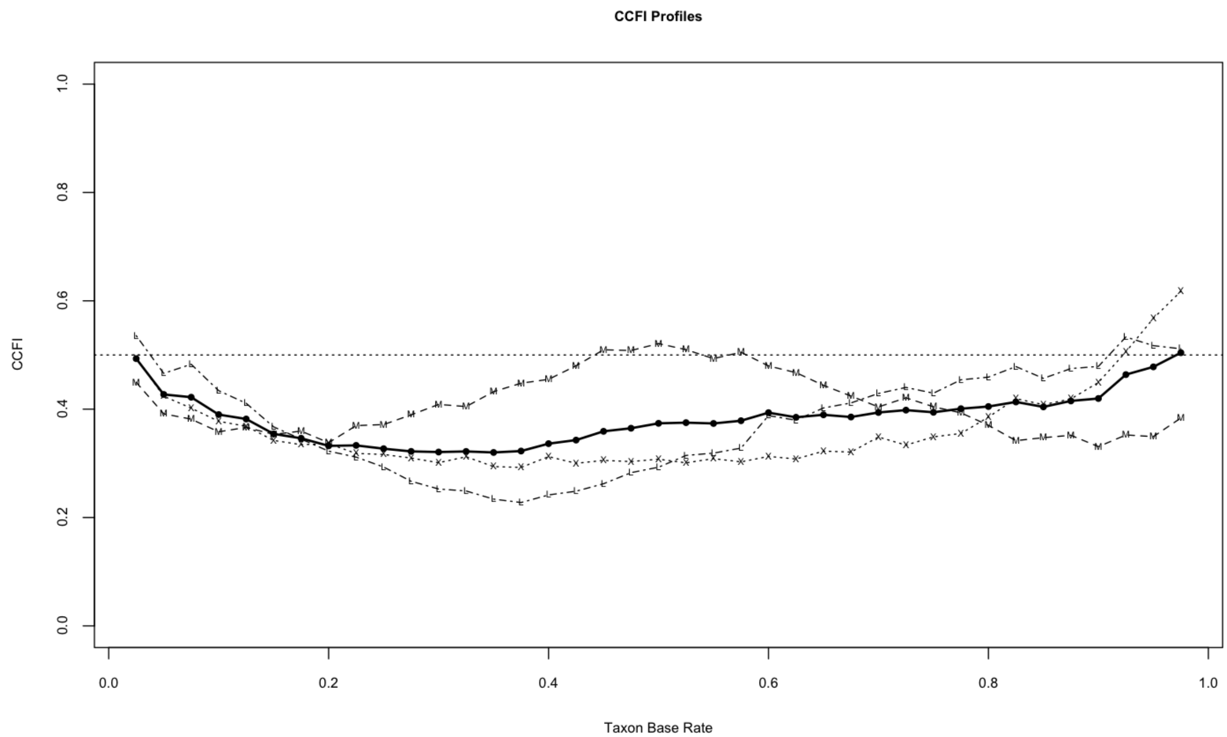
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 2. Comparison Curve Fit Indices (CCFIs) for D-KEFS Shifting (Ages 12-19)



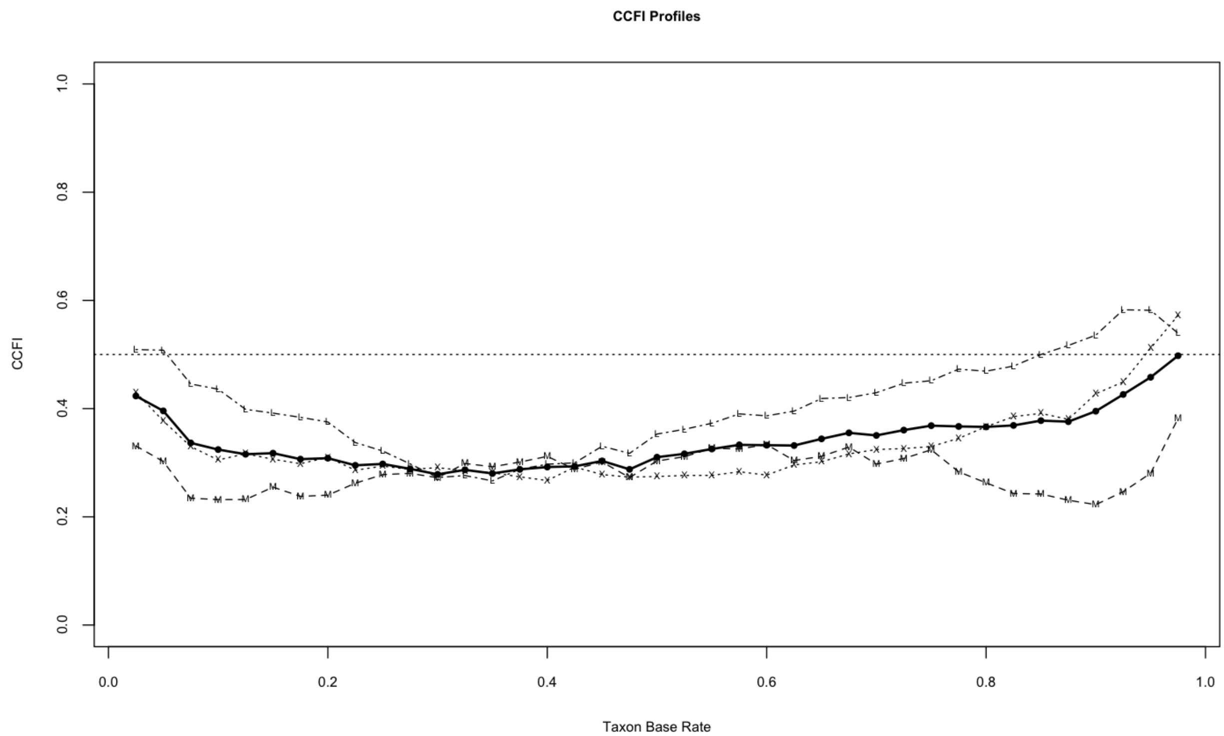
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 3. Comparison Curve Fit Indices (CCFIs) for D-KEFS Shifting (Ages 20-59)



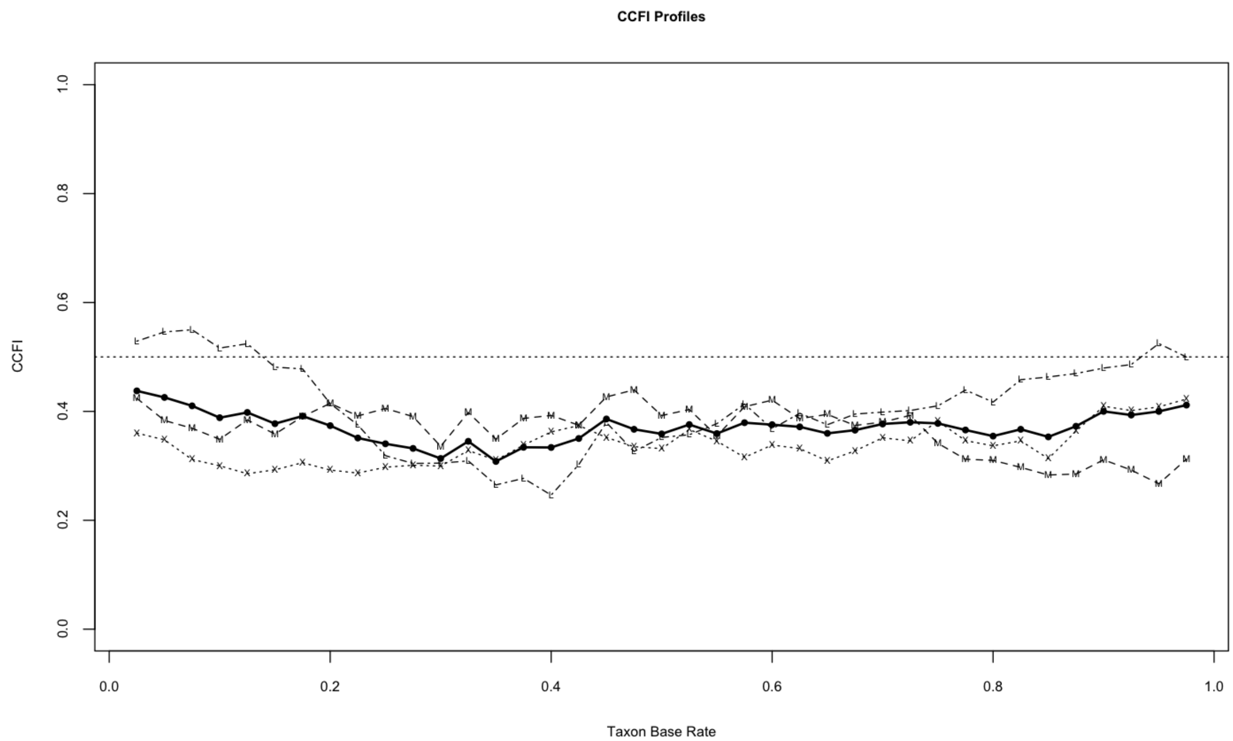
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 4. Comparison Curve Fit Indices (CCFIs) for D-KEFS Shifting (Ages 60-89)



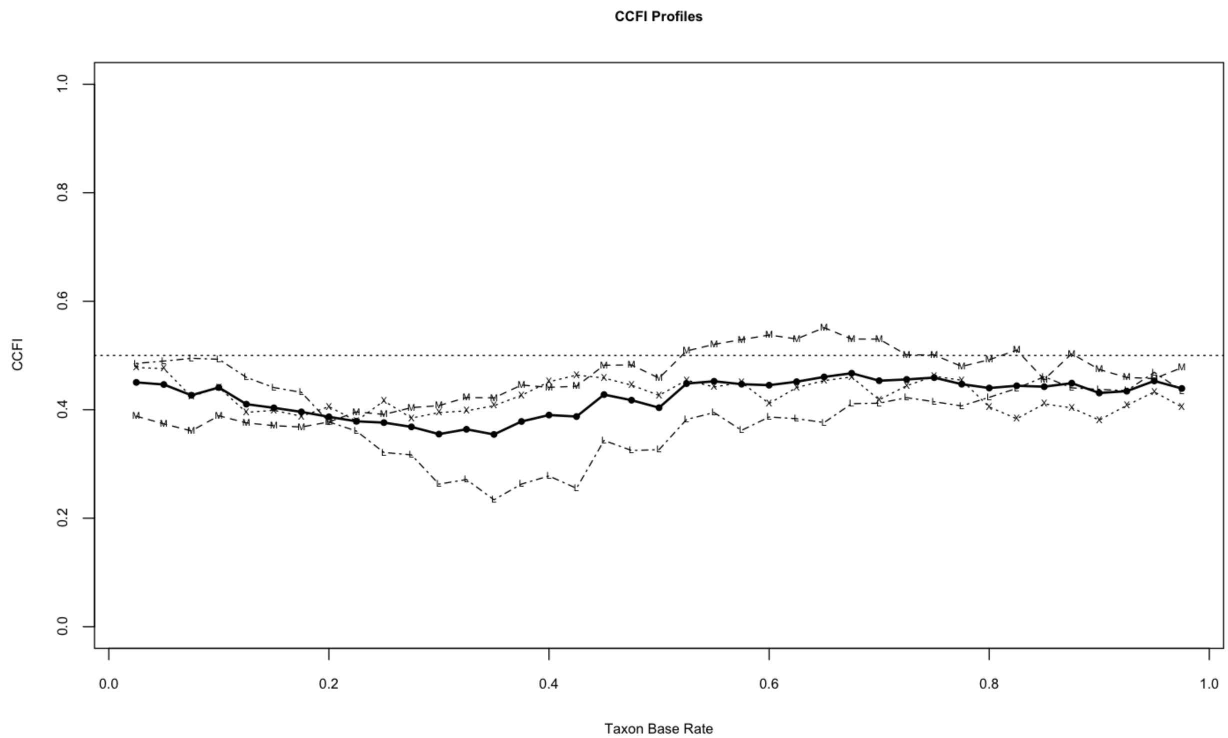
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 5. Comparison Curve Fit Indices (CCFIs) for D-KEFS Inhibition (Ages 8-11)



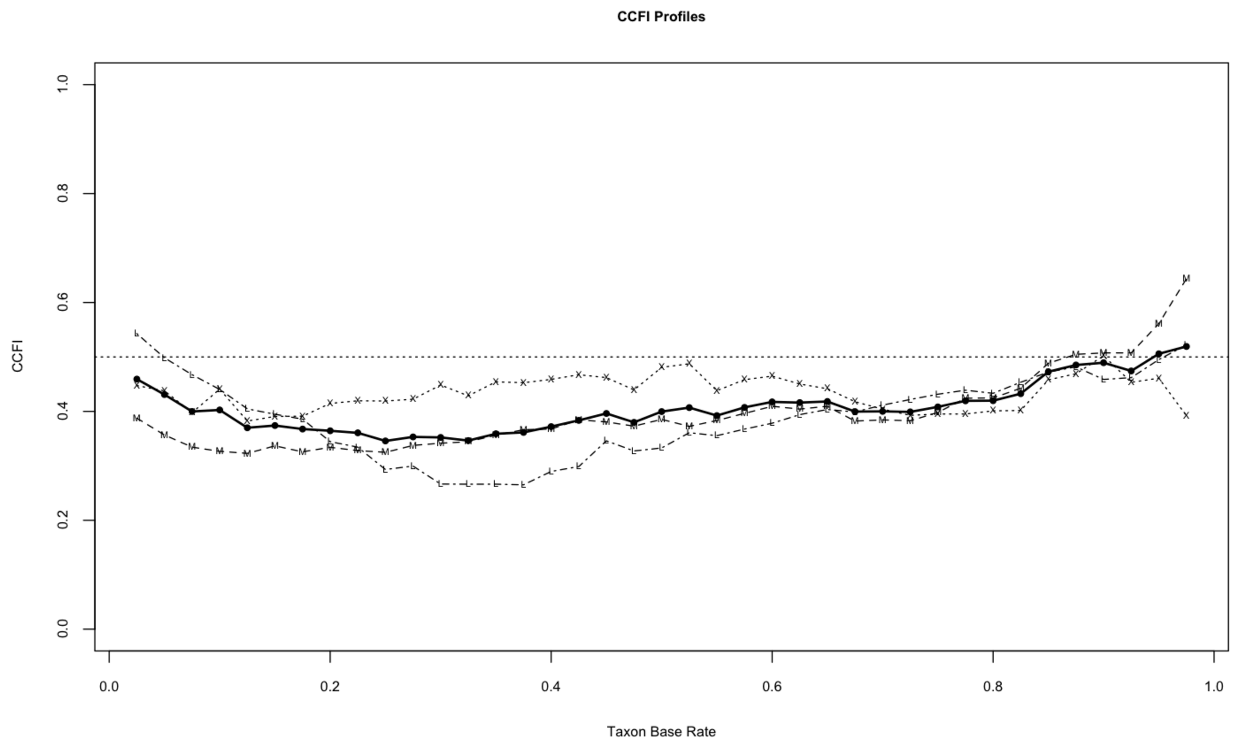
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 6. Comparison Curve Fit Indices (CCFIs) for D-KEFS Inhibition (Ages 12-19)



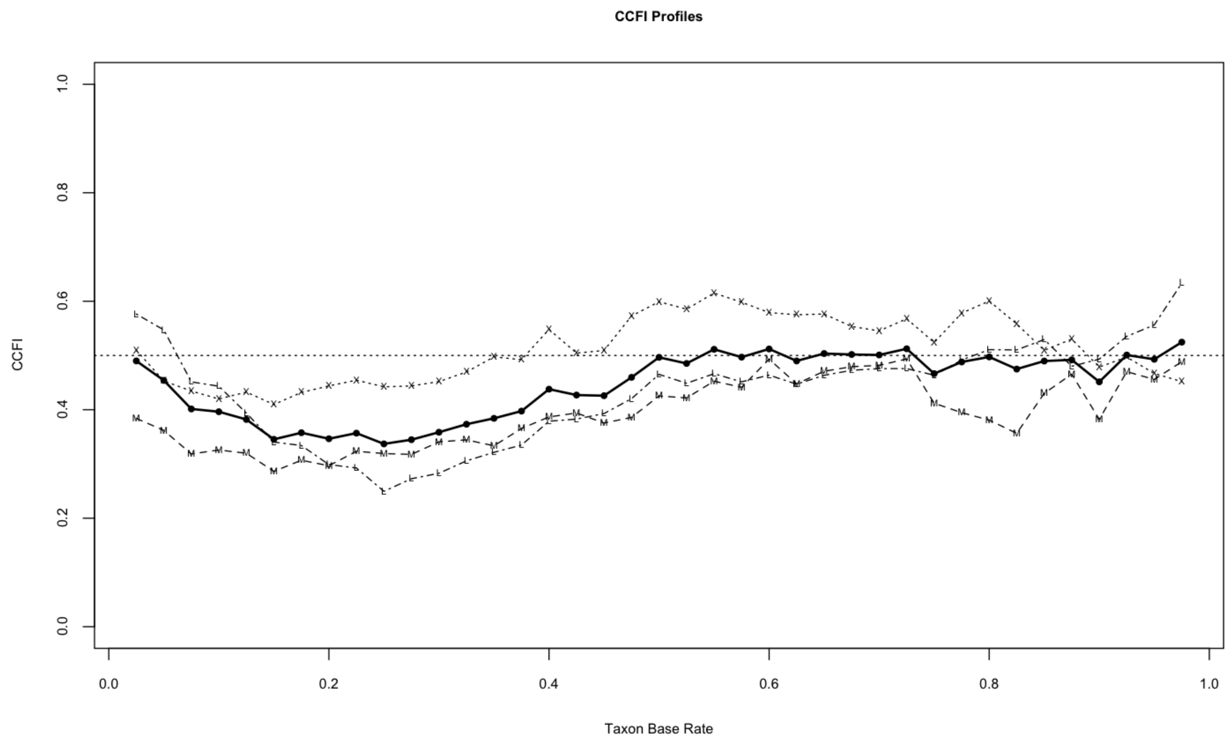
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 7. Comparison Curve Fit Indices (CCFIs) for D-KEFS Inhibition (Ages 20-59)



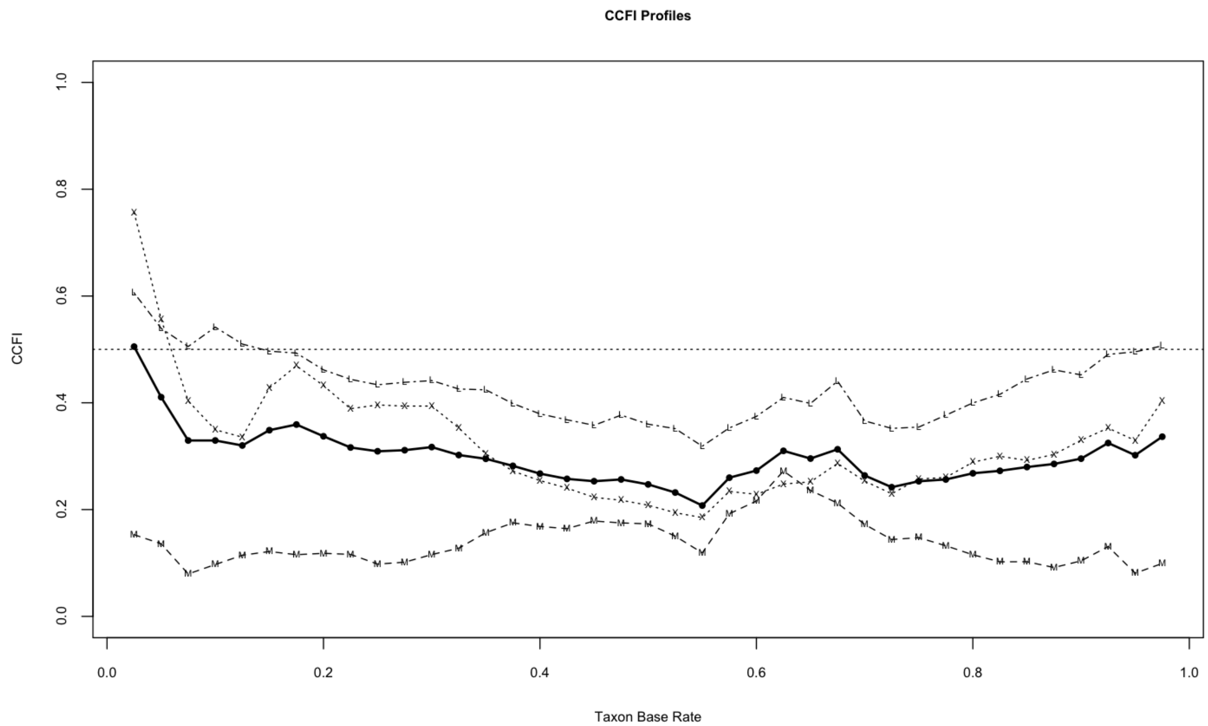
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 8. Comparison Curve Fit Indices (CCFIs) for D-KEFS Inhibition (Ages 60-89)



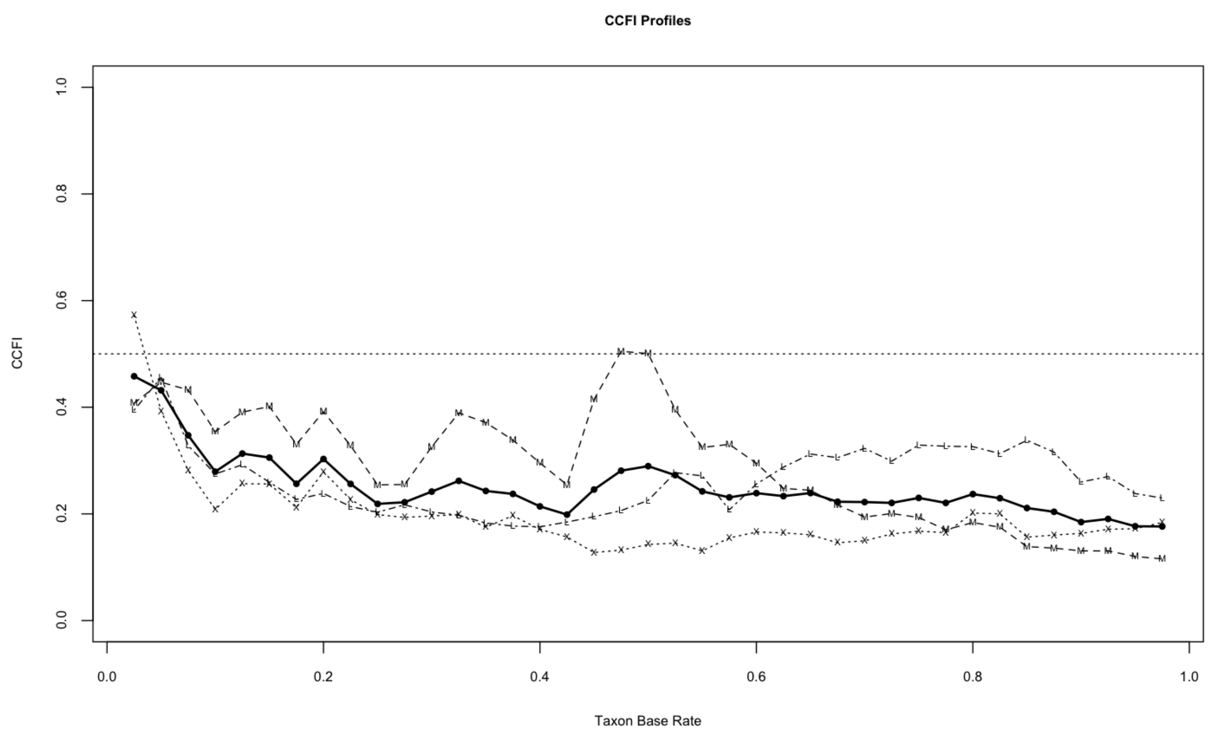
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 9. Comparison Curve Fit Indices (CCFIs) for BASC-3 PRS-P Attentional Control



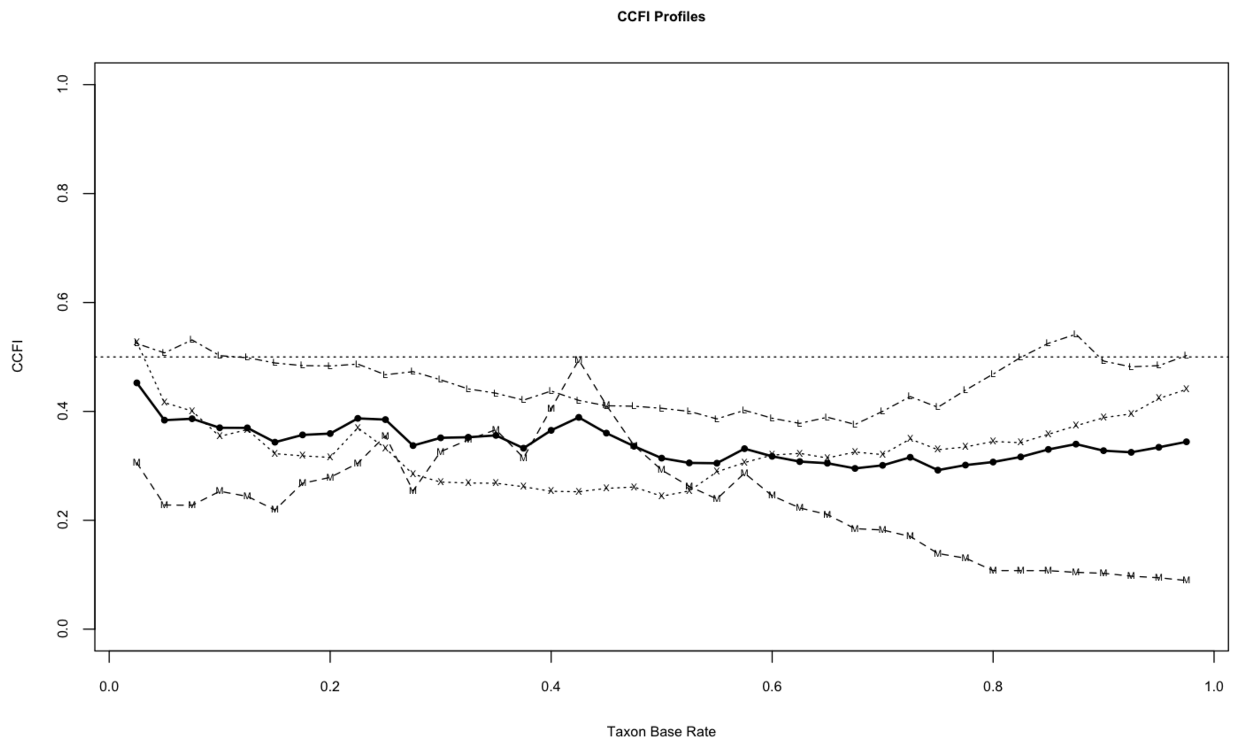
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 10. Comparison Curve Fit Indices (CCFIs) for BASC-3 PRS-C Attentional Control



