Determining the relationship between the *n*-Back Task, Symbol Span subtest, Digit Span subtest and Symbol Digits Modality Test.

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Abstract

Research in cognitive psychology has highlighted the importance of working memory and information processing speed in cognitive functioning (Chai et al., 2018; van der Fels et al., 2015). While the *n*-back test is widely considered a measure of working memory, its construct validity remains debated, with some evidence suggesting it may also reflect processing speed (Andrade, 2002; Jaeggi et al., 2010). This study examined the relationship between the *n*-back test, two established measures of working memory (Digit Span and Symbol Span), and a processing speed measure (Symbol Digit Modality Test) to investigate the *n*-back's concurrent and construct validity. Additionally, the influence of biological sex and socioeconomic status (SES) on cognitive performance was explored. A sample of 70 young adults (ages 18-25) completed these cognitive assessments. Results indicated that processing speed (SDMT) was the strongest predictor of *n*-back performance, suggesting that the *n*-back test may rely on cognitive mechanisms beyond core working memory. SES significantly influenced processing speed and higher-order working memory tasks, while biological sex differences emerged in the Digit Span Backward and 3-back tasks, with males showing an advantage. These findings contribute to the ongoing debate about the *n*-back test's validity as a pure working memory measure and emphasize the need to consider demographic factors when interpreting cognitive assessments. Future research should further examine the interplay between working memory, processing speed, and demographic influences in more diverse and larger samples.

Keywords: Working Memory, Processing Speed, *n*-back Task, Digit Span, Symbol Span, Symbol Digits Modalities Test, Biological Sex, Socioeconomic Status

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Chapter 1: Literature Review, Theoretical and Conceptual Background

Introduction

Working memory and information processing speed are critical components of general cognitive functioning, playing important roles in learning, decision-making, and reasoning (Alloway & Copello, 2013; Baddeley, 1992). Working memory refers to the short-term storage and active manipulation of information required for performing complex cognitive activities, including comprehension, problem-solving, and planning (Cowan, 2013). Information processing speed refers to the rapidity with which individuals can perceive, process, and respond to information, and it is closely linked to the efficiency of higher-order cognitive functions (Lichtenberger & Kaufman, 2012; Salthouse, 1996). The constructs of processing speed and working memory are interrelated, with faster processing speed often leading to more efficient working memory performance (Kim & Park, 2018; Nettelbeck & Burns, 2010).

The *n*-back test, the Symbol Span subtest from the Wechsler Memory Scale (WMS-IV; Wechsler, 2009a), and the Digit Span subtest from the Wechsler Adult Intelligence Scale (WAIS-IV; Wechsler, 2008a) are widely used measures of working memory in both clinical practice and research contexts. However, the specific cognitive processes underlying the *n*-back test are still debated. The *n*-back test, in particular, has been scrutinised for its validity as a measure of working memory, with some researchers suggesting it might better assess information processing speed rather than working memory capacity (Jaeggi et al., 2010; Miller et al., 2009). Understanding the intricate relationship between working memory and information processing speed is crucial for accurate research, cognitive assessment and diagnosis. Accurate assessments of these abilities are essential for diagnosing cognitive deficits and understanding individual cognitive variations (Mahendran et al., 2015). This study will contribute to the ongoing debate by examining the relationship between these widely used cognitive tests and the validity of the *n*-back test in measuring working memory.

Literature Review/Theoretical Framework

This study focuses on two key cognitive constructs: working memory and information processing speed, both crucial for cognitive functioning (Harvey, 2019; Vaughn-Blount et al., 2011). Working memory involves retaining a limited amount of easily accessible knowledge, vital for higher order cognitive functions, such as planning, comprehension, reasoning, and problem-solving (Cowan, 2013). Information processing speed, on the other hand, measures the rate at which basic cognitive tasks, like processing numbers and shapes, are performed under time constraints, reflecting concentrated attention (Yumba, 2017).

Historical Overview

History of Working Memory. The concept of memory has intrigued scholars for centuries, with early philosophical contributions from John Locke, who distinguished between contemplation and memory in 1690 (Locke, 1690). Contemplation refers to the mind's active focus on present ideas or thoughts, while memory is the faculty that enables the retention and recall of past experiences or impressions (Locke, 1690).

In the late 19th century, systematic studies began with Hermann Ebbinghaus, who used nonsense syllables to investigate memory retention and forgetting, laying foundational work for short-term memory research (Ebbinghaus, 1885/1913). The early 20th century saw a shift from behaviourism, which emphasised observable behaviours, to cognitive psychology. George A. Miller's seminal work in 1956 suggested that the capacity of short-term memory was limited to approximately seven pieces of information, emphasising the limitations and organisation of short-term memory (Miller, 1956). This finding contributed significantly to the understanding of memory processes and the development of the ‘chunking concept’ as a strategy for making memory more efficient (Cowan, 2014).

William James, in his 1890 work "Principles of Psychology", made a crucial distinction between the different types of memory, which he referred to as "primary" (p.408) and "secondary" memory (p.425), respectively. Primary memory involved the temporary retention of information, whereas secondary memory referred to the long-term storage of information. This differentiation laid the groundwork for later distinctions between short-term and long-term memory (James, 1890). In the mid-20th century, Donald Hebb introduced the concept of cell assemblies and phase sequences, proposing that repeated activation of a group of neurons would strengthen their connections, thus forming the neural basis of learning and memory. Hebb's theory suggested that short-term memory involved the temporary activation of these neural circuits, while long-term memory resulted from the growth of new synaptic connections (Morris, 1999).