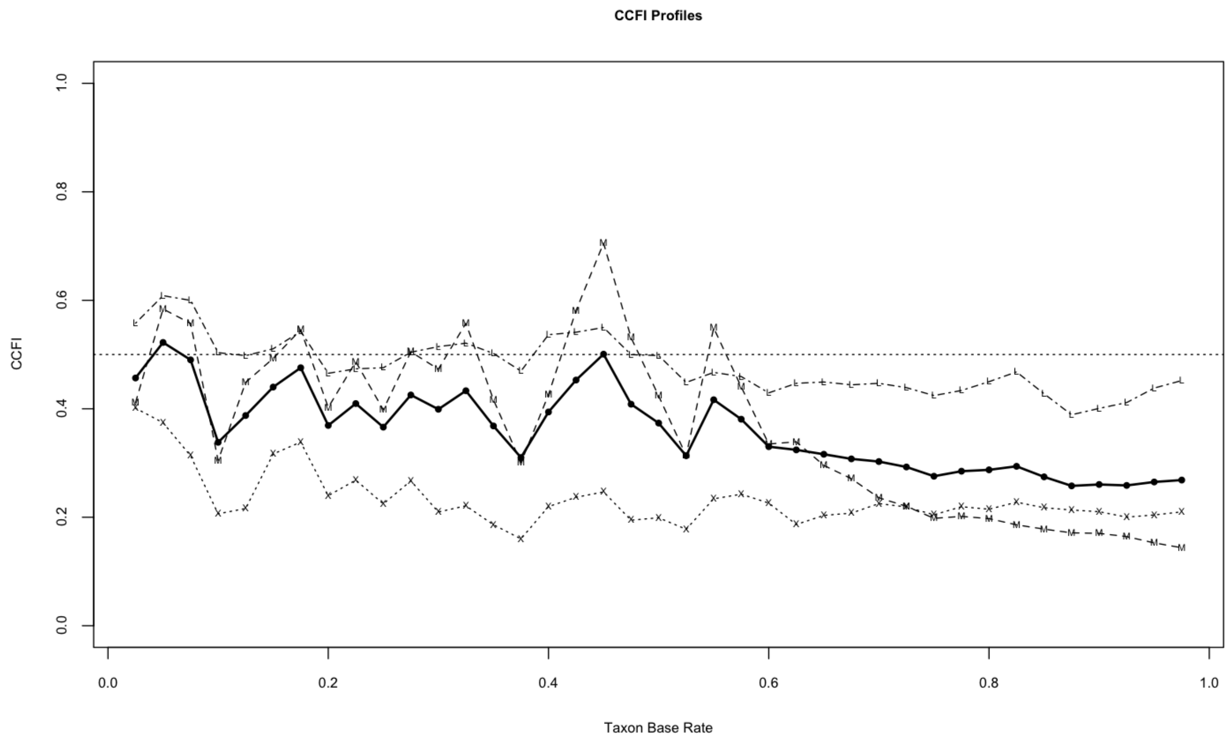
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 11. Comparison Curve Fit Indices (CCFIs) for BASC-3 PRS-A Attentional Control



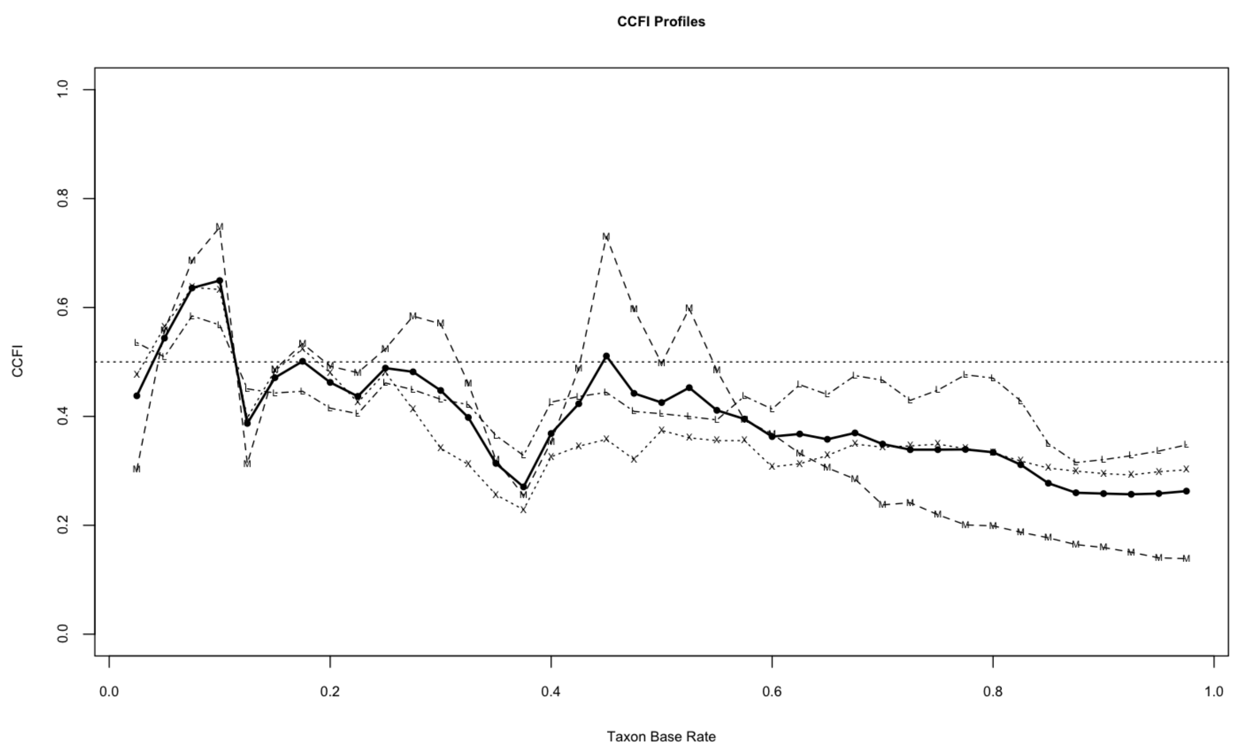
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 12. Comparison Curve Fit Indices (CCFIs) for BASC-3 TRS-P Attentional Control



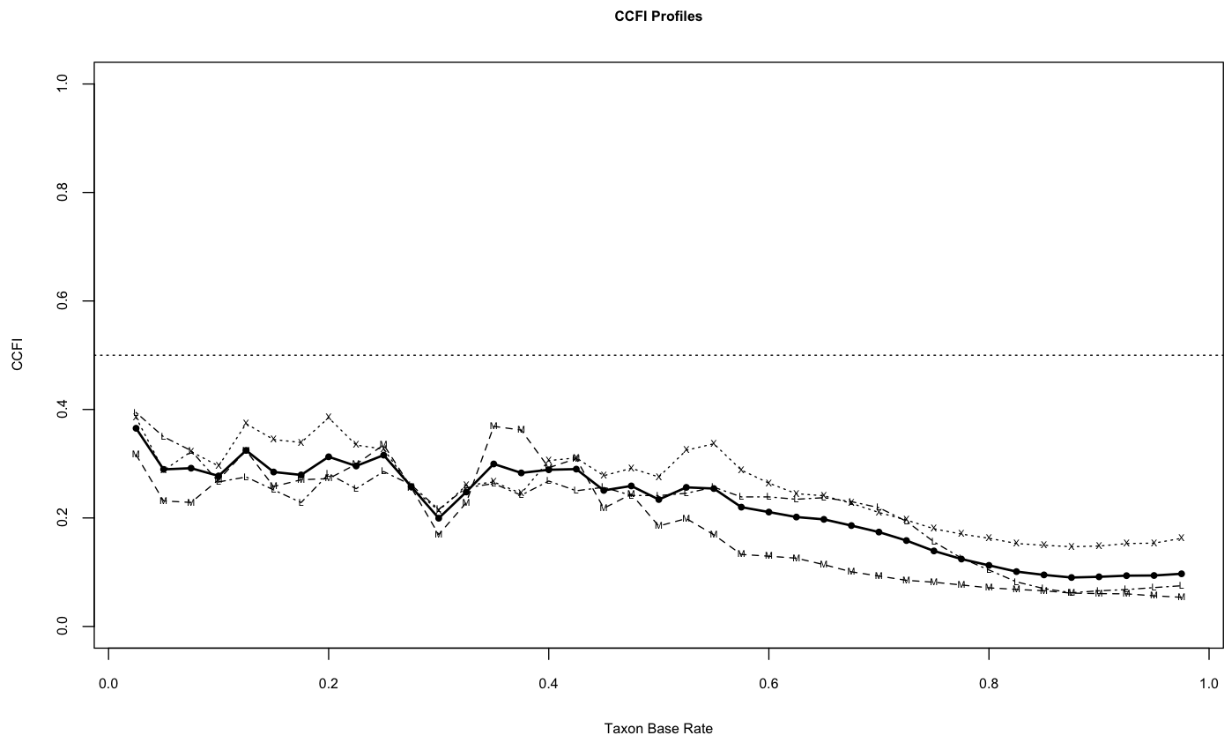
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 13. Comparison Curve Fit Indices (CCFIs) for BASC-3 TRS-C Attentional Control



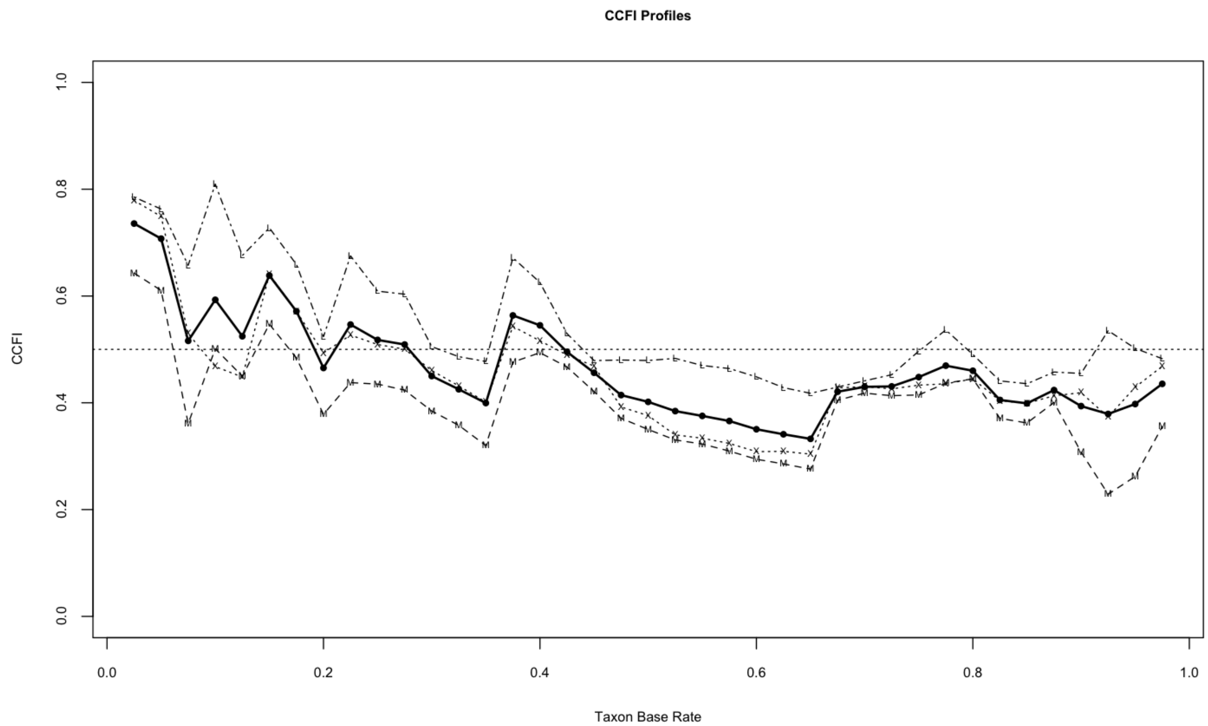
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 14. Comparison Curve Fit Indices (CCFIs) for BASC-3 TRS-A Attentional Control



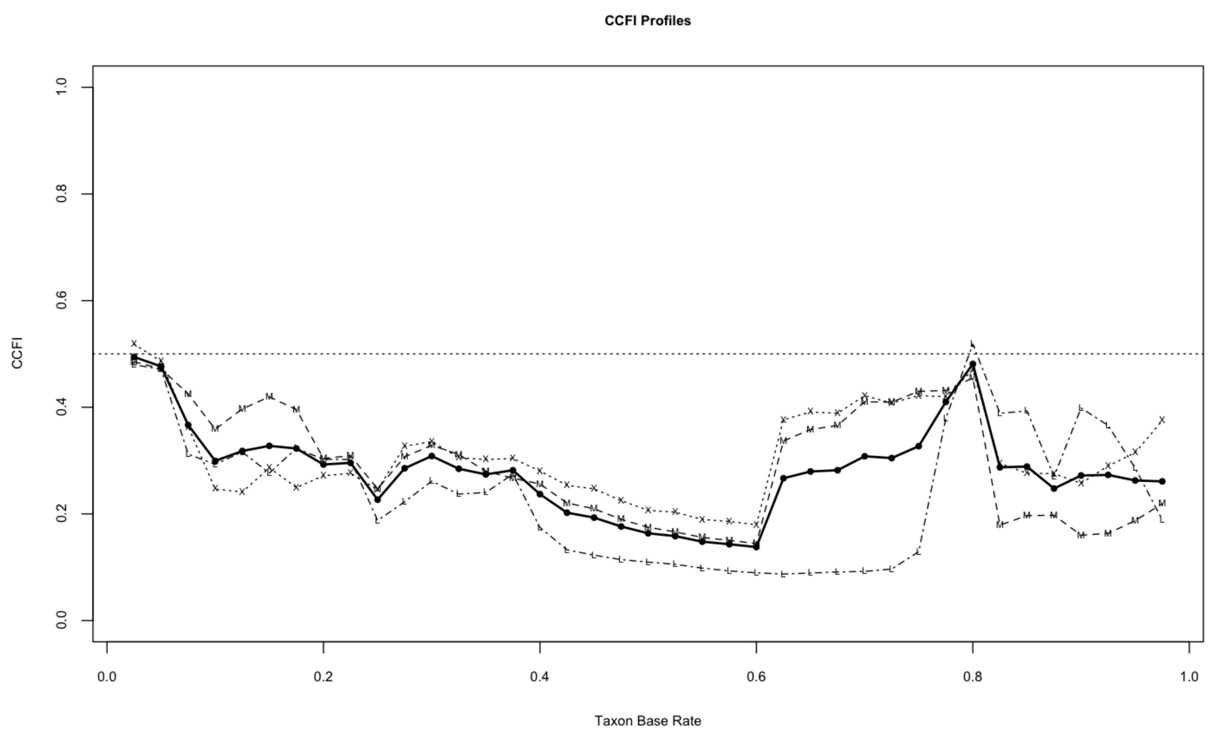
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 15. Comparison Curve Fit Indices (CCFIs) for BASC-3 PRS-P Behavioural Control



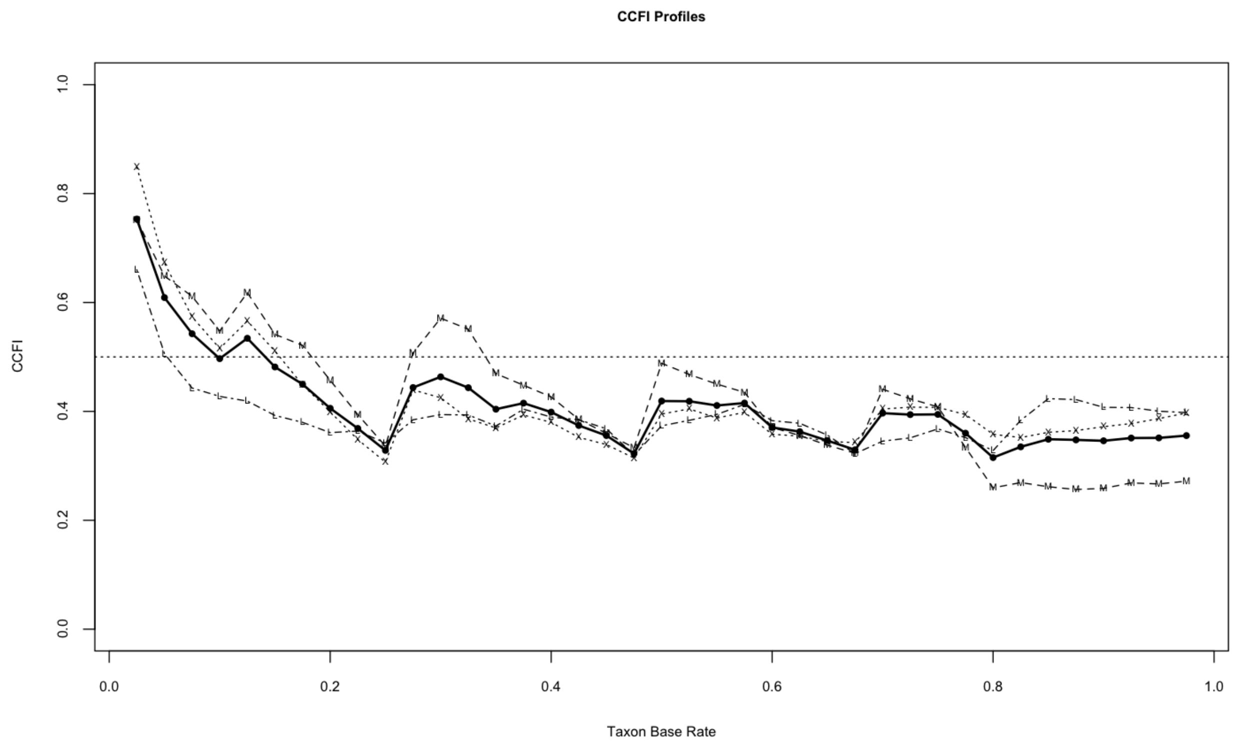
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 16. Comparison Curve Fit Indices (CCFIs) for BASC-3 PRS-C Behavioural Control



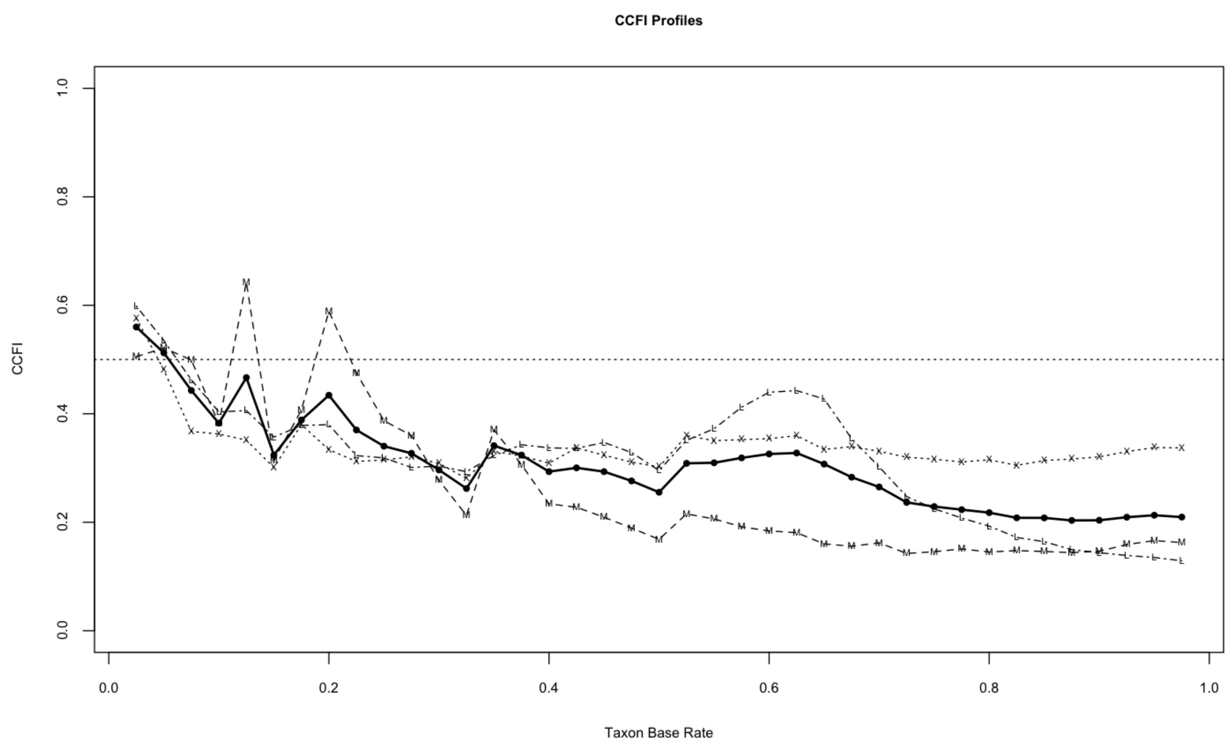
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 17. Comparison Curve Fit Indices (CCFIs) for BASC-3 PRS-A Behavioural Control



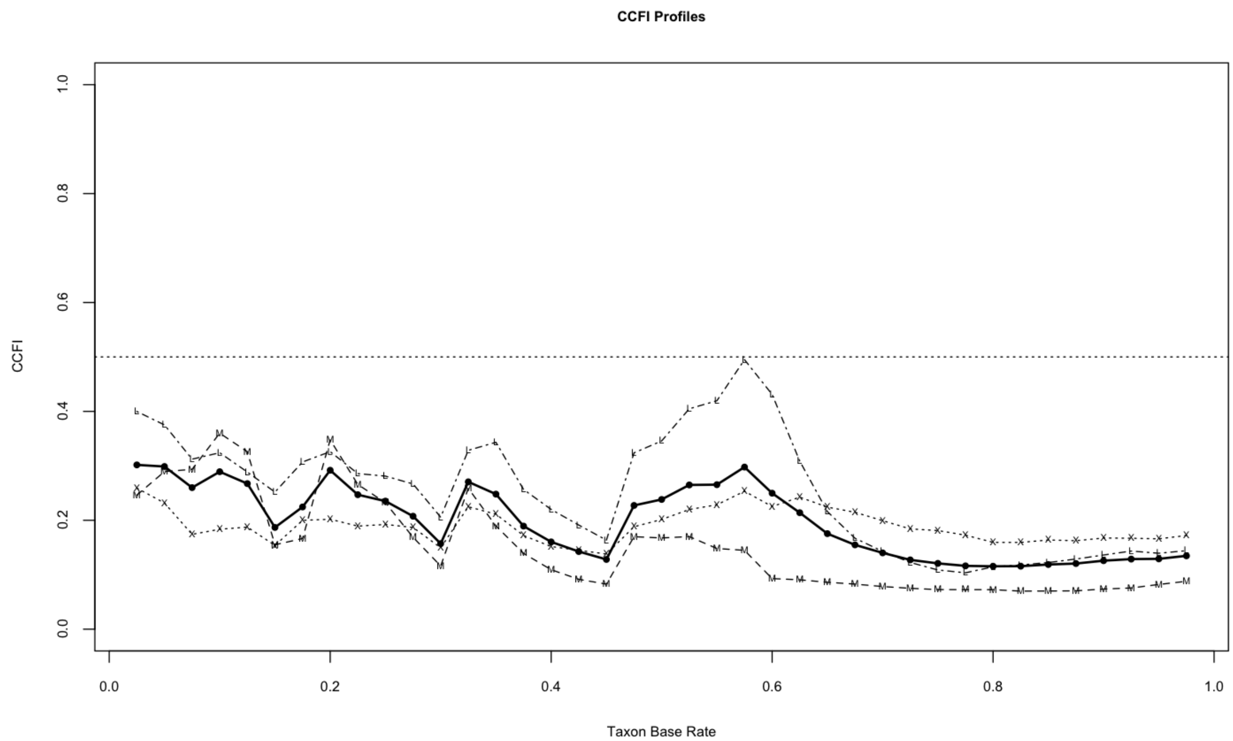
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 18. Comparison Curve Fit Indices (CCFIs) for BASC-3 TRS-P Behavioural Control



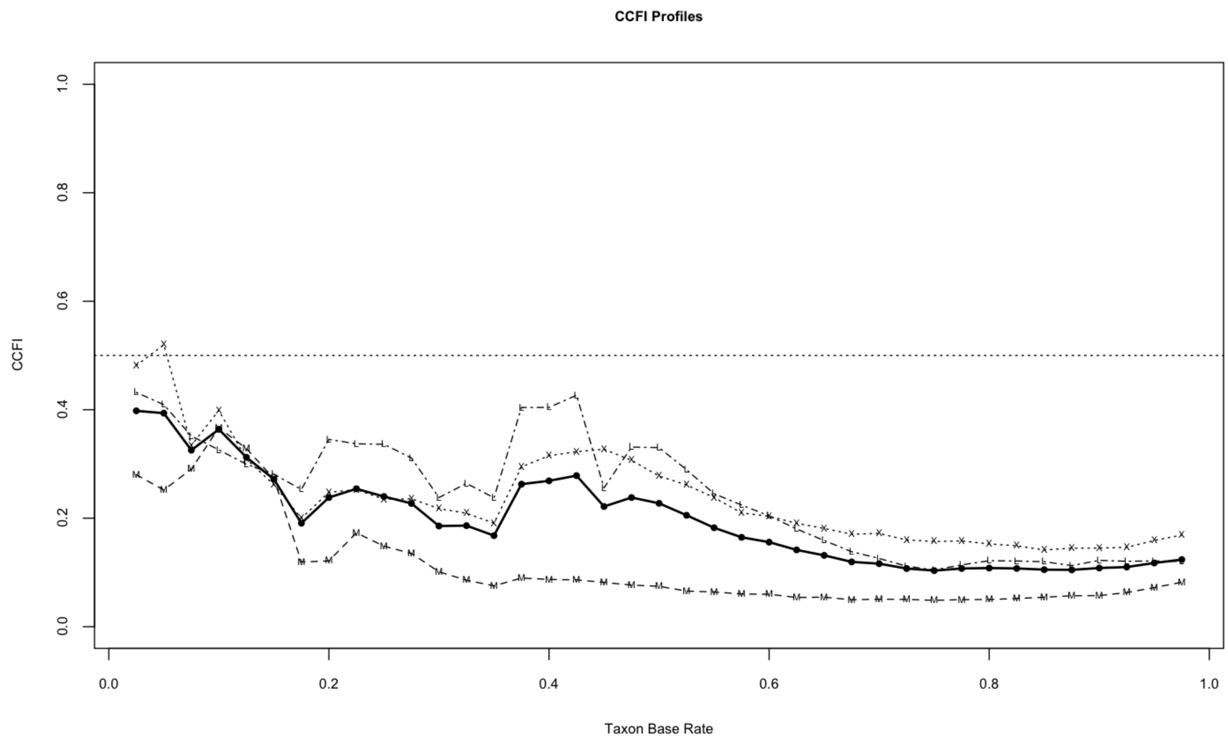
Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 19. Comparison Curve Fit Indices (CCFIs) for BASC-3 TRS-C Behavioural Control



Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Figure 20. Comparison Curve Fit Indices (CCFIs) for BASC-3 TRS-A Behavioural Control



Note: M = Mean Above Mean Below a Cute, X = Maximum Eigenvalue, L = Latent Mode

Chapter 3: Executive Functioning Networks: An Alternative to Latent Constructs

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Abstract

Executive function is a neuropsychological construct ascribed to dynamic frontal-parietal lobe networks and describes a number of cognitive processes thought to aid in complex, goal-directed behaviour. Despite their common usage over the past two decades, latent variable methodologies have struggled to unify competing conceptions of this construct and connect them to underlying neurobiology. As such, there may be reason to look for alternative methods to model this complex phenomenon in a more dynamic and clinically relevant manner. Using network models and the large, demographically representative, standardization samples of the D-KEFS and BASC-3, the current study explores the utility of network models to examine executive functions and discusses the implications of using network models in executive functioning research and clinical settings.

Keywords: executive functioning, network models, D-KEFS, BASC-3

Executive functioning networks: An alternative to latent constructs

Executive functioning is broadly defined as a collection of cognitive processes that govern complex goal-directed behaviour, self-monitoring, and self-regulation (Baggetta & Alexander, 2016). Over two decades have passed since the publication of Miyake and colleagues (2000) seminal paper that established the utility of factor models in executive function research, with over 16000 citations referencing this article to date. As our understanding of executive functions expanded rapidly, measurement models for a significant portion of the executive functioning field have largely adopted this framework of reflective factor models (i.e., an underlying latent executive function construct produces performance in manifest variables) to the point that even though the original researchers did not claim that the three executive functions specified in the original formulation (Inhibition, Updating Working Memory, & Set Shifting) were the only possible executive functions, they remain the most cited and examined functions (Baggetta & Alexander, 2016). This framework has generated an immense number of insights into how the development (or lack thereof) of various executive functions are generally associated with a number of important life outcomes like academic skills (Best et al., 2011; Jacob & Parkinson, 2015; Schmidt et al., 2017), health behaviours (Hillman et al., 2008), psychopathology (Diamond, 2013), substance abuse (Jester et al., 2019), and occupational or legal troubles (Barkley & Fisher, 2011). However, in spite of the overwhelming success and wealth of information derived from this approach, there remain a number of caveats or limitations to its utility for both research and clinical use, namely issues with convergent validity, construct clarity, and replicability.

Convergent validity, construct clarity, and replicability

Well-established measures of executive functioning generally do not correlate with one another, and this issue is particularly noticeable between performance-based tasks (e.g., computerized tasks) and behavioural ratings (e.g., questionnaires) that are both supposedly designed to measure the same executive functions (Toplak et al., 2009; Toplak et al., 2013) and several explanations have been provided to explain this concerning phenomenon. Firstly, there are fundamentally different response processes being tapped into by performance-based tasks and behavioural ratings, namely performance-based tasks are conducted in highly structured settings, are intended to draw out maximal performance, and concern themselves with accuracy and response times; whereas behavioural ratings ask about typical or general performance in unstructured settings and concern themselves with subjective judgements and not objective performance (Dang et al., 2020). However, this suggests that different assessment methods are possibly capturing different constructs.

Furthermore, the very nature of performance-based tasks means they often maximize within-person differences and minimize between-person differences to generate significant experimental effects (i.e., every participant should demonstrate the same response to the experimental manipulation and the difference within each participant should be large), whereas the opposite is true for behavioural ratings (Hedge et al., 2018; Dang et al., 2020). In other words, performance-based tasks often have low psychometric reliability compared to behavioural ratings, which have high psychometric reliability and mathematically speaking, this difference will inherently lead to weaker correlations (Dang et al., 2020).

Part of the difficulty in observing statistical relationships between different measures of what are supposed to assess the same construct may also stem from the fact that conceptually speaking, there over 30 distinct definitions for executive functioning (Eslinger, 1996) with contributions stemming from neurological (Stuss & Alexander, 2007), developmental (Denckla, 1996; Zelazo & Müller, 2010), and cognitive psychology perspectives (Baddeley, 1996; Miyake et al., 2000). In terms of specific functions, executive functions have included a number of lower-order processes such as inhibition (Barkley, 1997; Miyake et al., 2000), updating working memory (Baddeley & Hitch, 1974; Miyake et al., 2000), attentional control (Norman & Shallice, 1984), and verbal fluency (Lezak et al., 2004), as well as higher-order processes and behaviours such as problem solving (Zelazo et al., 1997), goal-setting (Anderson, 2002), decision-making (Lezak et al., 2004), and emotion regulation (Barkley, 1997). Indeed, this abundance of distinct definitions or conceptualizations has led to a number of competing models and an overall lack of clarity (Baggetta & Alexander, 2016). Such difficulties raise the specter of the jingle and jangle fallacies as forewarned by Block (1995), where jingle fallacies refer to the labelling of two different phenomena as the same and jangle fallacies refer to the provision of multiple terms for the same phenomena.

Furthering these concerns and mirroring the replication crisis across many scientific fields, the most popular executive function factor models do not consistently replicate across populations or measures. In a meta-analytic review of factor analytic models used in executive function research, including the original Miyake formulation, the most replicable model was a nested-bifactor model consisting of Updating, Shifting, and an executive bifactor that subsumed Inhibition, which at best replicated just over 50 percent of the time (Karr et al., 2018). For a construct that is seemingly ubiquitous across a multitude of psychological fields and intimately tied to important life outcomes, replicability at levels slightly better than a coin flip in the most optimistic estimates is cause for genuine concern.

This brief overview of these issues facing executive function research captures ongoing concerns within the field regarding the theoretical underpinnings of the construct, with some advocating for greater theoretical consistency and parsimony (Baggetta & Alexander, 2016), to others going as far as to advocate for disposing completely of the construct and re-orient towards neurobiological substrates and networks (Koziel, 2014). While the original conceptions of executive function emerged from frontal lobe lesion patients, there is increasingly strong evidence within contemporary conceptions of executive functioning to support the idea that executive functions operate within dynamic frontal-parietal networks and associated subcortical systems (Ardila, 2019). Yet despite this growing consensus and understanding about the neurobiological systems of executive functioning, the use of factor models to investigate this phenomenon has neither unified the various cognitive psychology models of executive functioning nor provided sufficient connection to the underlying neurology. Difficulties in replication, inconsistent measurement approaches, and mismatches between research and clinical conceptualizations have led to a relative stagnation in the theoretical development of executive functioning. To this end, the current study proposes an alternative method of conceptualizing and modeling executive functions that more closely adhere to historical and clinical conceptualizations of executive functioning, namely, network models.

Networks are characterized by nodes (i.e., variables) and edges (i.e., correlations or relationships) and while network models are plentiful in other domains of science, they have seen sporadic use in psychological research until the last decade with areas like intelligence (Kan et al., 2019; van der Maas et al., 2017), personality (Cramer et al., 2012), depression (Fried et al., 2016), substance use (Rhemtulla et al., 2016), post-traumatic stress disorder (Isvoranu et al., 2021; McNally et al., 2015), general psychiatric symptomatology and comorbidity (Afzali et al., 2017; Beard et al., 2016; Boschloo et al., 2015; Cramer et al., 2010), and even executive functioning (Karr et al., 2021), demonstrating the potential contributions of this approach to furthering our understanding of elusive phenomenon like executive functioning.

Latent variable approaches have been the predominant methodology for examining executive functions for the past 20 years but in contrast to latent variable approaches, which factor analysis is part of, network models reject the need for a latent construct that produces observed behaviour on variables of interest and instead propose that the relationship between the variables themselves form a system of causation that can be unidirectional, bidirectional, or unspecified in nature (Schmittman et al., 2013). In other words, the phenomenon known as executive functioning does not exist separately from the measures but instead is produced by the dynamic interplay between nodes as an emergent entity. Using two large standardization samples from commonly used psychological assessment tools, the current study will demonstrate how executive functioning might be modelled across the lifespan using network approaches and discuss the possible implications for theory and practice.

Methods

Sample

Two samples were obtained from the Delis-Kaplan Executive Function System (D-KEFS; Delis et al., 2001) and Behavior Assessment System for Children – 3rd Edition (BASC-3; Reynolds & Kamphaus, 2015) normative samples, respectively. The D-KEFS normative sample data collection procedure involved a standardized sampling of 1750 individuals with representation of sex, age, ethnicity, education, and geographic region in line with the 2000 U.S. Census (8-89 years old). The BASC-3 normative sample data collection procedure involved a standardized sampling of 3500 total individuals with representation of sex, age, ethnicity, socioeconomic status, and geographic region in line with the 2013 U.S. Census (12-18 years old). The BASC-3 sample can be further subdivided into the Parent Rating Scales (PRS; n = 3351) and Teacher Rating Scales (PRS; n =1946) with different forms for ages 2 to 5 (Preschool or P), 6 to 11 (Child or C), and 12 to 18 (Adolescent or A). Differences in total sample counts can be attributed to some children having only parent ratings, only teacher ratings, or both parent and teacher ratings. All data was provided by Pearson and was received as previously anonymized data.

Measures

The measures used in this study can be subdivided into two groups: performance-based measure (i.e., D-KEFS) and behavioural rating scales (i.e., BASC-3). While hundreds of different performance metrics can be extracted from the D-KEFS, many are repetitive and overlap significantly with one another, or are contingent on other variables (e.g., ratio or contrast scores). Therefore, D-KEFS test scores from each individual task were included on the basis of a priori determinations of item quality, construct coverage, and decisions were made to avoid repetitive measurement. At least one measure from each task was included in the estimation of D-KEFS networks. For the BASC-3, items were drawn from a previously derived Executive Behaviour Screener consisting of four subscales (Garcia-Barrera et al., 2011; Wong et al., 2018). All items were scored on a 4-point Likert-like scale, with higher scores indicating greater impairment in the target domain. It should be noted that not all items are the same across BASC-3 Parent and Teacher forms nor are all items the same across age ranges (i.e., Preschool, Child, and Adolescent forms).

D-KEFS Trail Making Test: A task that tests speed of processing, flexibility of thinking, and motor speed, via a paper and pencil visual-motor modality analogous to “connecting the dots". Lower completion times and error rates are indicative of better performance. Time to complete the switching condition and total errors on the switching condition were included as variables of interest.

D-KEFS Verbal Fluency Test: A task that assesses fluent verbal production to letter or category cues within a defined set of rules and requires a degree of cognitive flexibility and working memory. Greater number of words produced and fewer repetitions or rule-breaking words are indicative of better performance. Total category fluency, total phonemic fluency, and total switching fluency were included as variables of interest.

D-KEFS Design Fluency Test: A task that assesses fluent visual-motor production using an array of dots within a defined set of rules, requiring a degree of cognitive flexibility and working memory. Greater number of designs and fewer repetitions or rule-breaking designs are indicative of better performance. Total number of switching designs, total number of filled and empty designs, and total number of repetition errors were included as variables of interest.

D-KEFS Color-Word Interference Test: A task that assesses verbal inhibition, cognitive flexibility, and processing speed and is analogous to the classic Stroop Task. Greater number of correctly identified stimuli are indicative of better performance. Total performance on the third and fourth conditions were included as variables of interest.

D-KEFS Sorting Test: A task that assesses problem solving, concept formation, and cognitive flexibility where the participant is asked to sort a number of stimuli in as many unique ways as they can. A greater number of unique and correct sorts are indicative of better performance. Total number of correct sorts was included as the variable of interest.

D-KEFS Twenty Questions Test: A task that assesses problem solving and abstract reasoning where the participant is given a limited number of opportunities to ask yes/no questions in order to identify predetermined stimuli. Better performance is reflected by fewer questions used to correctly identify the stimuli. Total number of questions asked was included as a variable of interest.

D-KEFS Word Context Test: A task that assesses deductive reasoning based on the participants ability to identify the meaning of unfamiliar "words" based on their context. Better performance is reflected by fewer guesses required to correctly identify the meaning. Total words correctly guessed on the task was included as a variable of interest.

D-KEFS Tower Test: A task that assesses planning, reasoning, and impulse control using a set of concentric disks and pegs where the participant is asked to replicate specific configurations within a defined set of rules. Fewer number of moves required to complete the task and fewer number of errors or rule-breaking moves are indicative of better performance. Total number of completed towers and total number of errors were included as variables of interest.

D-KEFS Proverbs Test: A task that assesses abstract thinking and comprehension of increasingly metaphorical and uncommon proverbs. Better performance is reflected in more accurate and abstract descriptions of the true meaning of these proverbs. Total number of proverbs identified was included as the variable of interest.

BASC-3 Problem Solving: Consists of items designed to assess for a child's ability to make decisions and solve problems effectively in daily life, which is considered to be separate from the ability to solve abstract problems that might be found on an intelligence test. This subscale was not included in either of the Preschool Forms of the BASC-3 as the skills involved within this domain are considered to be more developmentally advanced and therefore are difficult to observe in this age range. For the PRS-A and PRS-C, the scale consisted of 9 items and 8 items, respectively. For the TRS-A and TRS-C, the scale consisted of 10 items and 9 items, respectively.

BASC-3 Attentional Control: Consists of items designed to assess for a child's ability to focus their attention and sustain it in the face of distractions. For the PRS-A and TRS-A, the scale consisted of 9 items. For the PRS-C and PRS-P, the scale consisted of 7 items, while the TRS-C consisted of 8 and the TRS-P consisted of 5.

BASC-3 Behavioural Control: Consists of items designed to assess for a child's ability to inhibit behaviours that may be considered impulsive or disruptive to others. For the PRS-A, the scale consisted of 7 items. For the PRS-C and PRS-P, the scale consisted of 6 items. For the TRS-A, TRS-C, and TRS-P, the scale consisted of 6, 7, and 5 items, respectively.

BASC-3 Emotional Control: Consists of items designed to assess for a child's ability to exert control over their emotions, particularly negative emotions, when they become elevated. For the PRS-A and PRS-C, the scale consisted of 4 items. For the PRS-P, it consisted of 7 items. For the TRS-A, TRS-C, and TRS-P, the scale consisted of 6, 7, and 8 items, respectively.

Data analysis

The normative data for the D-KEFS was split into four distinct age ranges: Childhood, Adolescence, Adulthood, Older Adults (i.e., 8-11, 12-19, 20-59, and 60-89), based on observed and theorized developmental trajectories in extant developmental literature (Delis et al., 2001). All normative data were age-corrected and standardized for all D-KEFS variables (M = 10, SD = 3). Items that were positively worded were reverse scored for all forms of the BASC-3 so that increasing index scores reflected greater difficulty in the target domain. All network analyses were conducted in R Version 4.0.4 (R Core Team, 2021) using the package bootnet (Epskamp & Fried, 2015).

Network estimation

The structure of 10 weighted networks (4 D-KEFS, 6 BASC-3) was estimated using bootnet. For the D-KEFS, this included all previously selected variables for each of the four age ranges. For the BASC-3, this included all variables from each subscale present in the respective forms. For example, the Teacher Rating Scale – Preschool form included only Attentional, Behavioural, and Emotional Control items, whereas the Teacher Rating Scale – Adolescent form included items from the aforementioned subscales as well as from the Problem-Solving subscale. The primary advantage of network approaches compared to traditional methods is that they allow for the visualization of multivariate dependencies that may not be easily discerned. In order to increase confidence in the estimation of each edge, a Gaussian Graphical Model (GGM) was produced that estimated a pairwise association (i.e., partial correlation coefficient) between all nodes using the least absolute shrinkage and selection operator (LASSO; Tibshirani, 1996). GGMs are considered to be one of the better methods for both ordinal and continuous data (Lauritzen, 1996). Furthermore, the rationale behind using a GGM over generating a network depicting simply zero-order correlations, is that zero-order correlations are not conditioned on any other variables in the network, whereas GGMs are conditioned on all other variables. As the proposed nature of executive functions involves dynamic, mutually-supportive, cognitive processes, zero-order correlations may not accurately capture the relationships between different executive functions and may over-inflate the strength of certain edges (Fried et al., 2018; Williams, 2022). Due to the number of nodes and edges being estimated, there is an increased risk of false positives, and the LASSO procedure is a regularization technique that only identifies edges that can pass this more conservative cut-off (van Borkulo et al., 2014). Density tables were also calculated by summing the edges of each respective network (Table 1).

Centrality estimation

While there are a number of different metrics used in the network literature to assess for network characteristics, given the relative novelty in executive function research, only a single metric of network centrality was calculated: Expected Influence

Expected Influence: A variant of Node Strength, where the sum of all edges of a given node with all other nodes whilst retaining the sign of the edge weights (e.g., positive or negative) and assesses the total impact a node has on a network (Robinaugh et al., 2016).

Accuracy and stability estimation

A major challenge with estimating networks is that the stability and accuracy of the estimated networks are relatively unclear (Epskamp et al., 2017). In any given network, it is difficult to determine whether a particular edge weight in the network is significantly stronger than a weaker edge. Similarly, it is sometimes unclear as to whether a particular node is significantly more central than another. In order to address these issues, the 95% confidence intervals of the edge weights were bootstrapped for each of the 10 networks, which provides an accuracy estimate of the edge weights within the networks. Additionally, the stability of the centrality estimates by subset bootstrapping all networks were examined, which involves reducing the number of subjects and re-running the analysis for network estimation. Assuming that the order of centrality estimates from the network remain highly correlated between the original network and the network that had participants removed, the centrality estimates of the original network can be considered stable. Previous literature suggests that centrality stability coefficients (CS-coefficient) values should be at least 0.25 to be considered stable, though there is preference for values greater than 0.5 (Epskamp et al., 2017).

Visualization

To standardize interpretability across networks, positive edges are printed in green and negative edges in red. The thickness and colour saturation of an edge corresponds to the strength of the connection used the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991) to place nodes with stronger and more connections closer together. Maximum edge values across all D-KEFS networks and BASC-3 networks were set to 1, which allows the saturation and thickness of edges to be comparable with similar networks. Additionally, the minimum edge value across all networks were set to 0 to aid in interpretability of graphs.

Results

D-KEFS Network Estimation: Figures 1-4 show a visualization of the network structure for each age range of the D-KEFS. Overall, nodes tended only to be strongly and positively related to other nodes derived from the same neuropsychological tasks (e.g., Stroop Condition 3 & Condition 4; Verbal Fluency Phonological, Category, & Switching). Nodes associated with more complex executive processes (e.g., Proverbs, Sorting, and Word Context) also tended to be positively related. The Tower Total score was not positively related to any other tasks in the 8-11 or 12-19 age groups but demonstrated positive edge weights in the 20-59 and 60-89 age groups. A visual inspection of all 4 D-KEFS networks suggests increasing network connectivity as networks are estimated for increasing age ranges. This was corroborated after calculating network density values, with the 60 to 89-year-old network having the highest density values (5.777), followed closely by the 20 to 59-year olds (5.569). D-KEFS network density values can be found in Table 1. Interestingly, though density calculations tend to be greater with larger sample sizes, this trend held, even with smaller samples for the oldest age group. The standardized estimates for Expected Influence for each D-KEFS network are presented in Figures 5-8. Reflecting the relative sparsity of the D-KEFS network and the strong associations between nodes derived from the same measures, the nodes with the strongest Expected Influence tended to be those with the strongest associations (i.e., Stroop Condition 3, Verbal Fluency Phonological & Category, Trail Making Test Condition 4).

BASC-3 Network Estimation: Figures 9-14 show a visualization of the network structure for each form of the BASC-3 PRS and TRS. Overall, most nodes showed a positive association with one another and tended to show the strongest associations between nodes derived from the same subscale (i.e., Problem Solving, Attentional Control, Behavioural Control, Emotional Control). As each network differs slightly in node composition, it is difficult to make direct visual comparisons between them; however, similarities emerge across all networks. Attentional Control items tend to cluster together in two groupings, with one of these groupings showing relatively strong connections to Problem Solving nodes. Problem Solving nodes tended not to associate with any Behavioural or Emotional Control nodes. Behavioural Control and Emotional Control nodes tended to have strong positive within-subscale and between-subscale connections across all networks. When comparing network density for the different age groups, preschool forms for both the PRS and TRS showed the lowest values, and the adolescent forms showed the highest density values. BASC-3 network density values can be found in Table 1. Similar to the D-KEFS, adolescent ratings had the highest density values despite having smaller sample sizes than the child ratings. The standardized estimates for Expected Influence for the BASC-3 are presented in Figures 15-21. For preschoolers, the nodes with the greatest Expected Influence tended to come from the Emotional Control Subscale for both the PRS and TRS. For children and adolescents, the nodes with the greatest Expected Influence tended to be more evenly distributed between Emotional Control and Problem Solving for the TRS or Behavioural Control and Problem Solving for the PRS.

Network Accuracy & Stability: Bootstrapping results for each D-KEFS and BASC-3 network are presented in Supplemental Figures 1-10. The edge weight bootstrap for the D-KEFS indicate that the vast majority of edges in all D-KEFS networks are effectively zero and do not differ from one another as their 95% confidence intervals overlap; however, edges consisting of nodes from the same measure were estimated accurately and were consistently strong. The subset bootstraps showed satisfactory correlation stability coefficients for the D-KEFS, ranging from 0.360 to 0.594. For the BASC-3, correlation stability coefficients were excellent and were nearly or equal to 0.750. As described previously, values should not be under 0.25 and ideally should be above 0.50. A full table of coefficients as well as minimum and maximum estimated values can be found in Table 2.

Discussion

Based on the results of this study, executive functioning networks can be established using both neuropsychological test data and behavioural ratings and the strength and stability of the edges can be reliably estimated.

For the D-KEFS, the relative sparseness of the networks is striking, particularly in the younger sample of networks, which suggests that few of the neuropsychological task performances had an impact on the others. Indeed, the strongest edges consistently lay within tasks performance across all ages (e.g., one measure of verbal fluency task performance is related to another measure of verbal fluency performance). The only tasks that appeared to have some kind of connection outside of within-task measures were the more complex executive tasks (e.g., Tower, Proverbs, and Word Context), potentially reflecting the importance of multiple executive functions required to successfully complete the tasks themselves. These connections were also strongest in the latter age ranges, suggesting a certain developmental cognitive maturity might be required as well to sufficiently integrate various executive functions to support performance in more complicated tasks.

For the BASC-3, items that were previously categorized as being part of the same subscale (i.e., construct) tended to cluster together. While this is not unsurprising in itself, what is interesting is the Attentional Control subscale items appear to be split into two sub-groups. One grouping stands alone and contains items more related to the inability to focus whilst the other grouping appears to relate more closely to Problem Solving and revolve around the ability to organize one's thoughts, suggesting a divergence within the Attentional Control subscale between items measuring outright attentional difficulties and those potentially contributing to foundational processes for more advanced cognition. This result aligns in part with the notion that lower-order executive functions are necessary to produce higher-order processes, though without specified causal networks, this remains in the realm of conjecture.

In a separate vein, while Problem Solving or Attentional Control do not appear to be strongly connected to Behavioural or Emotional Control, these latter two subscales appear deeply intertwined. While outside the scope of the current study, community detection methods such as exploratory graph analysis (Golino & Epskamp, 2017) or clique percolation (Farkas et al., 2007) might have utility in aiding this discussion to provide quantitative support to qualitative observations. An example of what these methods can produce can be found in Supplemental Table 1.

Interestingly, the most influential nodes differed between the parent and teacher forms for children and adolescents but not for preschoolers. Specifically, the most influential nodes for children and adolescent parent rating networks tended to be ones from the Behavioural Control subscale, while the most influential nodes for teacher rating networks in the same age ranges tended to be the ones from the Emotional Control subscale. For preschoolers, the most influential nodes for both forms were the Emotional Control items. Taken together, this implies that while emotional difficulties were flagged as the most impactful problem within very young children for both teachers and parents, changes in developmental expectations as children age may lead parents to rate behavioural problems as a source of greater disturbance compared to teachers. This difference may be influenced by the relative exposure each type of rater experiences with children's problems as parents may find behavioural outbursts particularly distressing compared to teachers, who may have seen more instances of behaviour problems in the children they teach. Furthermore, differing expectations within the home and school environments may produce conditions that selectively draw for particular types of problems (e.g., school rules are relatively rigid and the environment is controlled, making behavioural problems less likely, while home rules can be more inconsistent, producing conditions for parent-child conflict).

It is notable that the network models for both the DKEFS and BASC-3 exhibited increasing network densities with age as the theoretical developmental trajectories for executive function posit a unitary executive construct in early life that becomes more fractionated and specialized with age, with a reversal in this process as one approaches their later years (Ferguson et al., 2021; K. Lee et al., 2013; Reilly et al., 2022). This result stands in contrast to what was observed by Karr and colleagues (2021) where network density in their study demonstrated a U-shaped curve that at least visually mimicked this developmental phenomenon. However, like the current study, that result was found in a large cross-sectional sample, which poses issues with making any firm conclusions about whether increasing or decreasing network density is reflective of this developmental process. Additionally, the difference in findings may also be reflective of the greater number of measures used in this study where greater network density over time may be indicative of more integrated executive functions across a multitude of tasks or measures. Following this line of thought, increasing network density may not necessarily have a direct or positive relationship with the developmental trajectory of specialized executive functions as increasing density (i.e., connectivity) may actually be reflective of increasing reliance on a combination of executive processes to produce the expected performance. Indeed, increasing network density in this light may be representative of learning processes across a lifetime.

The importance of theory in executive functioning research

From the perspective of improving our theoretical understanding of executive function, what emerges from this study is the importance of generating a theory of the phenomenon in question. While the D-KEFS was generated as a collection of classic neuropsychological tasks used to assess executive function (Delis et al., 2001), consistent with the current findings, the tests themselves have been previously observed to have relatively weak correlations between different measures (Toplak, 2013). This lack of relationship may stem from the atheoretical nature of the tool as each of the original measures was designed to assess specific neuropsychological deficits that generally stemmed from distinct neurological lesions. While it remains a gold-standard measure for clinicians who wish to measure executive functions (Delis et al., 2001), it remains incumbent on the user to selectively administer measures based on an a priori understanding of executive functioning and to not assume that this work has already been done for them. In contrast, the BASC Executive Function Screener is based on a theory of executive functioning (Garcia-Barrera et al., 2011) and as such, demonstrates a more integrated network structure and is more theoretically consistent, which ultimately produced more interpretable results in this study.

Implications for executive dysfunction in clinical settings

In recent years there has been a concerted effort to move away from latent disease entities in psychological treatment settings (Hanfstingl, 2019) and to replace them with more flexible conceptualizations, in other words, networks. These efforts have spawned a flurry of new research in applying network approaches to clinical work and producing individualized psychological networks for clients in healthcare settings (Epskamp et al., 2018). Using methods like ecological momentary assessment (EMA) or repeated batteries, clinicians could theoretically produce individualized networks of executive function for each of their clients and using these networks as a framework for targeted intervention as well as a metric for change.

Interestingly, this sort of clinical thought process has long been implemented in treatments and rehabilitative settings (Lutz et al., 2021), with the only difference being the lack of overarching network theory and metrics. Indeed, clinicians may recognize this approach as being extremely familiar to their regular practice as there is an explicit acknowledgement that specific symptoms can exacerbate others and targeting one issue might have a beneficial cascading effect on other areas of function (Micco, 2017; Moorey, 2010; Tkachenko et al., 2014). As the body of research grows for executive function networks, there may be additional improvements to proposed networks by including edges that denote causal relationships (i.e., directionality). Certainly, these directed acyclic graphs (DAGs) must have a theoretically coherent basis but there exist neuropsychological models that might prove useful in this regard. For example, the Hierarchical Model of Cortical Functioning (Luria, 1973) is one possible framework that provides a conceptual directionality of cognitive processing that does not explicitly exist in other models relevant to executive functioning while simultaneously rooting them in the underlying neurological systems (e.g., Unit 1 → Unit 2 → Unit 3). In this conception of their executive functioning, it may be prudent to intervene on more basic attentional processes as opposed to inhibitory control as that may be producing a bottleneck effect on a patient's ability to adequately perform executive behaviours.

This study is one of the first to model executive functioning within a network model using neuropsychological test data and provides support for the potential utility of network approaches in neuropsychological research. Given their potential for modeling dynamic interactions, network models appear to be a plausible alternative to examining executive functions. While conceptual and exploratory in nature, this is one of the first steps of many towards more theoretically parsimonious and clinically useful models of executive functioning.

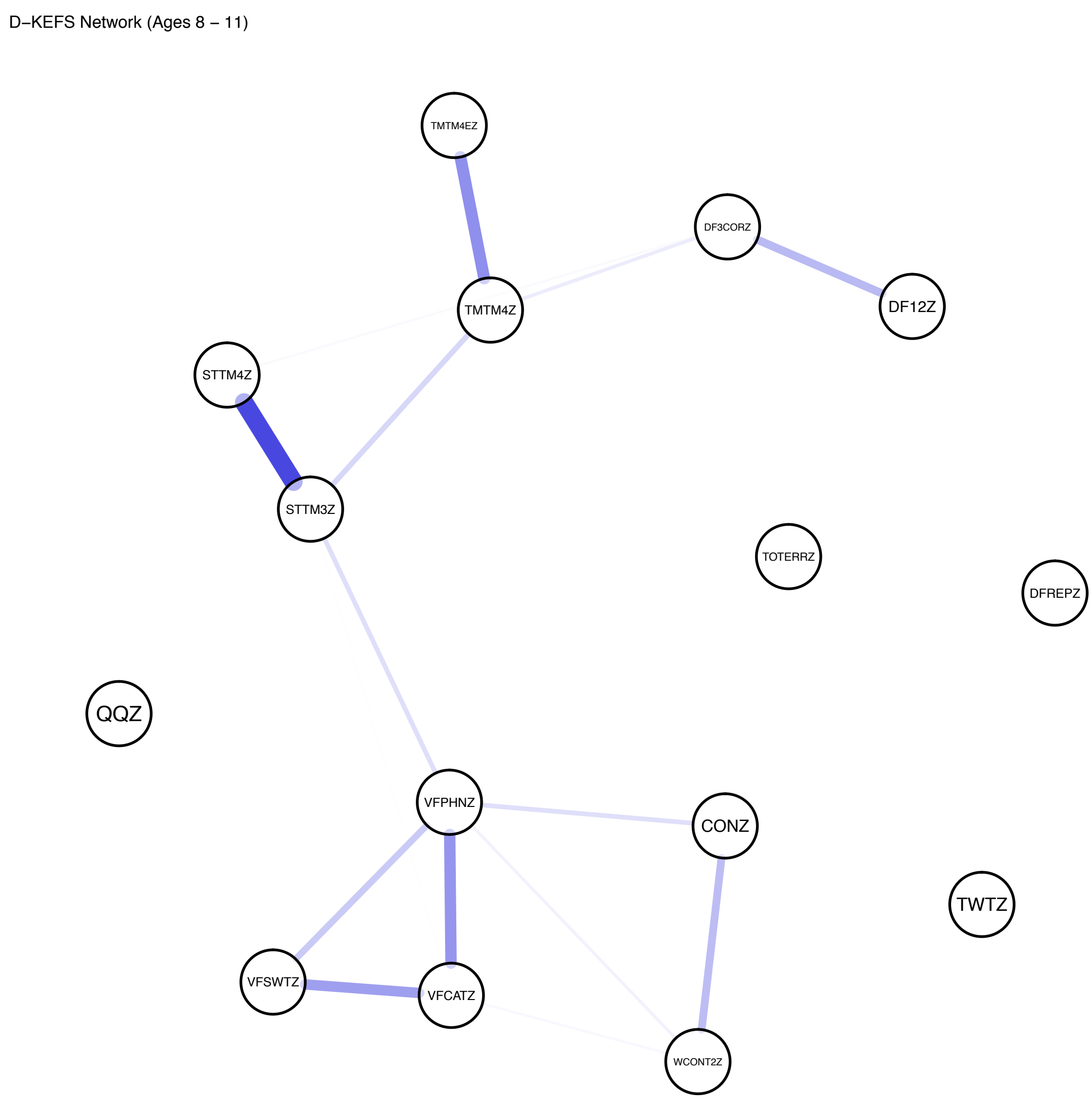
Table 1. Network Density

Network	n	Nodes	Non-Zero Edges	Total Edges	Mean Weight	Density
D-KEFS						
8-11	300	15	24	105	0.024	2.515
12-19	575	16	53	120	0.033	3.919
20-59	525	16	75	120	0.046	5.569
60-89	350	16	73	120	0.048	5.777
BASC-3						
PRS-P	937	20	116	190	0.039	7.498
PRS-C	1216	25	178	300	0.028	8.544
PRS-A	1198	29	196	406	0.029	11.926
TRS-P	483	18	84	153	0.036	5.492
TRS-C	847	31	201	465	0.025	11.417
TRS-A	616	31	188	465	0.026	11.901

Table 2. Correlation Stability Analysis

Network	Expected Influence (EI)	EI Min.	EI Max.
D-KEFS			
8-11	0.360	0.283	0.440
12-19	0.438	0.362	0.517
20-59	0.594	0.516	0.672
60-89	0.440	0.360	0.517
BASC-3			
PRS-P	0.750	0.672	1.000
PRS-C	0.750	0.672	1.000
PRS-A	0.750	0.672	1.000
TRS-P	0.749	0.673	1.000
TRS-C	0.750	0.672	1.000
TRS-A	0.750	0.672	1.000

Figure 1. D-KEFS (Ages 8-11) Network



Note: This network could not be fixed to match the other networks as it does not contain all the nodes the other D-KEFS age groups have

Figure 2. D-KEFS (Ages 12-19) Network

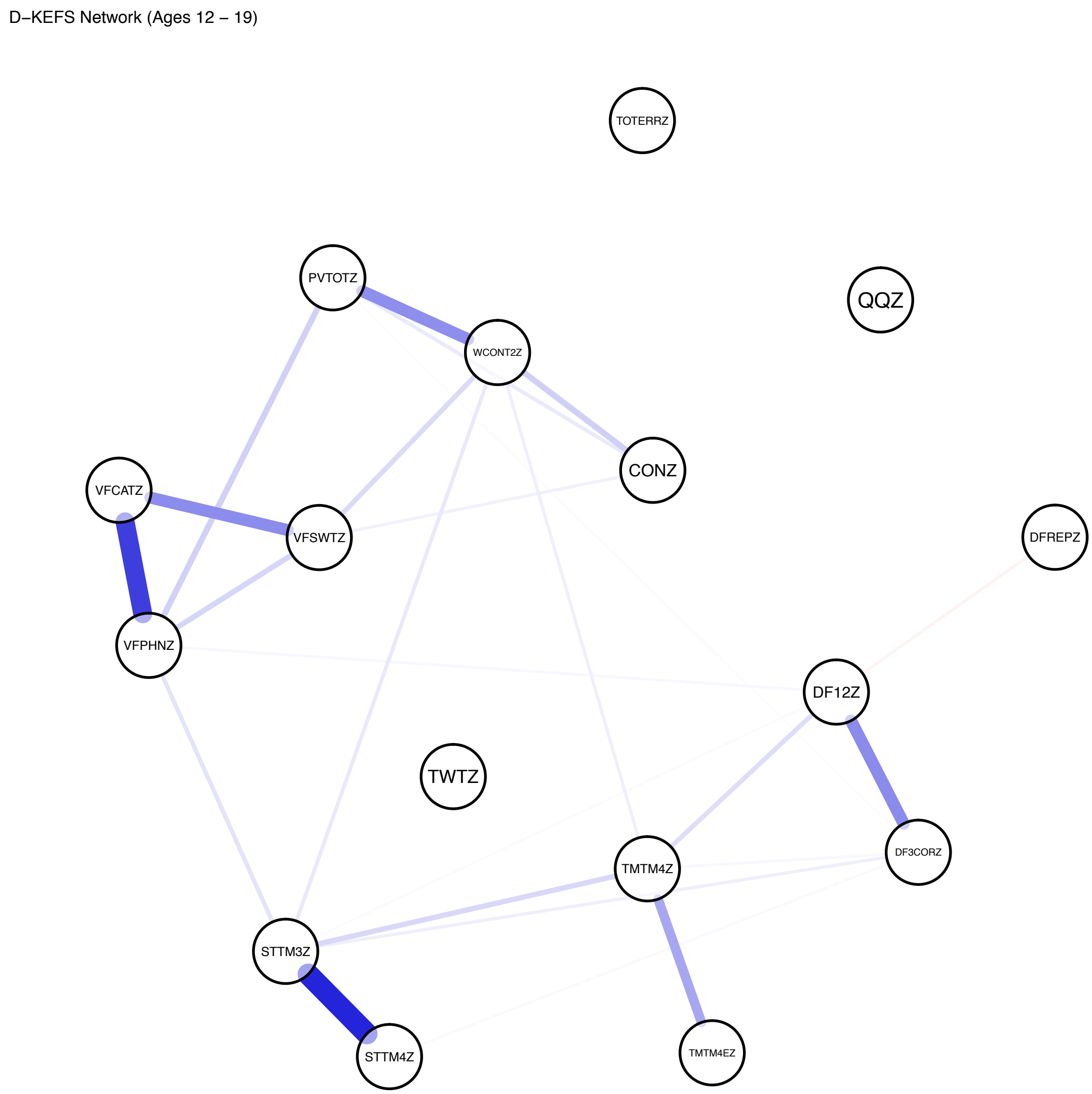


Figure 3. D-KEFS (Ages 20-59) Network

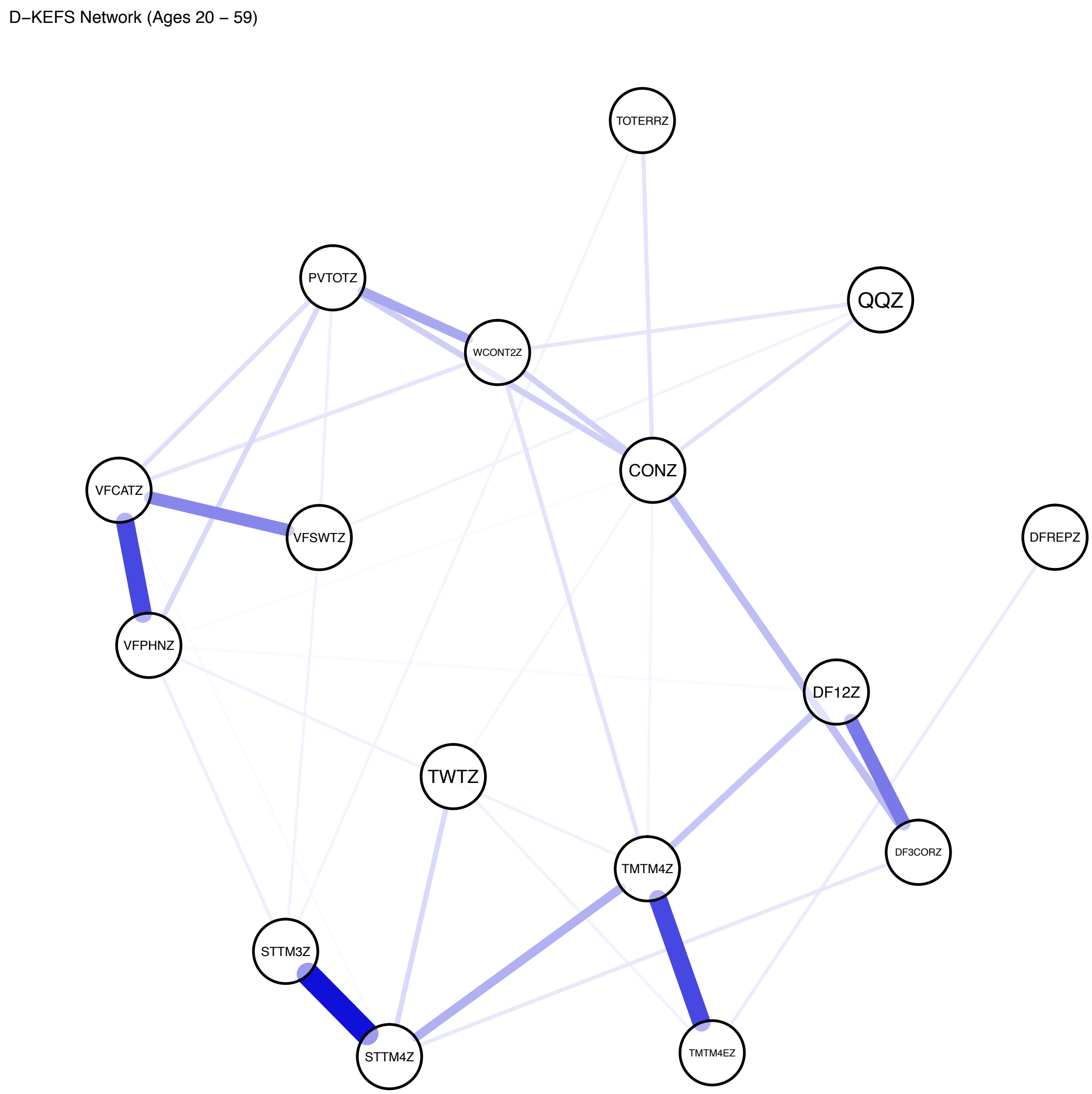


Figure 4. D-KEFS (Ages 60-89) Network

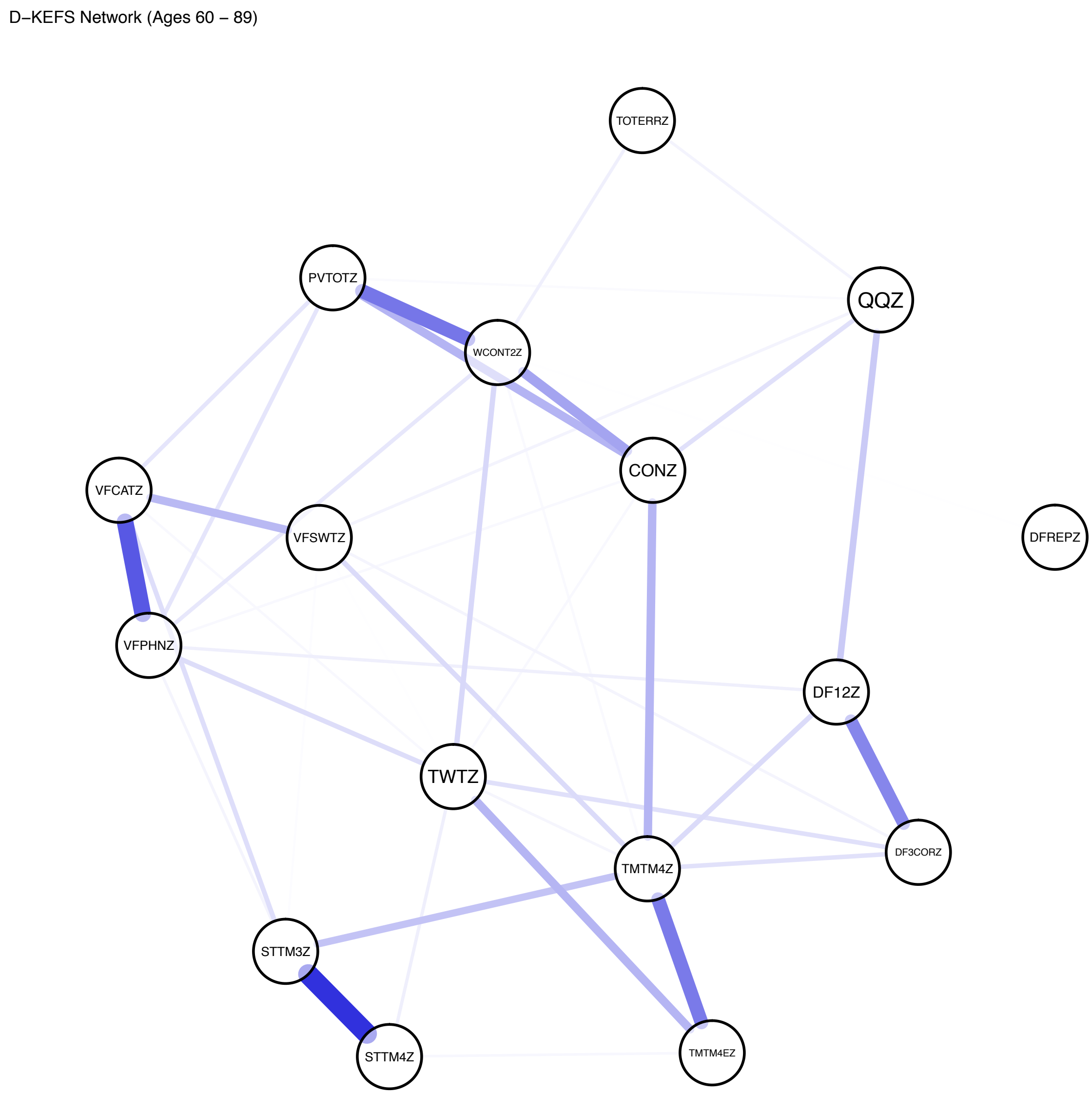


Figure 5. D-KEFS (Ages 8-11) Network Centrality Indices

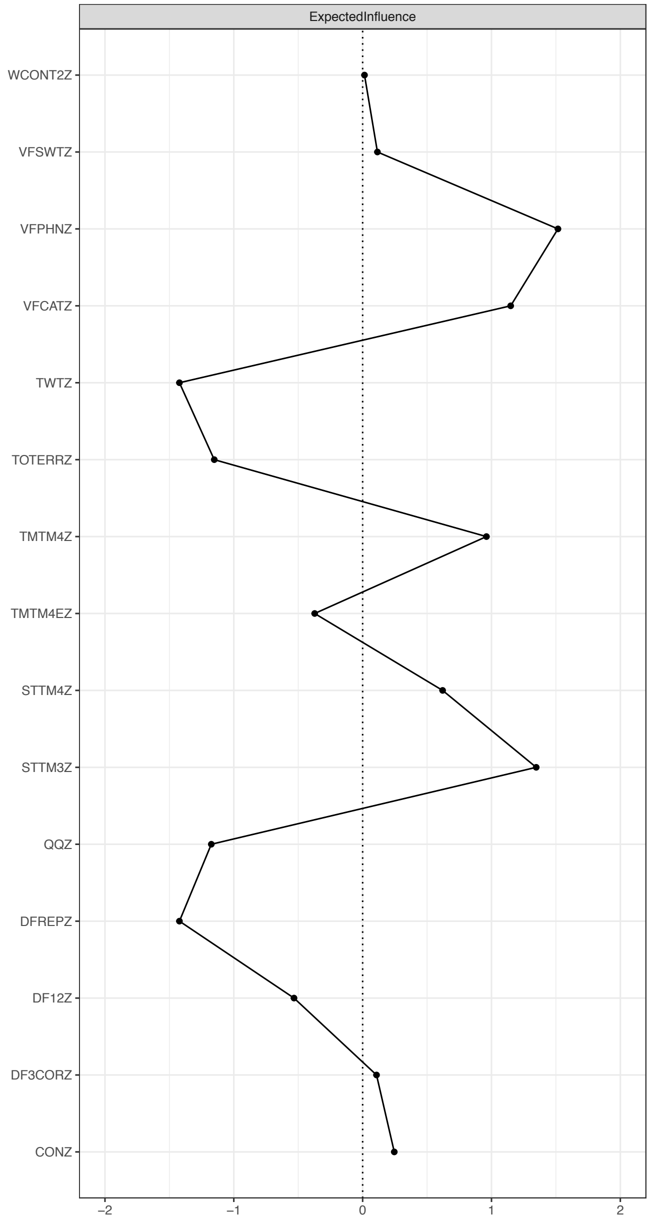


Figure 6. D-KEFS (Ages 12-19) Network Centrality Indices

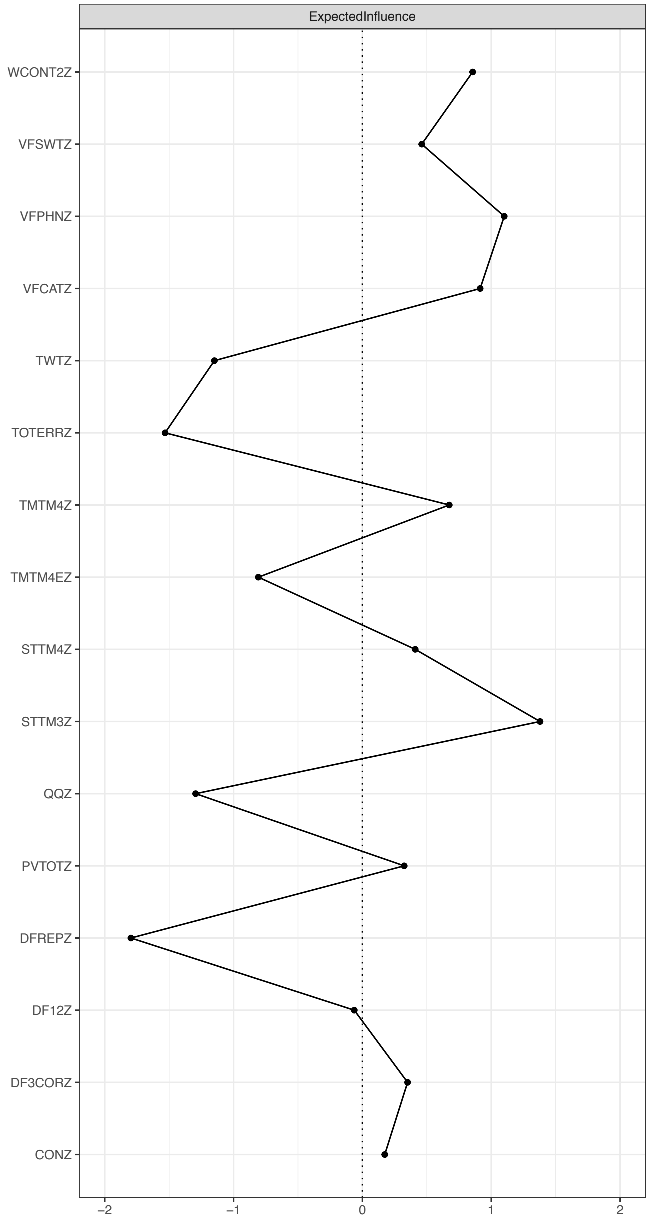


Figure 7. D-KEFS (Ages 20-59) Network Centrality Indices

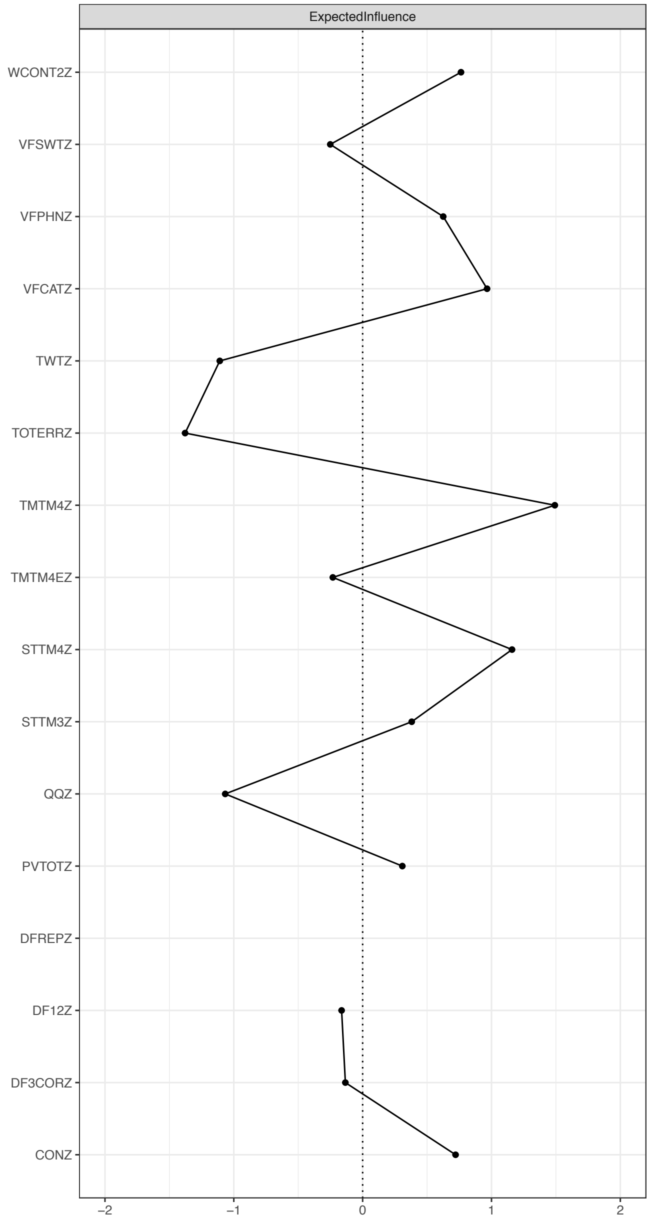


Figure 8. D-KEFS (Ages 60-89) Network Centrality Indices

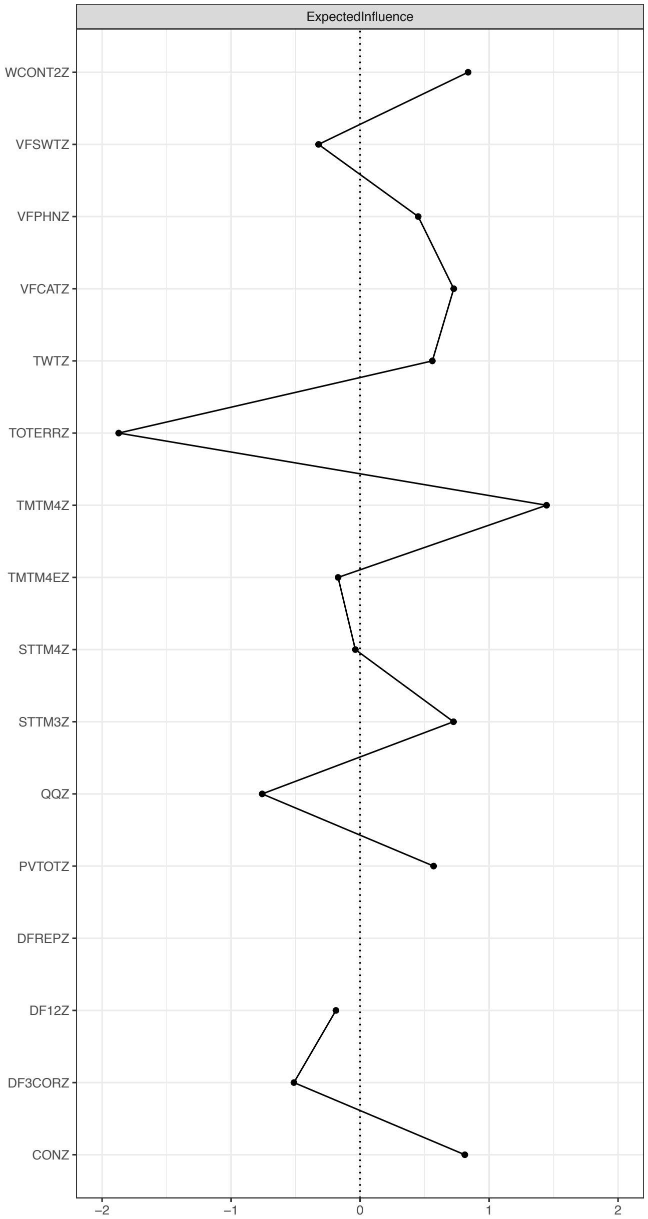


Figure 9. BASC-3 PRS-P Network

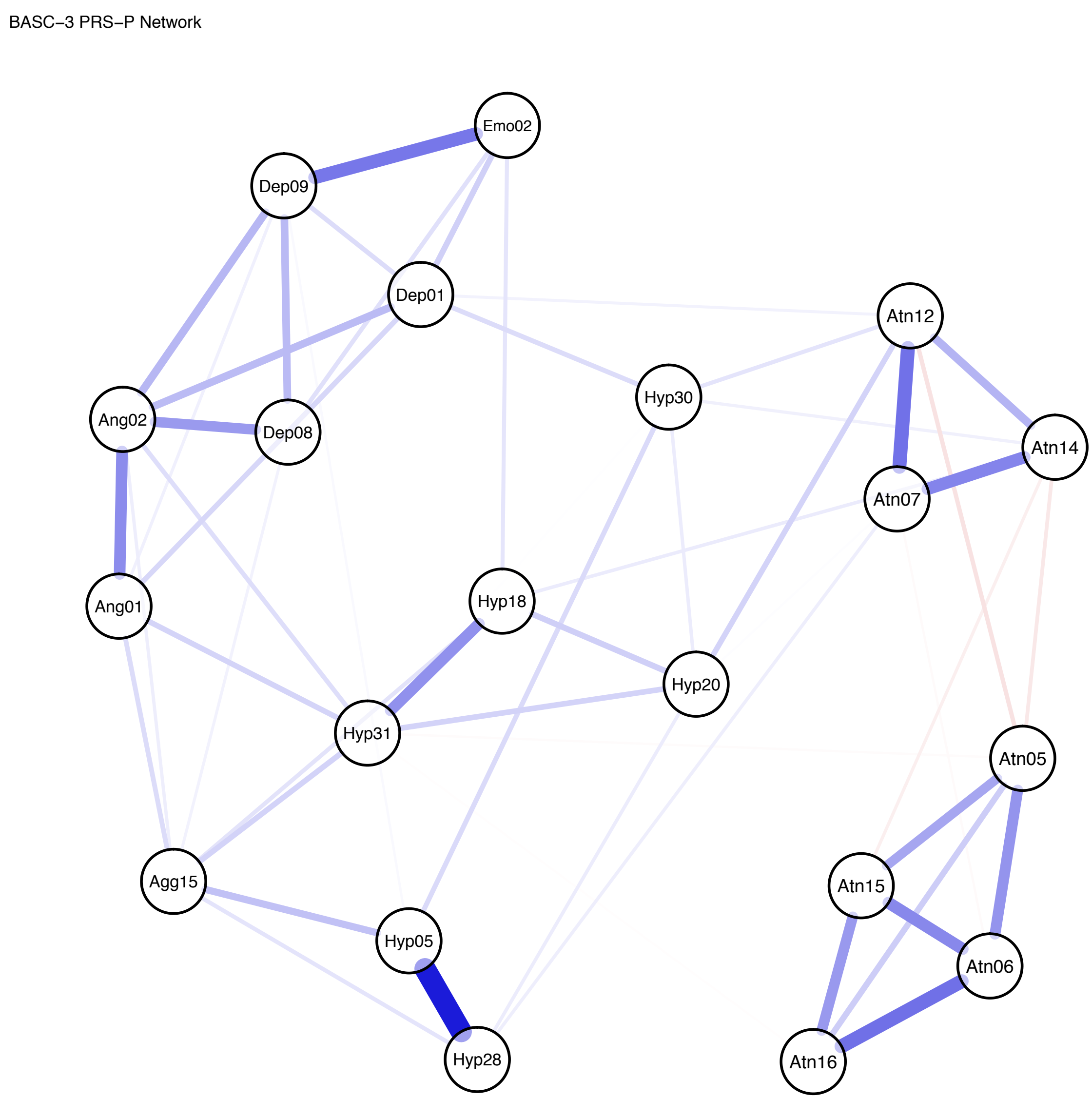


Figure 10. BASC-3 PRS-C Network

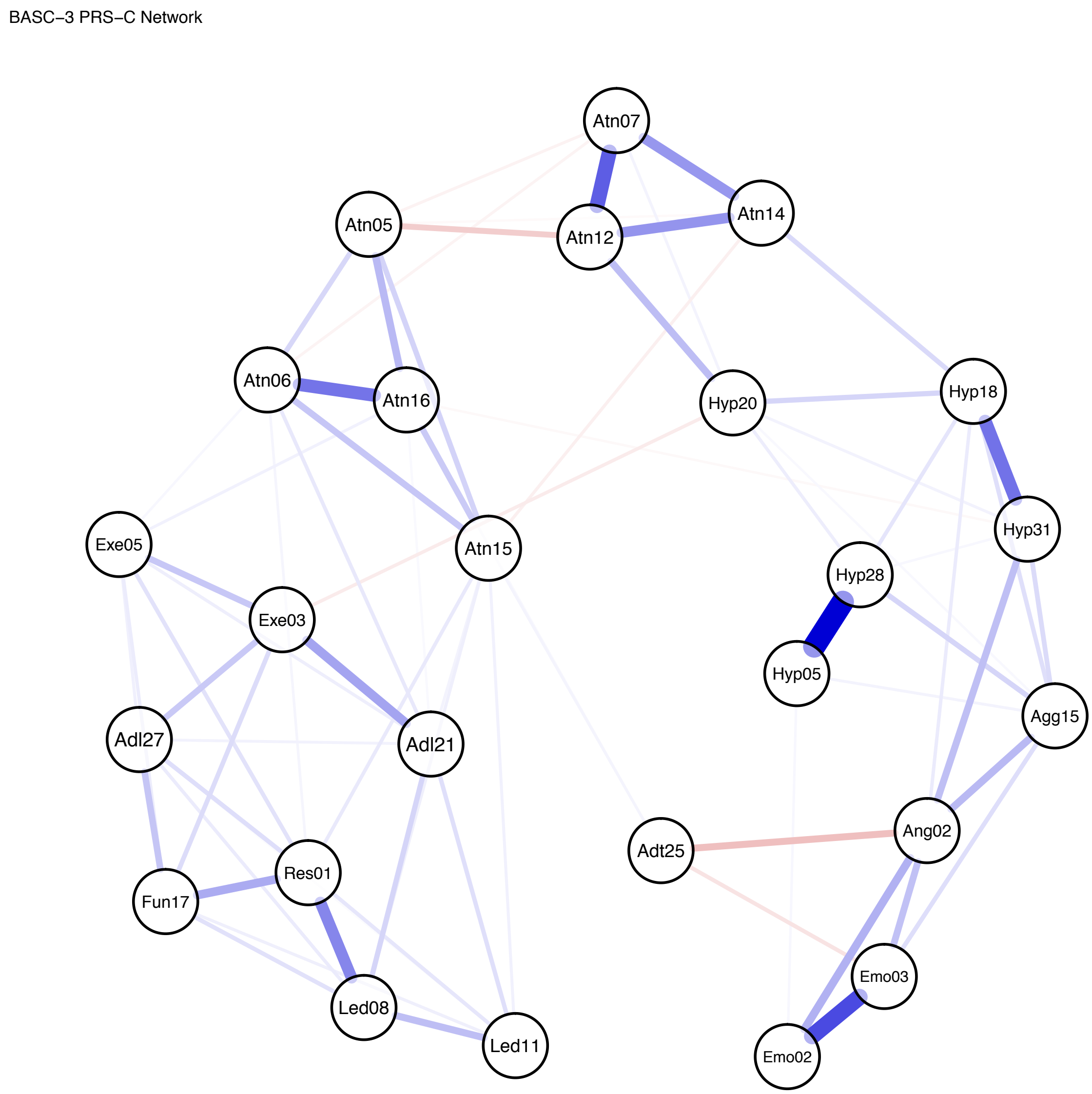


Figure 11. BASC-3 PRS-A Network

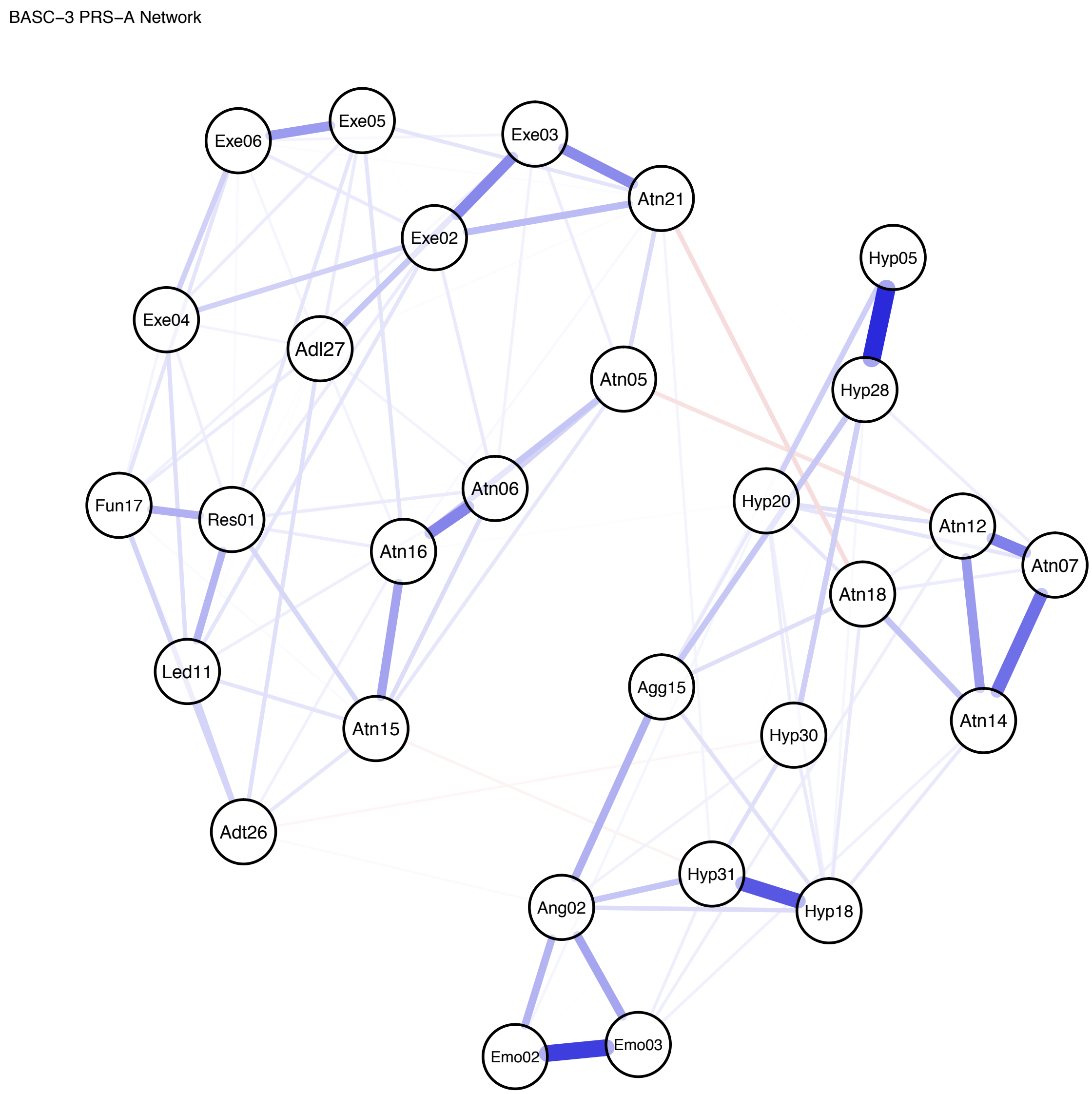


Figure 12. BASC-3 TRS-P Network

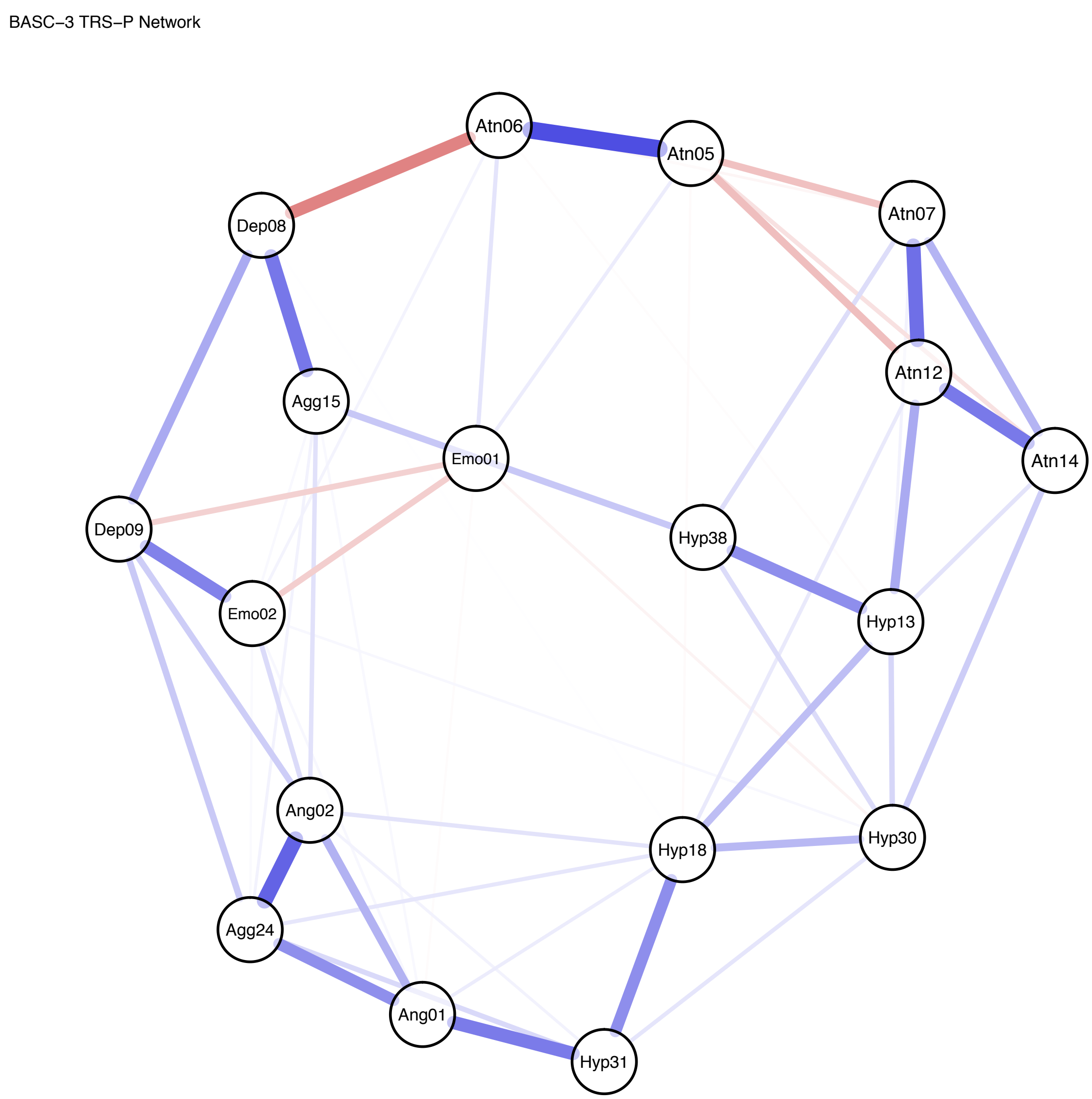


Figure 13. BASC-3 TRS-C Network

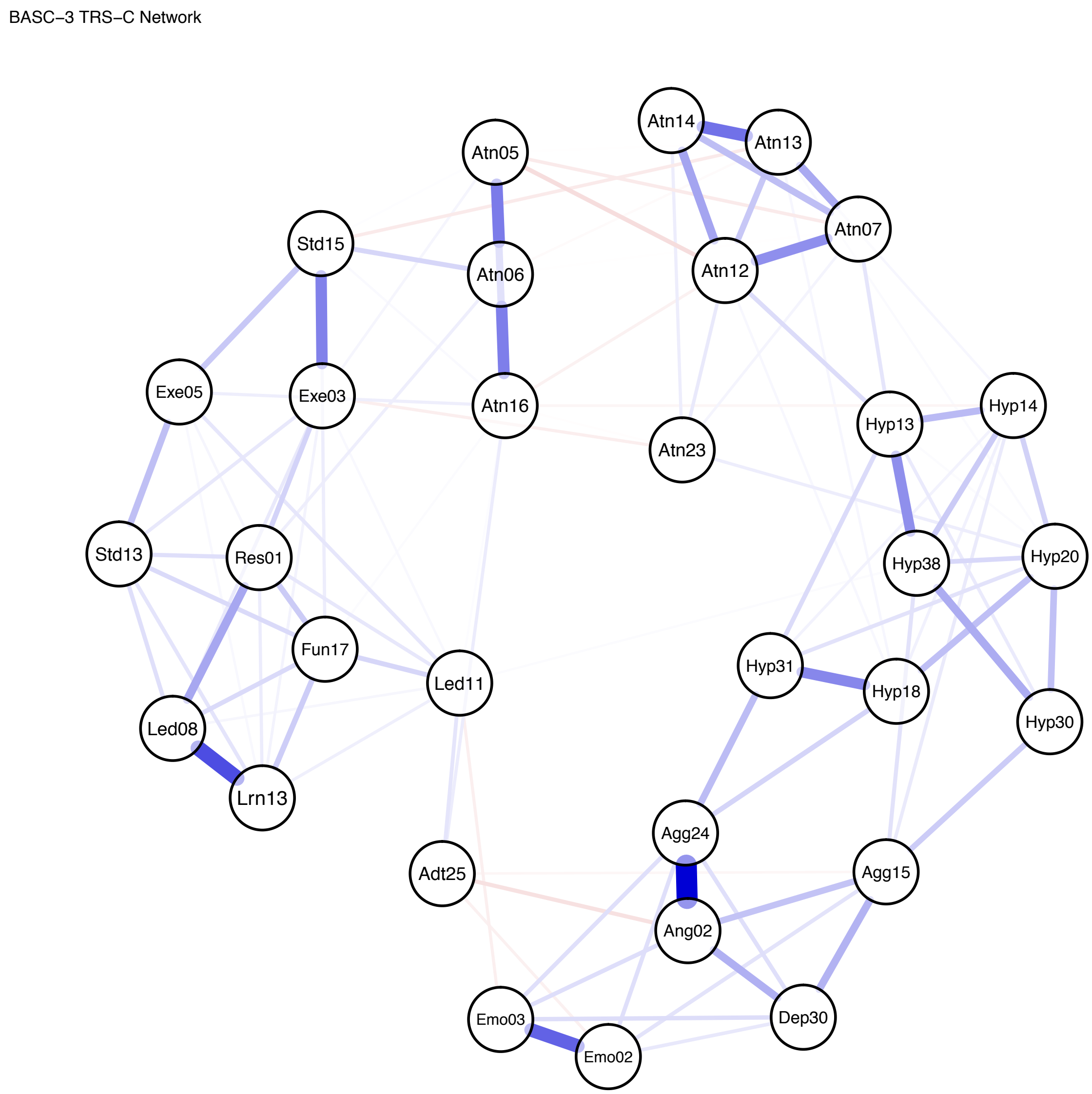


Figure 14. BASC-3 TRS-A Network

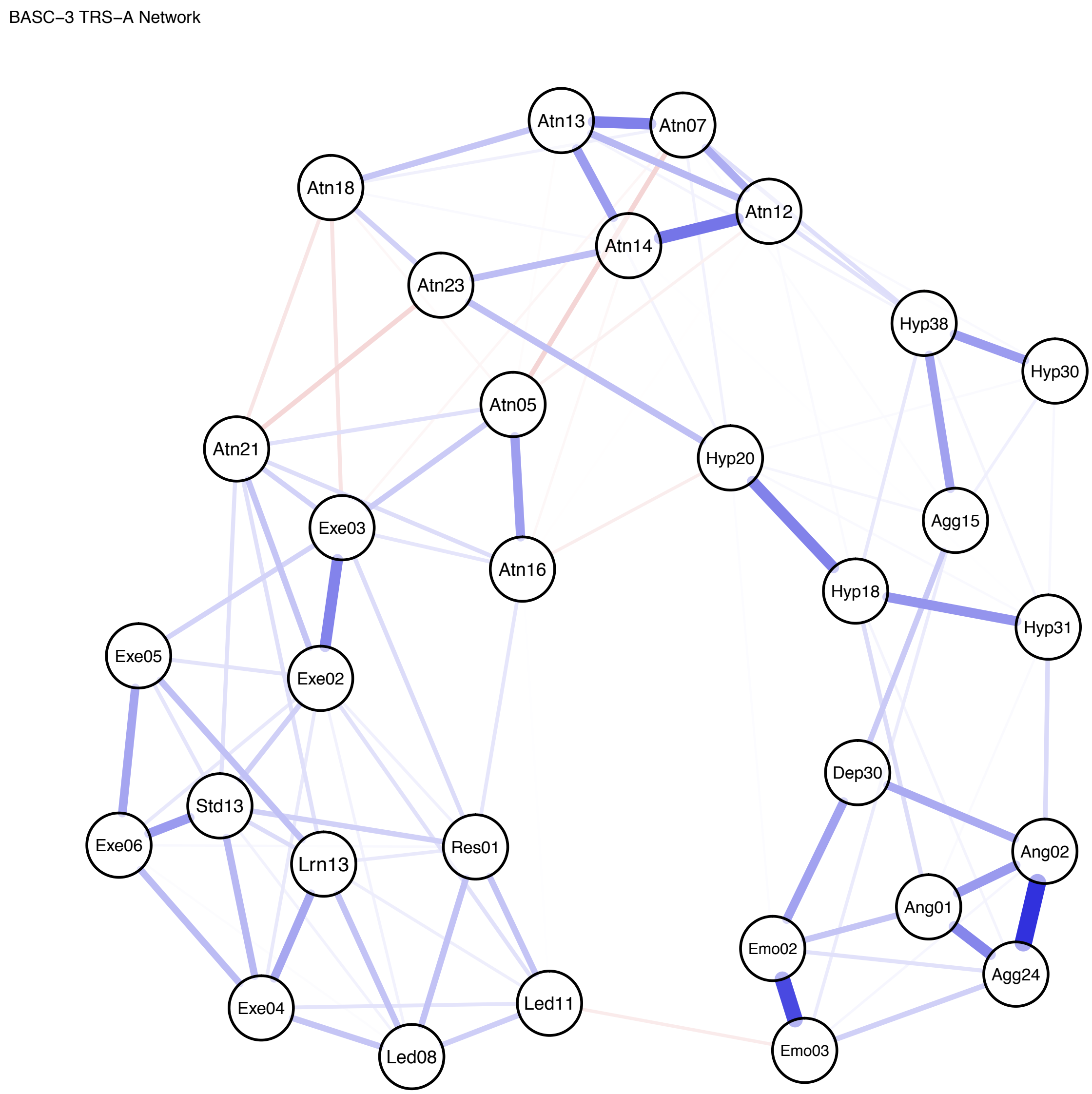


Figure 15. BASC-3 PRS-P Centrality Indices

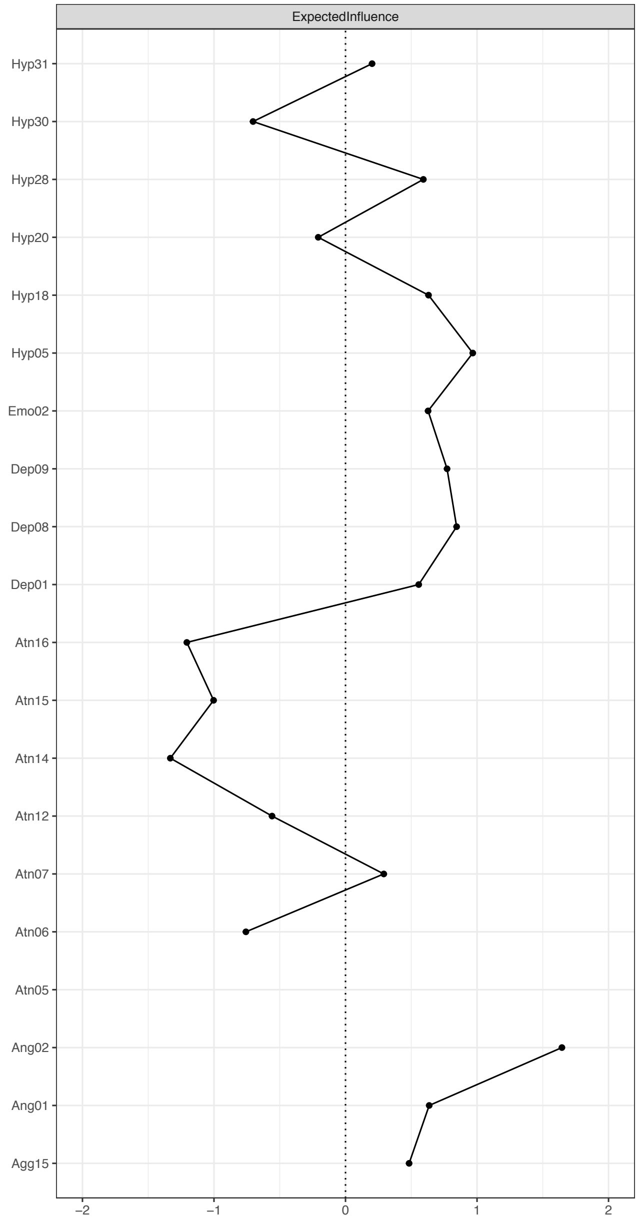


Figure 16. BASC-3 PRS-C Centrality Indices

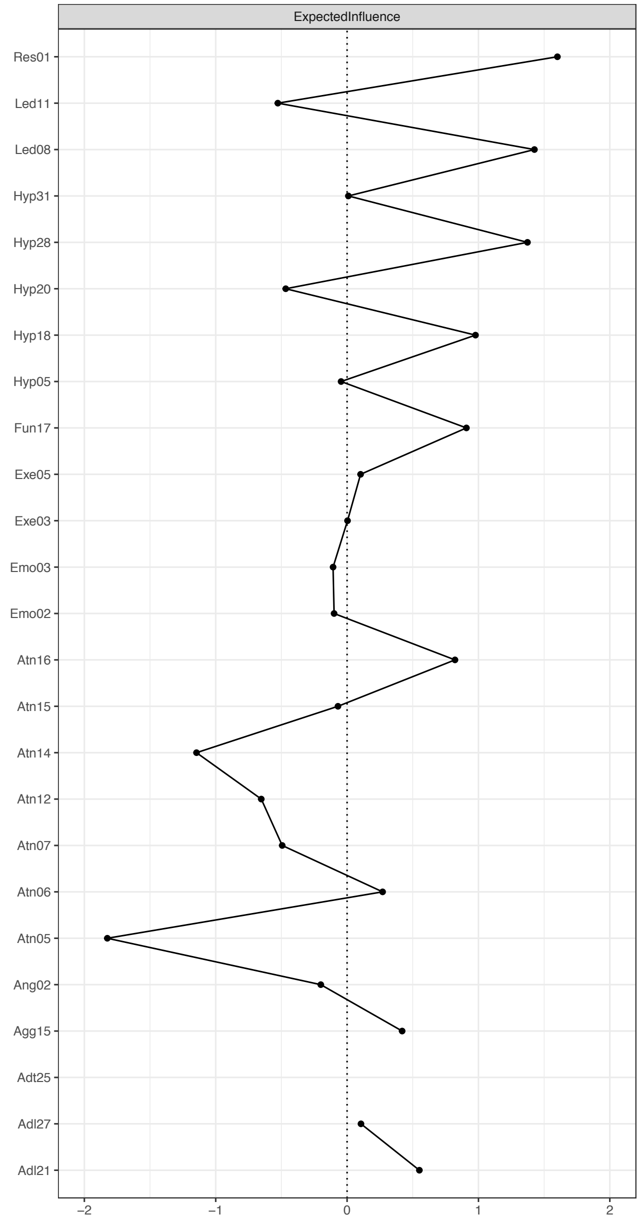


Figure 17. BASC-3 PRS-A Centrality Indices

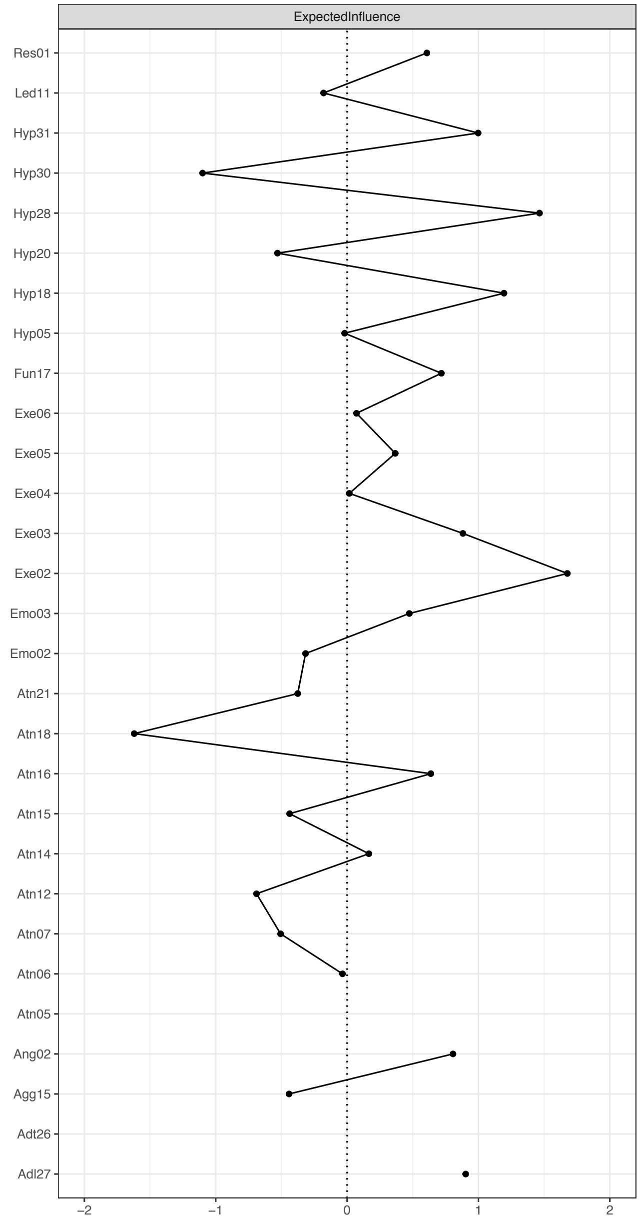


Figure 18. BASC-3 TRS-P Centrality Indices

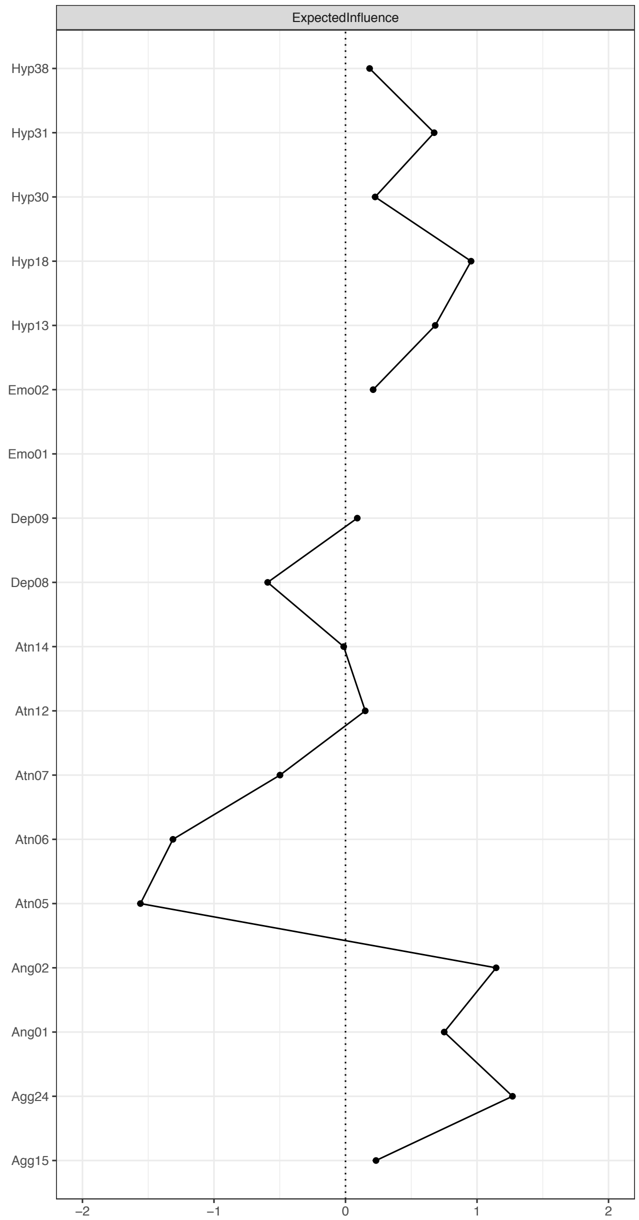


Figure 19. BASC-3 TRS-C Centrality Indices

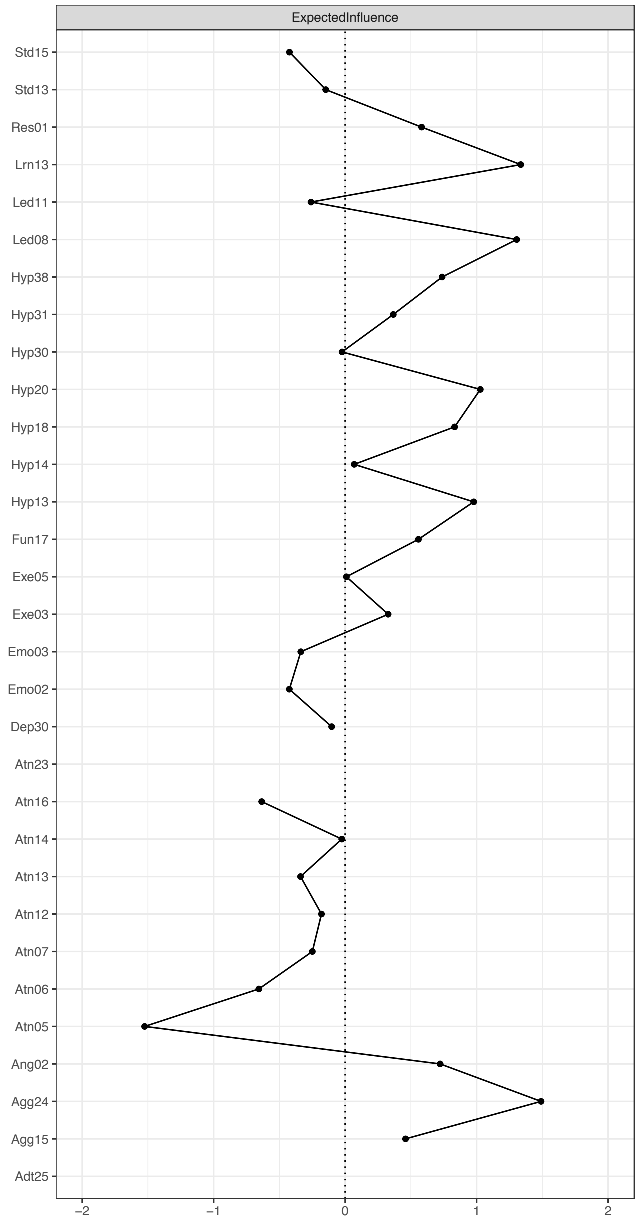
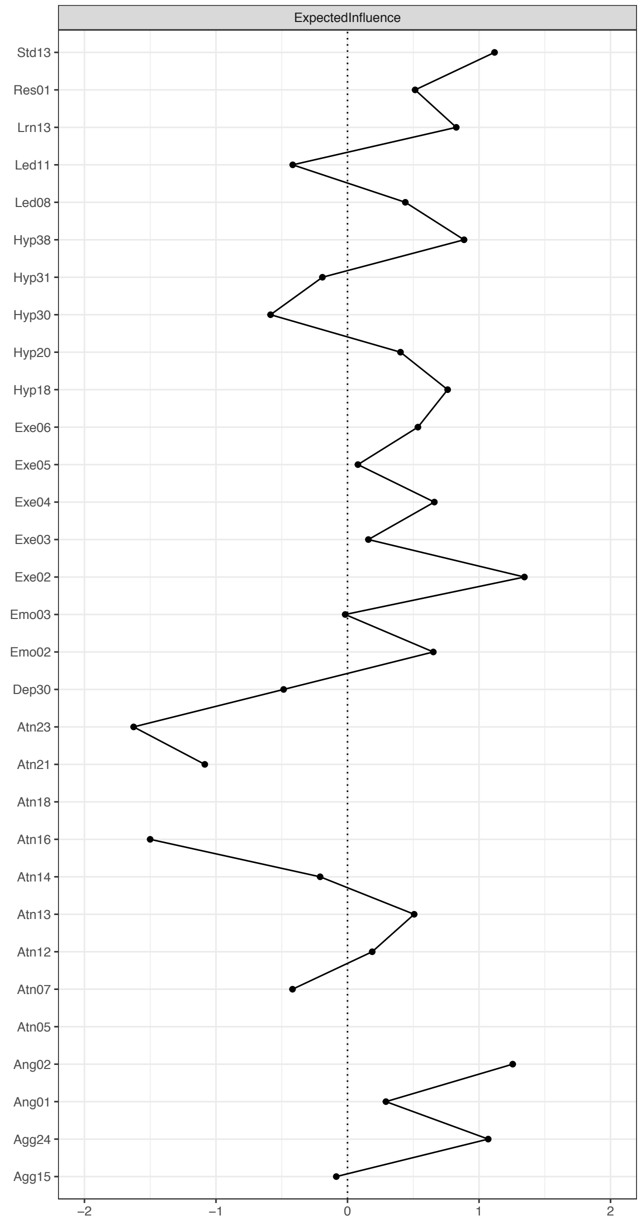


Figure 20. BASC-3 TRS-A Centrality Indices



Chapter 4: General Discussion

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General Discussion

Executive functioning remains one of the most complex and complicated cognitive phenomenon in neuropsychology. From inhibiting pre-potent responses to problem solving, executive functions are required to navigate a plethora of novel, unexpected, or cognitively demanding situations but consistently identifying their constituent parts in the context of typical brain functioning has proven to be difficult.

The main goal of this research program was to provide two examples out of many possible different ways executive functioning can be explored aside from the most popular Miyake-related methodologies, namely to examine the assumption of latent dimensionality in executive function and provide an alternative conception of how to approach executive functioning research. Using two large-sized, demographically matched samples to the US population, the first study, *Latent structure in executive functioning: A taxometric approach,* showed consistent support for latent dimensionality across the lifespan in typically developing populations using both performance-based and behavioural rating scales. Using the same samples as the first study, the second study, *Executive functioning networks: An alternative to latent constructs,* examined the potential utility of network approaches for studying executive functioning and how their use can be expanded into clinical settings for both assessment and intervention. This study demonstrated executive functioning, not only can be modelled as a network but in doing so, provides new possibilities in which assessment and interventions may be framed.

In the following sections, the findings of the two manuscripts will be couched in the broader context of executive functioning research history and theory and discuss how the current research follows in the traditions of the field while also highlighting new possibilities.

What more do we know about executive functioning?

Measuring and explaining invisible psychological phenomenon has historically been a process fraught with unverified assumptions, educated guesswork, and incremental gains, with the field of executive functioning hardly an exception to this. Indeed, early Western philosophers initially proposed that the mind or soul resided in various locations or organs around the body, including the brain but it was not until the 1800s, where scientific exploration regarding the primacy of the central nervous system in the production of psychological experience and cognitive ability began (Finger, 2001).

In the absence of modern imaging techniques, early neuropsychological studies relied heavily on clinical case studies, where the isolation of specific functions to specific neurological structures was the primary goal (Benton & Sivan, 2007; Finger, 2001). Eventually, it was discovered that the pursuit of isolated executive functions was untenable as there was a growing body of evidence indicating that not all patients with a specific lesion saw the same deficits and many patients with a variety of different lesions, showed the similar deficits and upon this realization, the field moved towards an understanding of dynamic cognitive processes and interconnected neurological structures that formed whole-brain functional networks (Rabinovici et al., 2015). The advent of functional imaging techniques and detailed structural scans only served to further this understanding as researchers could view in real-time the structures involved in executive functioning. Yet, despite the immense utility of imaging techniques, they require the use of behavioural outputs or known sensory inputs to be interpretable (Raichle, 2009), necessitating the use of the same measures found in non-imaging studies.

Contemporary executive functioning research has followed a parallel development, with the statistical pursuit of individual executive functions extracted from latent variable models being the standard practice in most neuropsychological studies of the construct. However, as discussed at many prior points, this methodology does not reliability replicate at levels much better than the flip of a coin (Karr et al., 2018). Indeed, the limitations of this method are similar to those encountered in the previous orthodoxy of lesion-based studies, namely, the isolation of executive functions constituent parts is insufficient in explaining the dynamism of the whole. Latent variable methods have attempted to provide more all-encompassing models of executive function with the inclusion of latent bifactors; however, bifactor models will invariably “fit” better than non-bifactor models by virtue of increased model complexity (Bornovalova et al., 2020; Decker, 2021) but may not necessarily be the best representation of the underlying executive processes.

Executive function and latent dimensionality

Despite being a single study, the results of the taxometric analysis are clear and given the use of a large, demographically-matched sample, provides strong support that the assessed executive functions are dimensional constructs. Latent dimensionality was observed irrespective of age, measurement type, or executive construct. Indeed, there is increasing evidence across most realms of psychological research that most psychological constructs can be considered dimensional constructs with relatively few exceptions (Haslam et al., 2012). Theoretically, dimensional psychological constructs are produced when there is a confluence of multifactorial inputs on human behaviour and development as opposed to singularly impactful genes or experiences (Sakaluk, 2019). For example, Attention Deficit Hyperactivity Disorder (ADHD) a neurodevelopmental disorder that is effectively a disorder of executive functioning, has been found to be dimensional (Haslam et al., 2006; Marcus & Barry, 2011)) and this is in line with the proposed multifactorial etiology of the condition (Nigg, 2018; Sciberras et al., 2017). While executive functioning has been observed to have nearly perfect heritability coefficients (Friedman et al., 2008), no single gene or sequence of genes has been identified as determining executive abilities. Similarly, the development of executive functioning, as well as related neurological systems, has been shown to be impacted by socioeconomic status (Hackman et al., 2015; Lawson et al., 2018), familial behaviours (Bridgett et al., 2015), and adverse childhood experiences (DePrince et al., 2009), suggesting that the underlying essence of executive functioning remains at the nexus of genetic code and environmental conditions. Given the sample characteristics for both the D-KEFS and BASC-3, it is perhaps unsurprising that latent dimensionality was observed.

Interestingly, the few exceptions to dimensionality within psychology in general that have been observed in the extant literature are notable in that they all involve conditions that have known profiles of executive dysfunction or atypical brain development (e.g., Autism Spectrum Disorder or addictions), which suggests there remain areas in neuropsychology where categorical executive functions may be found. Some populations that might be prime candidates for further taxometric examination due to known or suspected profiles of executive dysfunction or abnormalities in frontal-parietal brain systems include but are not limited to: acquired brain injuries (Garcia-Barrera et al., 2019; Hunt et al., 2013; Muscara et al., 2008), fetal alcohol spectrum disorder (Rasmussen, 2005), intellectual disability (Danielsson et al., 2010; Spaniol & Danielsson, 2022), and schizophrenia (Eisenberg & Berman, 2010; Velligan & Bow-Thomas, 1999). As it stands, it would be relatively safe to assume latent dimensionality when studying executive functions in typically developing, neurologically intact populations. The further one deviates from these types of normative samples, the assumption of latent dimensionality becomes more tenuous and should be assessed empirically. Should evidence of categorical latent structure emerge in atypically developing populations, researchers might benefit from considering alternative statistical models that can account for latent taxons (e.g., latent class models; Sakaluk, 2019)

What if executive function is a network?

Scientific progress often happens in fits and spurts, with old concepts and theories being revived with new information. The understanding that neural systems and by extension, executive functioning, operate as dynamic networks and treating them as such in scientific inquiry is just one more example of how past knowledge can be re-introduced to a field in a novel fashion.

Grounding neuropsychological phenomenon in the foundation of organic brain function and prototypical developmental trajectories is not only theoretically consistent but anchors scientific examination to an identifiable source (i.e., dynamic and integrated neurological systems) and follows in the footsteps of early neuropsychologists who understood the importance of having their theories and models reflected in neural substrates. Most measurement models to this point have neglected to address the dynamism of these networks and do not reflect the processes inherent in changes in cognitive processes like executive functioning over time. While the argument could be made that latent-factor models are not necessarily designed for this type of use, it remains the case that the majority tools used in clinical practice are directly derived from a long tradition of factor analysis. These are the same tools used to assess for changes in cognitive status over time and inform clinical decision-making around treatment targets.

Consistent with a network conceptualization, the emergence of executive functioning and the development of executive dysfunction occurs in a step-wise but dynamic and iterative fashion (Zelazo et al., 2004; Zelazo & Müller, 2010). Indeed, this network perspective has already been elucidated at length within the most well-known cognitive construct, intelligence (Van Der Maas et al., 2006). Given the many conceptual similarities between the two constructs as well as the shared underlying neurological systems (Duggan & Garcia-Barrera, 2015), there is already a significant amount of groundwork that has been laid out in terms of examining executive functioning from this perspective. In fact, this explanatory framework may even be a better fit for executive functioning than intelligence given that a singular psychometric *e* factor (i.e., an executive *g* factor) has not been consistently demonstrated in the extant literature, making the network-based explanation of executive functioning even more attractive as an alternate way to examine this phenomenon.

To highlight the potential of network models in the assessment and treatment of executive dysfunction, Figures 1-3 provides a series of hypothetical networks of executive functioning, using a series of common neuropsychological measures used to assess aspects of executive functioning.

Figure 1 depicts an idealized executive functioning network. Operating under the unverified assumption that a well-integrated network is a well-functioning executive network, this is potentially what could be seen in a neurologically intact adult, where contributions from each node supporting the others. Potential uses for this type of network might include assessing how integrated a new patient's executive network is compared to the norm and whether or not this is reflective of a pathological network. These types of networks may also provide additional material to develop new working models of executive functioning in academic research.

Figure 2 depicts an executive functioning network that has been disrupted by injury. In this example, one of the nodes (e.g., inhibition) and its most proximal edges have been impacted by a traumatic brain injury. As a result, changes within the network reflect the new level of functioning and may provide insights into behavioural difficulties observed in that person's day-to-day life, particularly when there appear to be self-reinforcing patterns of between nodes that are contributing to concerns (e.g., the connection between inhibition and other executive functions become weaker and as a result produce impaired performance in other domains requiring multiple inputs like problem solving).

Figure 3 depicts the executive functioning network in Figure 2 but where the damaged nodes and edges are identified and addressed in treatment. This may involve directly addressing the concerns at the affected node or adding more supports to improve functions the surrounding areas. It may be the case these types of network models can be used as a tool for monitoring changes within individuals through intervention periods and provide intuitive visual aids in explaining treatment progress and future directions.

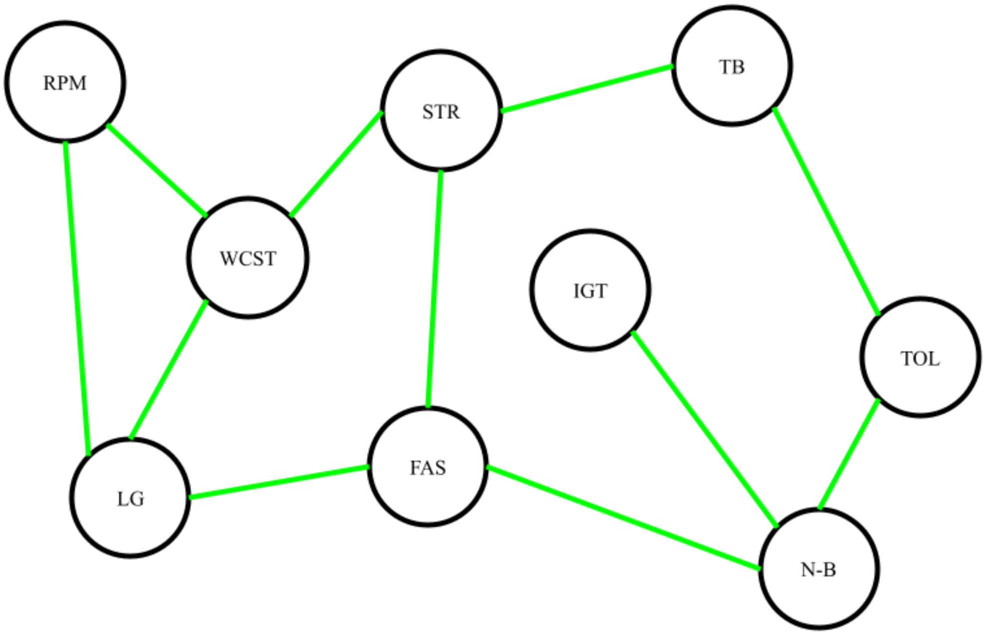
Similarly, Figure 4 details a hypothetical developmental trajectory of executive functioning in a single individual from childhood to adulthood. In this hypothetical scenario, the nodes become increasingly interconnected with one another as the individual develops and grows. This increased network density might represent a more integrated and efficient neurological system that is better equipped to navigate unfamiliar situations. These types of hypotheses can be tested on longitudinal datasets and may provide additional insights into the neurodevelopmental trajectory of executive functions and where they may differ in atypically developing populations.

A greater pluralism in methods used to examine the nature of executive functioning can only serve to improve the productivity of the research and the utility of the findings. An added benefit of greater plurality in research methodology and theory is it provides a robustness to the field that provides researchers with increased and potentially firmer ground on which to root their foundations. Indeed, this conversation need not maintain a latent construct versus causal network dichotomy where one methodology fights for domination over the other. There continues to be work to bring the two approaches closer as latent constructs can also be modelled within network approaches (Epskamp et al., 2017). Even should those efforts prove to be less than satisfying, the use of latent networks in executive functioning research and clinical practice stands to revitalize the field and provide a fertile ground in which new ideas can grow from the old.

Conclusion

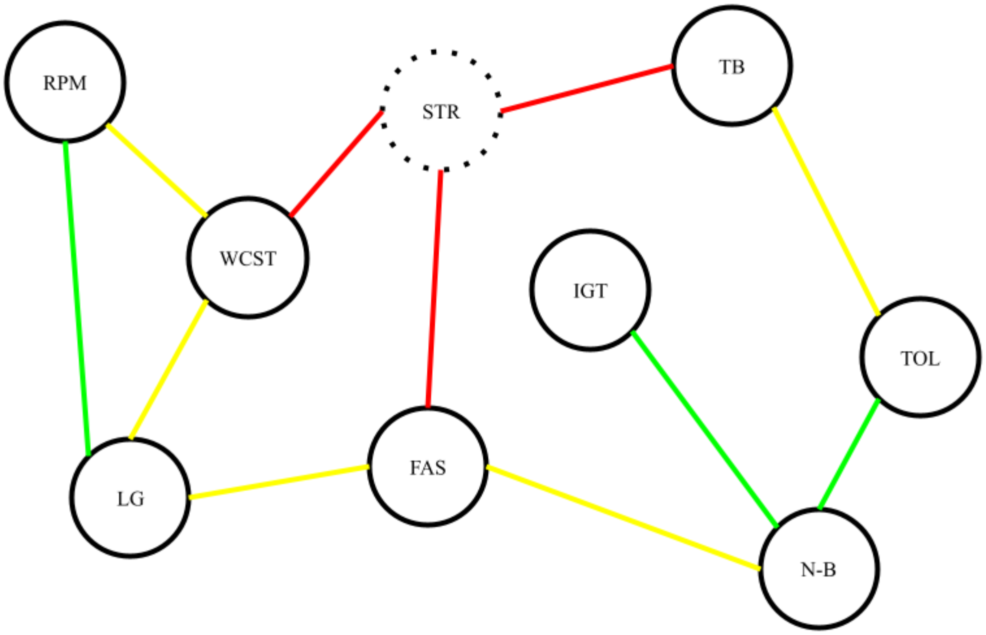
Taken together, the findings from these two studies contribute to the field's understanding of executive function by provide two additional ways to further scientific knowledge and insights. In the first manuscript, using taxometric methodologies, executive functioning clearly demonstrated a dimensional latent structure. On the second manuscript, executive functioning was modeled as a network as the very idea of a latent executive function construct was questioned. Both manuscripts offer evidence and support for the importance validating and extending basic theory in executive functioning research and methods. Considering how reliant the field has become on latent variable approaches, it is fortunate that the basic assumption of latent dimensionality was supported in typically developing populations as support for latent categories would have potentially upended years of epistemological orthodoxy in the field. However, this does not absolve future executive functioning researchers from taking the time to properly assess the true nature of their data and this will become increasingly important when straying from populations displaying normative development and working with populations with known executive function problems due to significant environmental or genetic causes. Additionally, when it comes to assessing or treating executive function problems, network models may offer a theoretically relevant, historically consistent, and clinically useful scaffold in which intervention can be focused and changes be examined.

Figure 1. Hypothetical intact executive function network



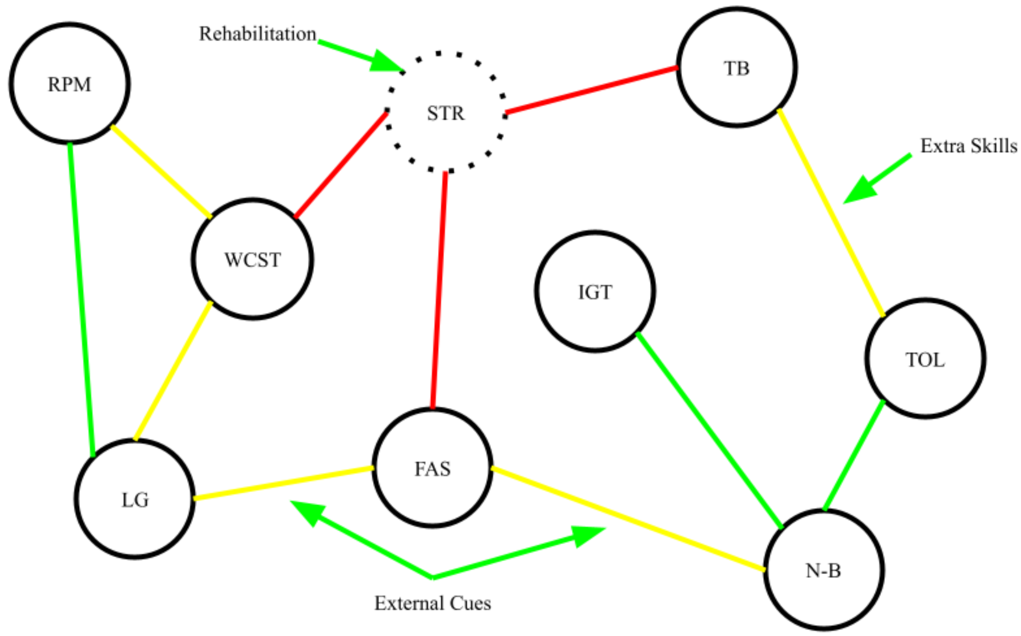
Note: Green edges denote positive associations between nodes; RPM = Raven's Progressive Matrices, LG = Local-Global, WCST = Wisconsin Card Sort, STR = Stroop, FAS = FAS Verbal Fluency, IGT = Iowa Gambling Task, TB = Trails B, N-B = N-Back, TOL = Tower of London

Figure 2. Hypothetical damaged executive function network



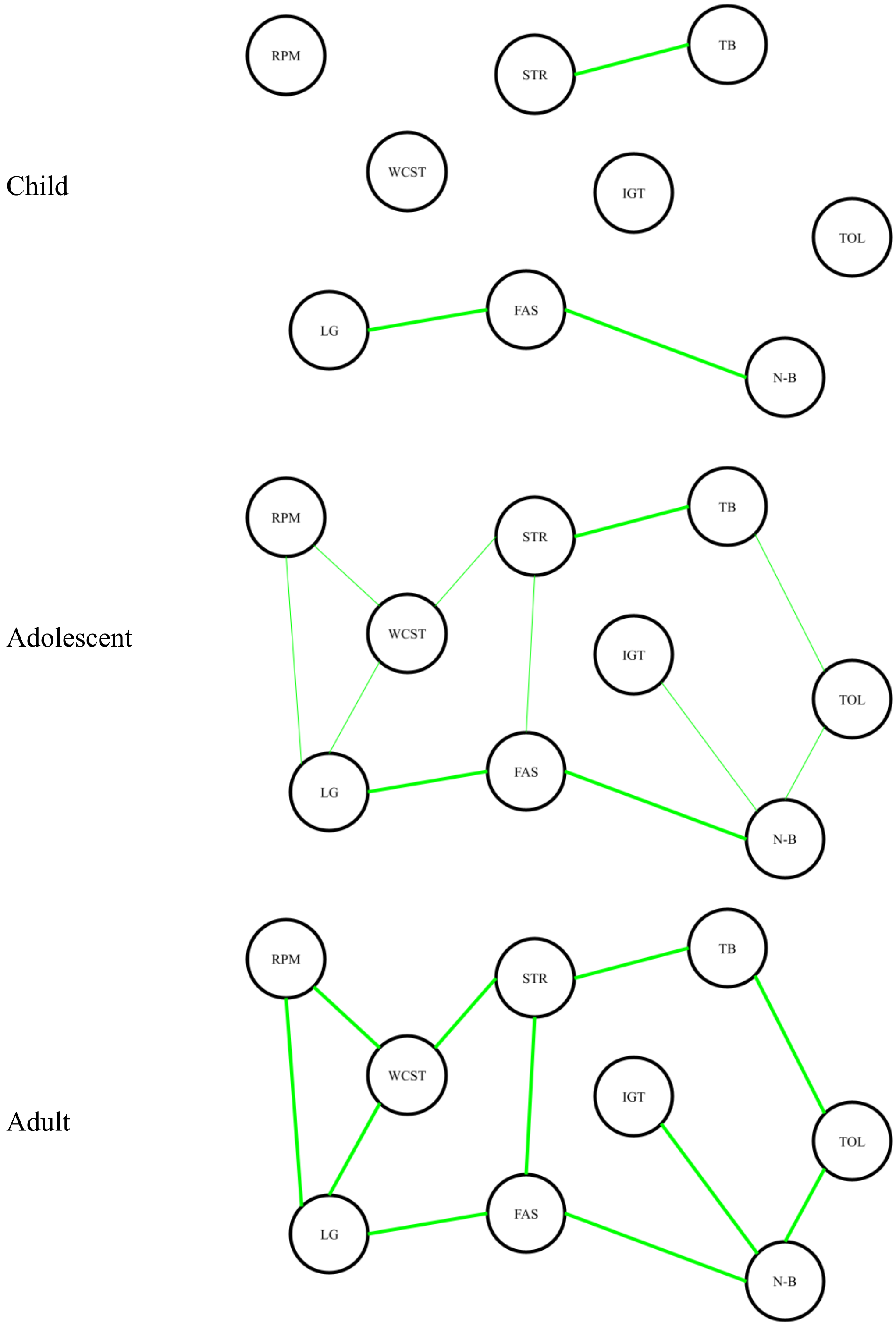
Note: Green edges denote positive associations between nodes, red edges denote negative associations, yellow edges denote diminished associations; RPM = Raven's Progressive Matrices, LG = Local-Global, WCST = Wisconsin Card Sort, STR = Stroop, FAS = FAS Verbal Fluency, IGT = Iowa Gambling Task, TB = Trails B, N-B = N-Back, TOL = Tower of London

Figure 3. Hypothetical treatments of damaged executive function network



Note: Green edges denote positive associations between nodes, red edges denote negative associations, yellow edges denote weaker associations; RPM = Raven's Progressive Matrices, LG = Local-Global, WCST = Wisconsin Card Sort, STR = Stroop, FAS = FAS Verbal Fluency, IGT = Iowa Gambling Task, TB = Trails B, N-B = N-Back, TOL = Tower of London

Figure 4. Hypothetical development of an executive function network



Note: Green edges denote positive associations between nodes; Thicker lines denote stronger associations

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Appendix A: Supplemental Figures

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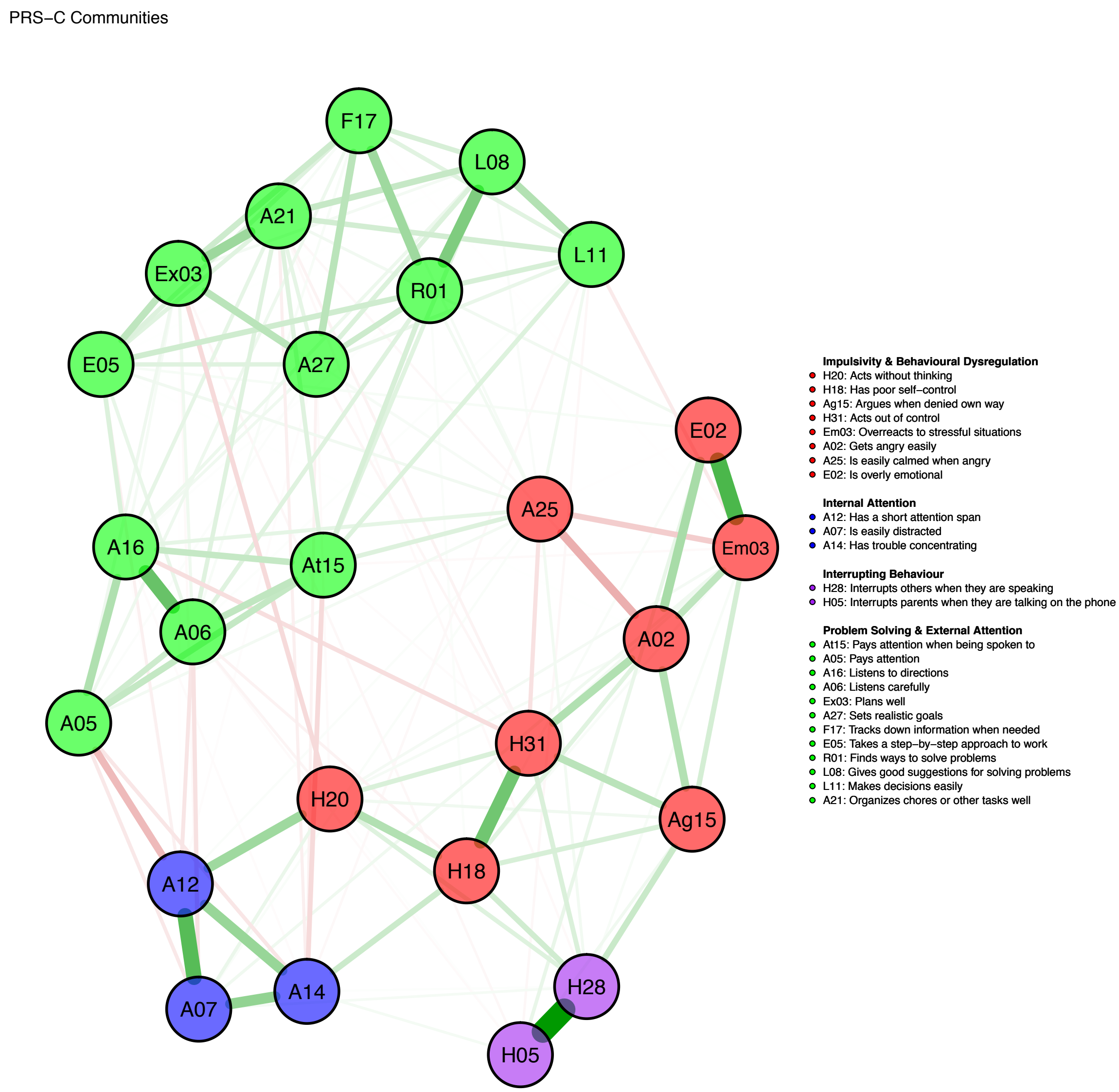
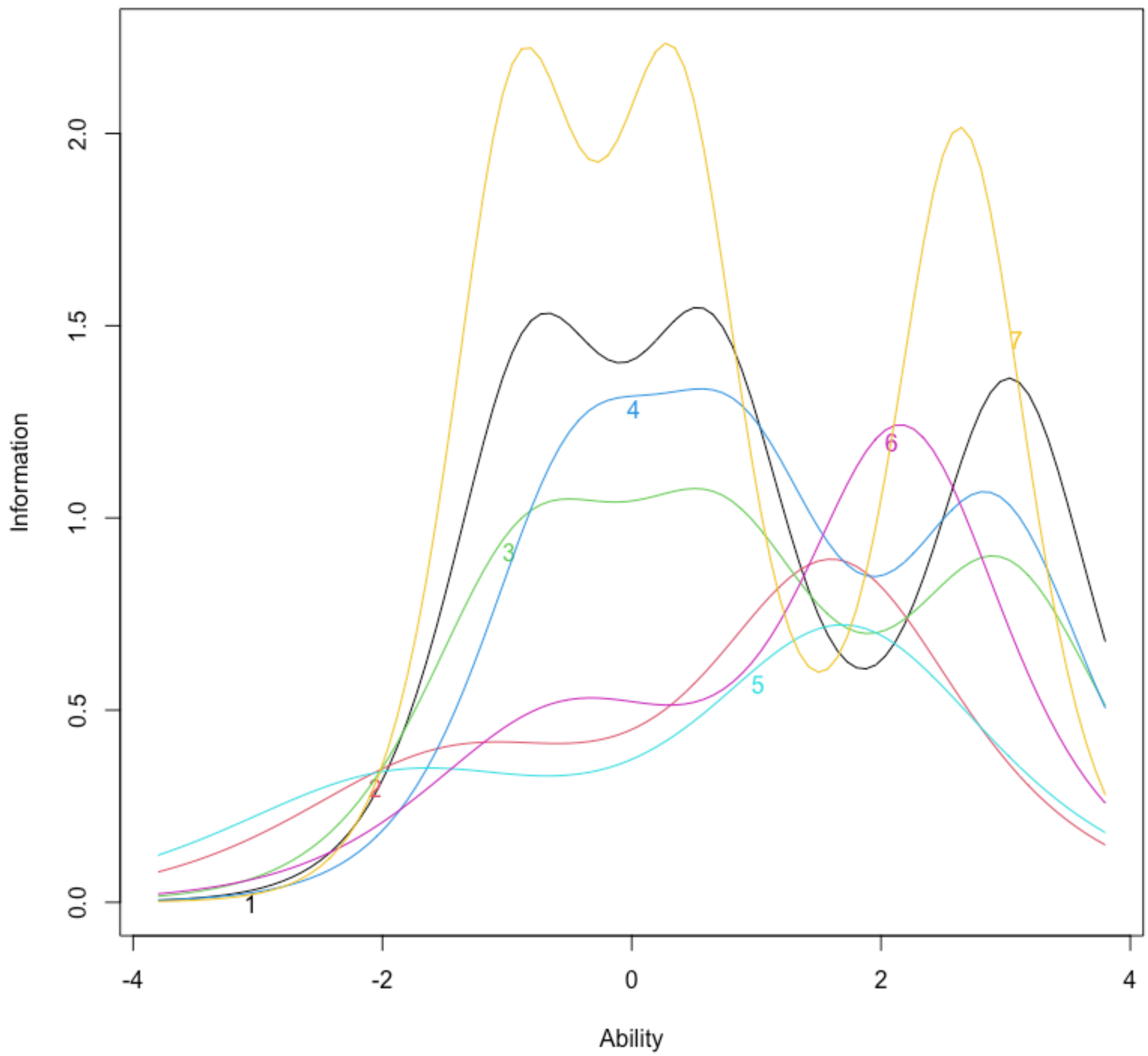
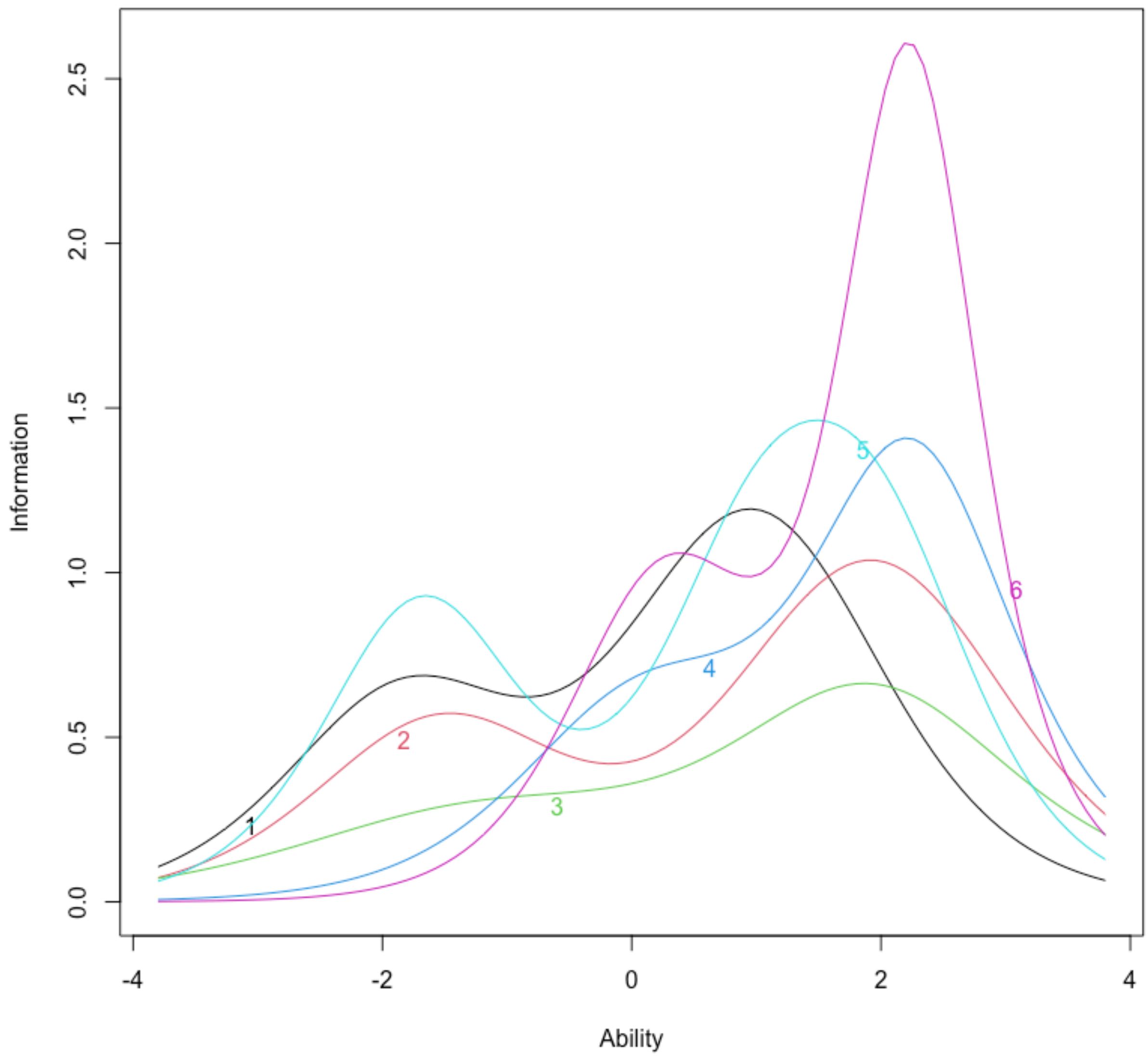
Supplemental Figure 1. Example of Exploratory Graphing Analysis Output (BASC-3 PRS-C)



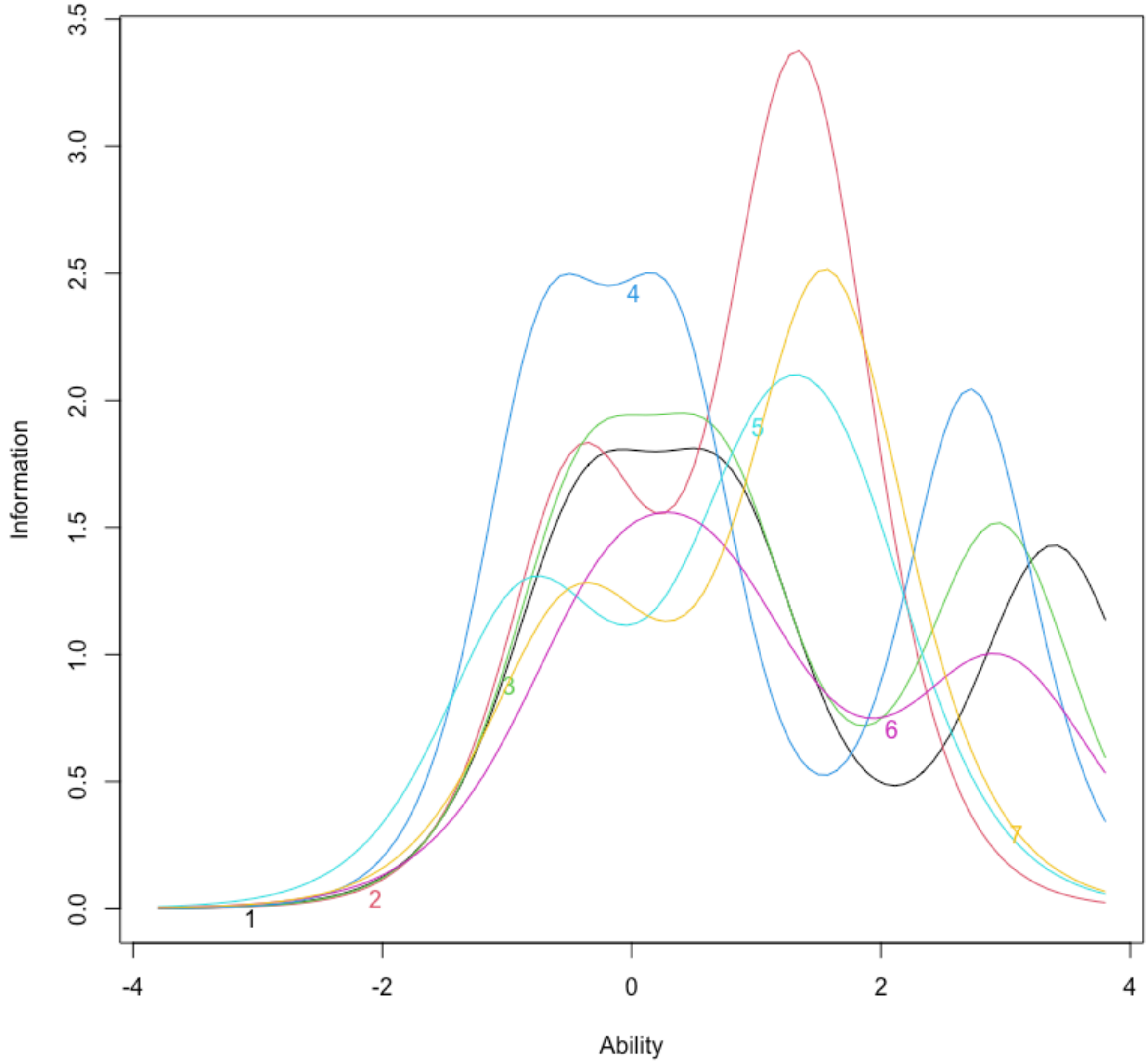
Supplemental Figure 2. BASC-3 PRS-P Attentional Control Item Information Curves (IICs)



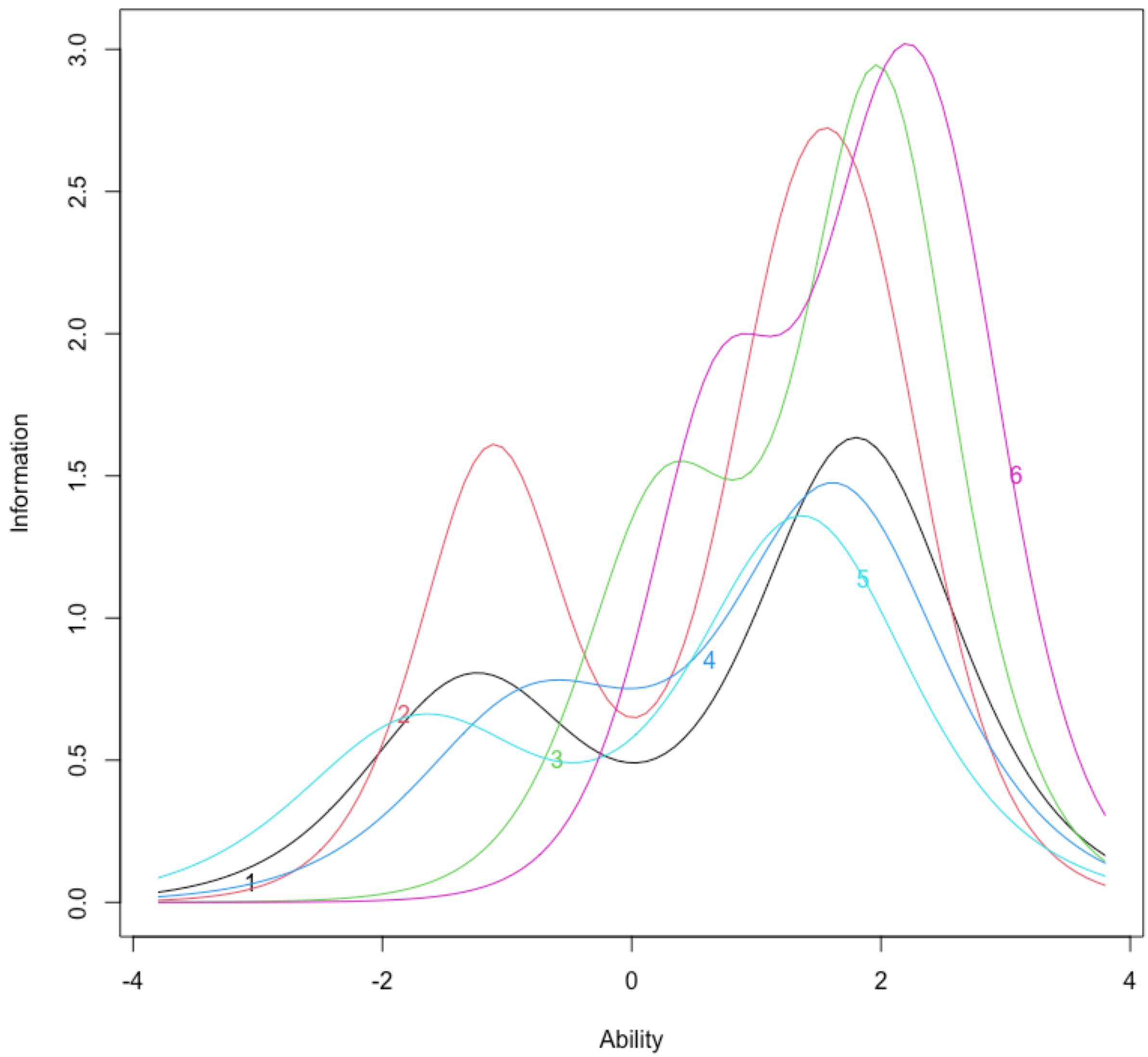
Supplemental Figure 3. BASC-3 PRS-P Behavioural Control Item Information Curves (IICs)



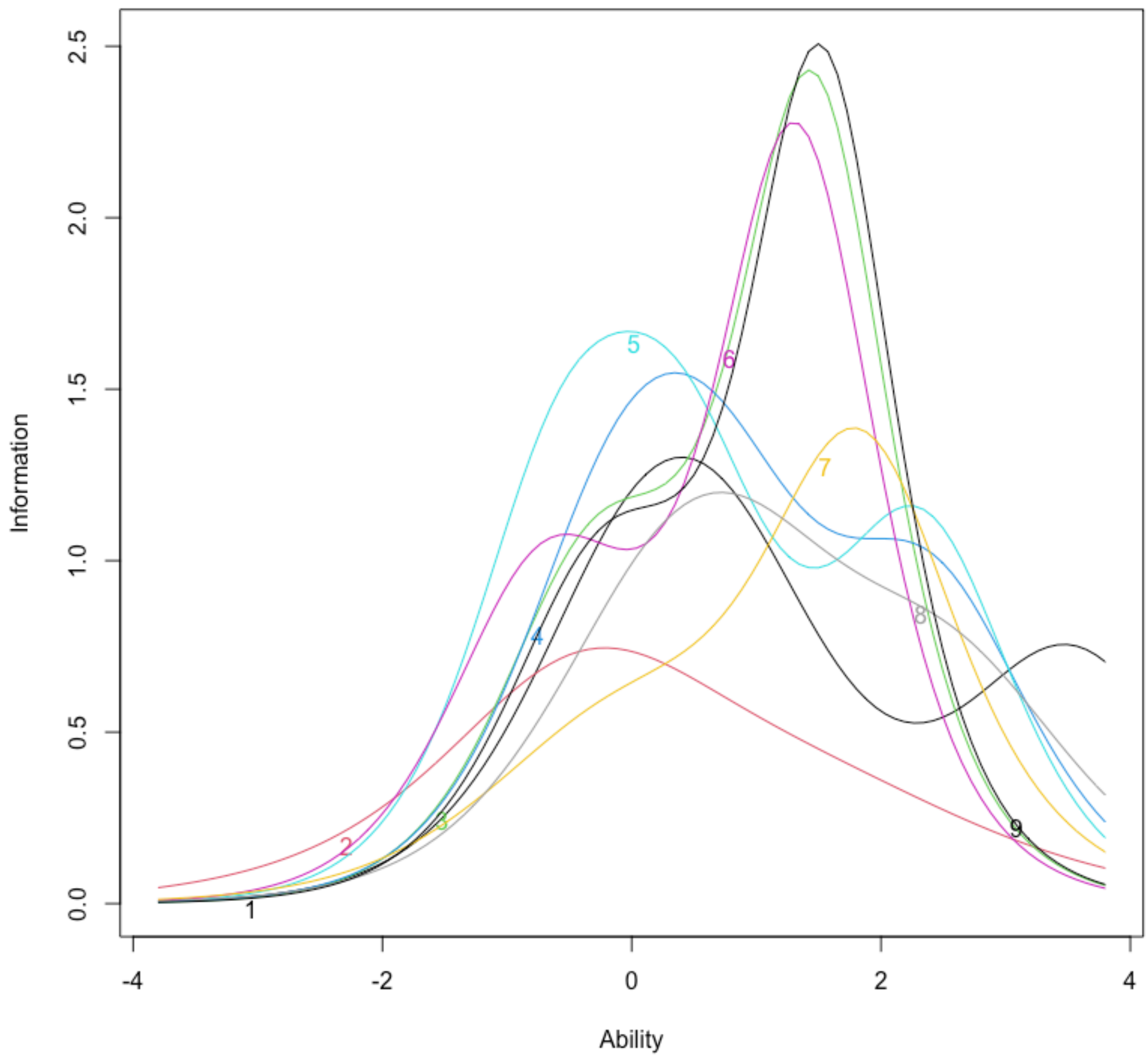
Supplemental Figure 4. BASC-3 PRS-C Attentional Control Item Information Curves (IICs)



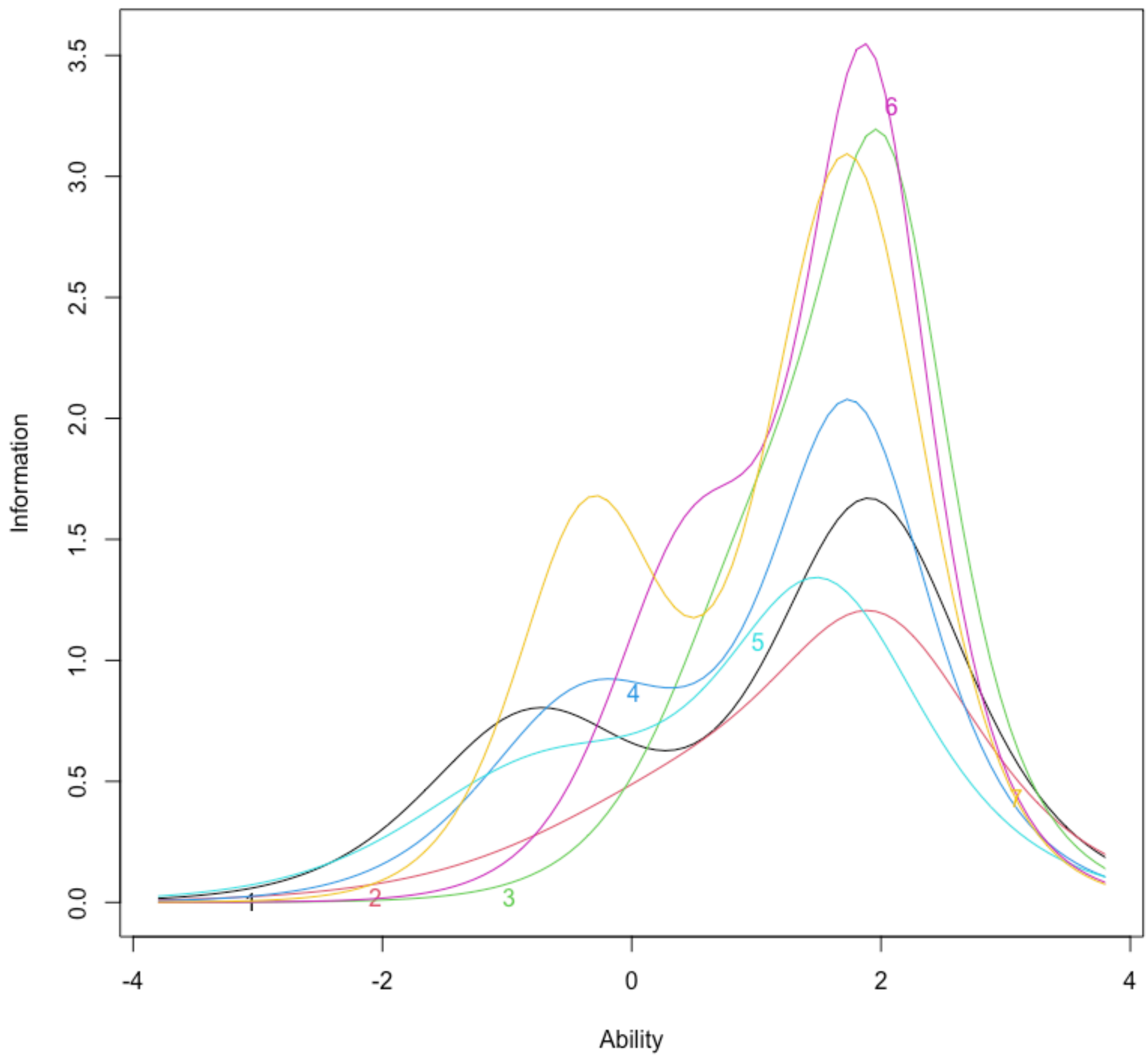
Supplemental Figure 5. BASC-3 PRS-C Behavioural Control Item Information Curves (IICs)



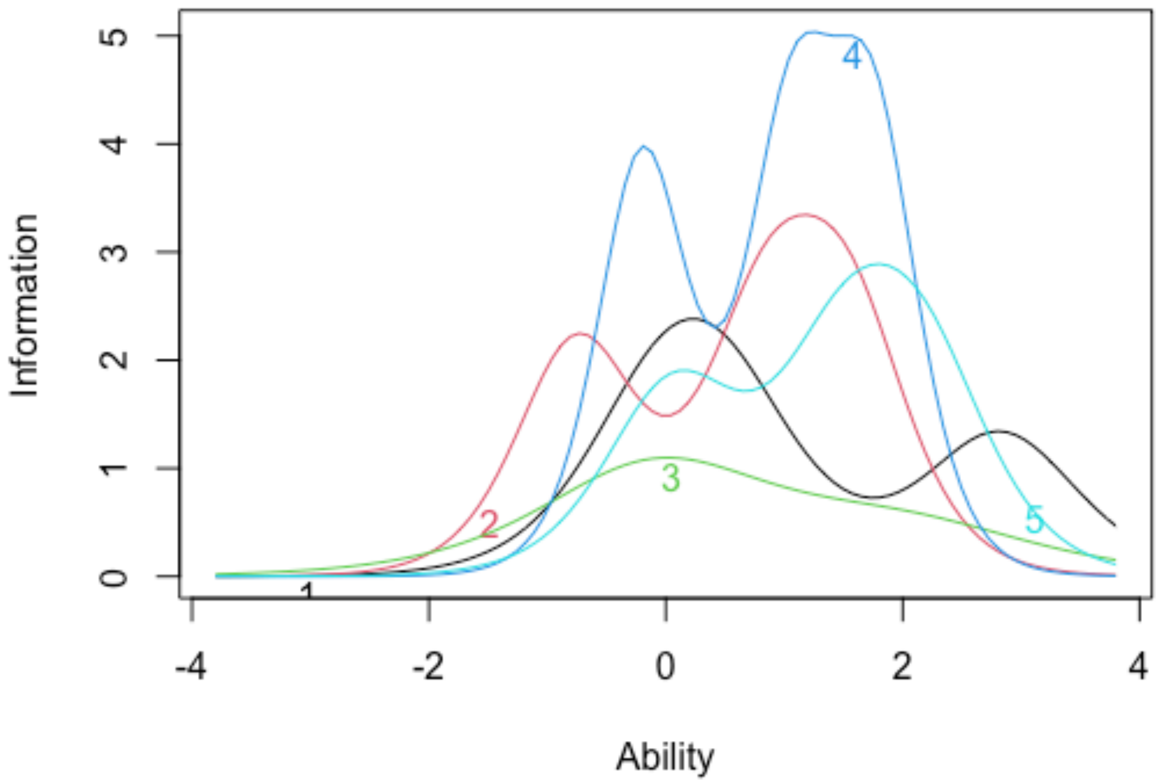
Supplemental Figure 6. BASC-3 PRS-A Attentional Control Item Information Curves (IICs)



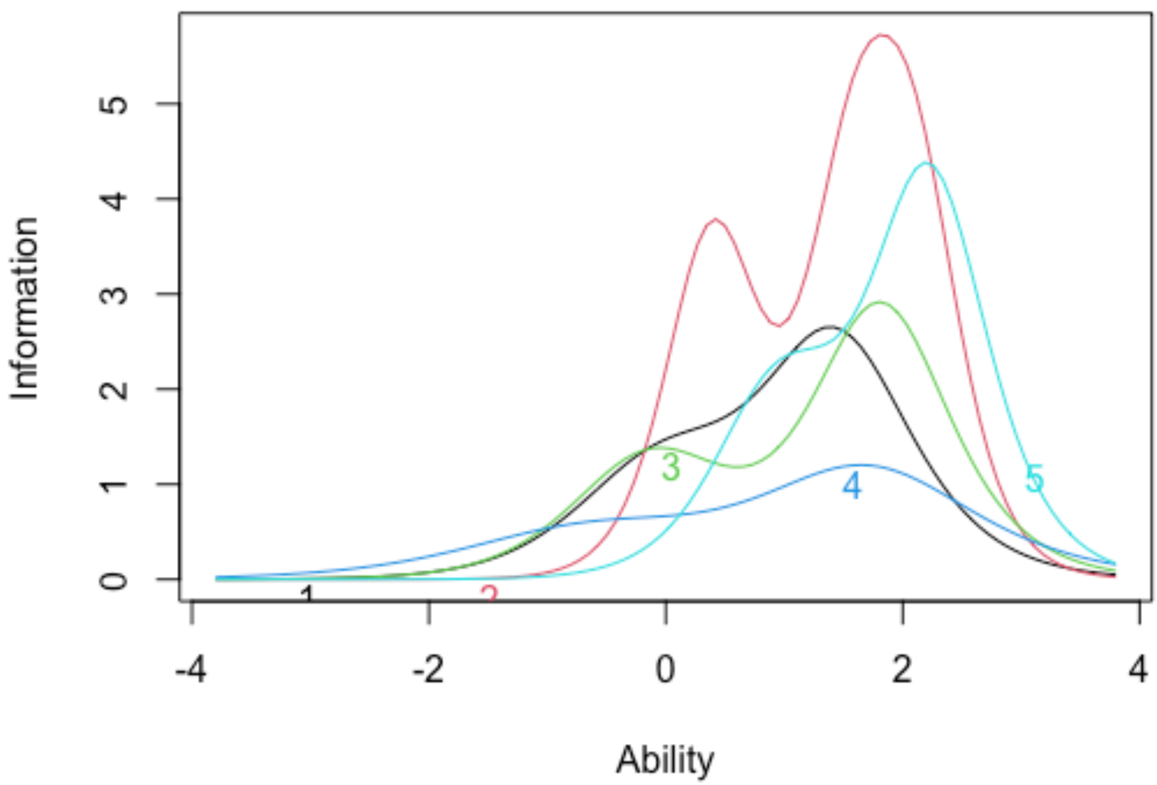
Supplemental Figure 7. BASC-3 PRS-A Behavioural Control Item Information Curves (IICs)



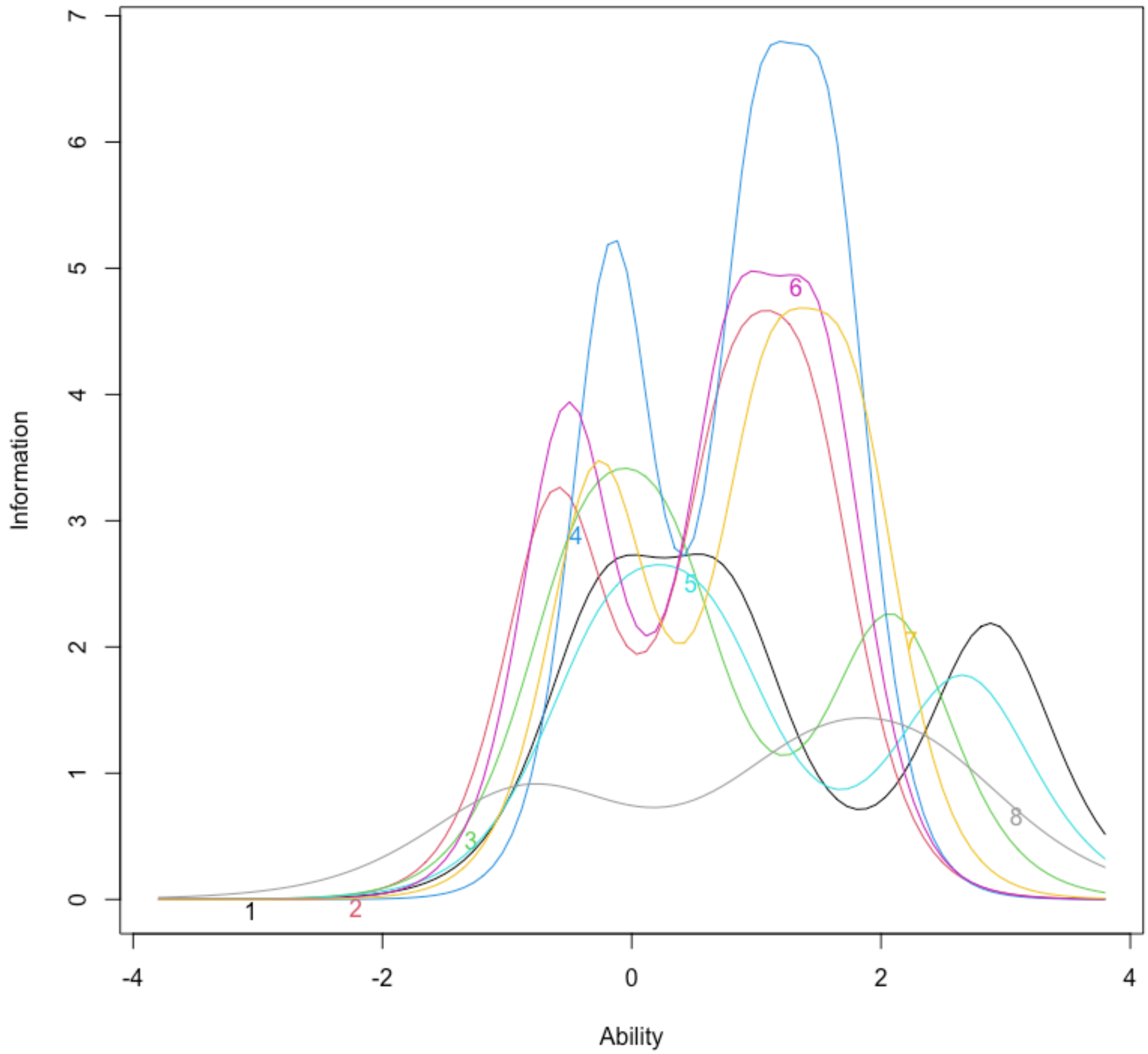
Supplemental Figure 8. BASC-3 TRS-P Attentional Control Item Information Curves (IICs)



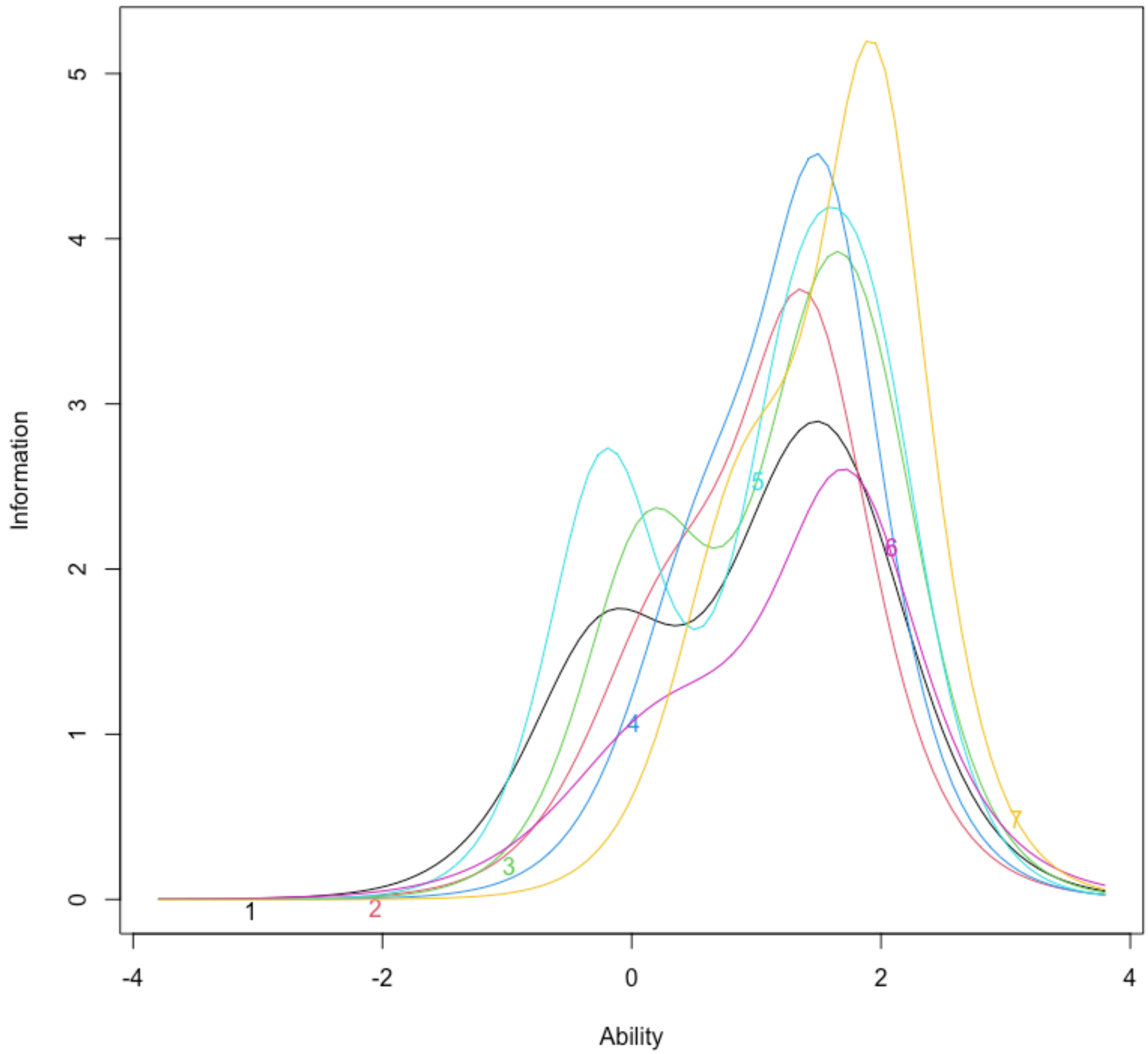
Supplemental Figure 9. BASC-3 TRS-P Behavioural Control Item Information Curves (IICs)



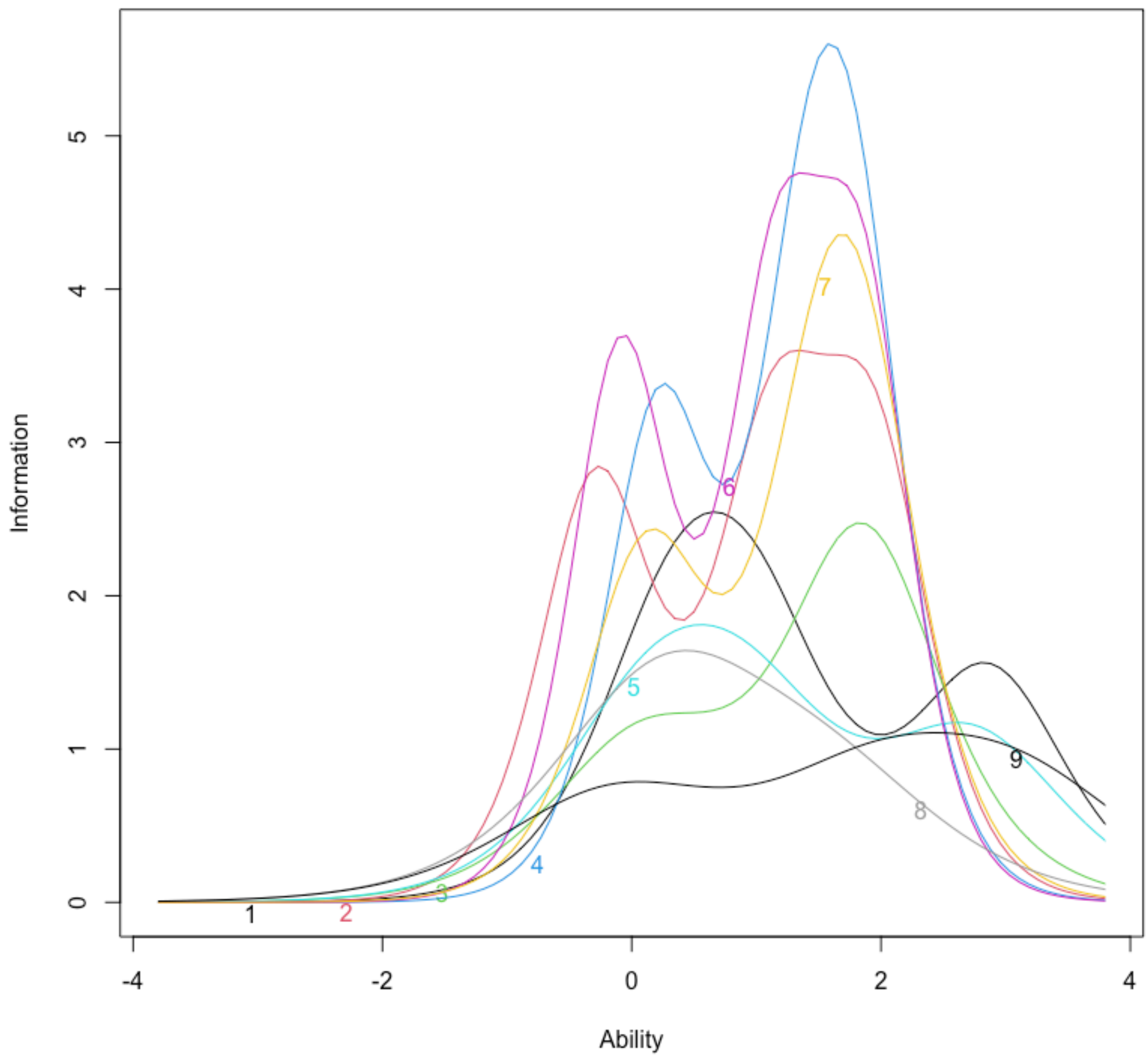
Supplemental Figure 10. BASC-3 TRS-C Attentional Control Item Information Curves (IICs)



Supplemental Figure 11. BASC-3 TRS-C Behavioural Control Item Information Curves (IICs)



Supplemental Figure 12. BASC-3 TRS-A Attentional Control Item Information Curves (IICs)



Supplemental Figure 13. BASC-3 TRS-A Behavioural Control Item Information Curves (IICs)