Lloyd Peterson and Margaret Peterson conducted experiments in the late 1950s that provided empirical support for the limited duration of short-term memory. Their studies involved presenting participants with consonant trigrams (groups of three consonants; e.g. SLM). To prevent rehearsal of these trigrams the participants had to count backwards by threes while looking at the trigrams. The findings indicated that short-term memory decayed rapidly without rehearsal, typically within 18 seconds (Peterson & Peterson, 1959). John Brown's 1958 study on forgetting also contributed to the understanding of short-term memory. Brown proposed that forgetting in short-term memory was due to a decay process, where information would gradually fade unless it was actively rehearsed. This concept of decay was integral in shaping subsequent theories of memory processes (Brown, 1958). Furthermore, Broadbent established the notion of selective filtering in 1958. He proposed a model in which information enters a sensory store and is then filtered to let only a few items into a temporary storage depot before being processed into long-term memory. This model proposed the existence of a short-term memory store as an interim buffer between sensory stimuli and long-term memory (Broadbent, 1958; Cowan, 1998). By the end of the 1960s, evidence for dissociable memory stores had accumulated, leading to the rejection of the unitary memory system concept (Cowan, 1998).

The work of Karl Lashley in the early to mid-20th century also provided important insights, despite his unsuccessful attempts to localise memory in the brain. Lashley's experiments on the brains of rats resulted in the significant finding that memory was not localised to a single area but was distributed across the cortex. This idea of distributed processing influenced later models of memory, including those proposing separate systems for short-term and long-term storage (Lashley, 1950).

The development of memory theories continued to evolve with significant contributions from Alan Baddeley and Nelson Cowan. Baddeley’s Working Memory Model (1974) expanded on earlier concepts of short-term memory by introducing a multi-component system, which included the phonological loop (for verbal information), the visuospatial sketchpad (for visual and spatial data), and the central executive (for coordinating and managing these subsystems). In 2000, Baddeley added the episodic buffer, which integrates information from different sources and links working memory to long-term memory. This model emphasized memory as an active system for processing and manipulating information, rather than a static storage unit (Baddeley, 2000).

On the other hand, Cowan's Embedded Processes Model (2005) viewed working memory as a subset of activated long-term memory, with a limited focus of attention that can handle around four items at a time. Cowan argued that working memory capacity reflects the attentional processes required to maintain and manipulate information (Cowan, 2005). These theories will be discussed in more detail later on.

The History of Information Processing Speed. The study of information processing speed also has a rich, but slightly shorter, history that originated in the 19th century (Sweet, 2011). This journey began with the pioneering work of Franciscus Donders, a Dutch physiologist, who conducted some of the first systematic research in this field during the 1860s. Donders is often credited with laying the groundwork for the study of mental chronometry, the measurement of time taken for cognitive processes. His reaction time experiments were revolutionary in that they introduced a method to infer the speed of mental processes by calculating the time taken to respond to stimuli. Donders' experiments typically involved two tasks: a simple reaction-time task and a choice reaction-time task (Posner, 2005; Sweet, 2011).

In the simple reaction-time task, participants were told to press a button as soon as a light appeared. This task measured the time it took to perceive the light and respond by pressing the button. In the choice reaction-time task, participants had to press one button if a light appeared on the left and another button if it appeared on the right. This task added an element of decision-making to the reaction time, thereby measuring not only perception and response but also the decision-making process. Donders discovered that the difference in reaction time between the simple and choice tasks could be attributed to the time required to make a decision. This ground-breaking insight demonstrated that mental processes could be studied scientifically by measuring behaviour (Donders, 1969; Sweet, 2011).

Furthermore, Hermann von Helmholtz, a German physiologist and physicist, made significant contributions to the understanding of information processing speed through his work on perception. Helmholtz proposed the theory of unconscious inference, which suggests that some of our perceptions are the result of unconscious assumptions we make about the environment based on past experiences. This theory highlights that much of what we perceive, and process happens instantaneously and without conscious effort, thereby emphasising the rapid nature of cognitive processing (Patton, 2018).

Hermann Ebbinghaus further advanced the study of information processing speed with his experiments on memory (Ebbinghaus, 1885). In the 1880s, Ebbinghaus used lists of nonsense syllables to measure how quickly information could be learned and relearned. He introduced the concept of the savings method, which quantified memory retention over time. Ebbinghaus found that the time required to relearn a list decreased with each subsequent learning session, and he plotted this relationship in what became known as the forgetting curve (Murre & Dros, 2015; Roediger & Yamashiro, 2019). His work provided a quantitative approach to studying memory, indirectly shedding light on the speed of mental processing involved in learning and memory recall (Roediger & Yamashiro, 2019).

Furthermore, Sir Francis Galton's contributions to this field are particularly noteworthy (Galton, 1869). He was one of the first to suggest that intelligence could be measured by simple sensory and motor tasks, such as reaction times and sensory discrimination tests (Jensen, 2002). His belief was that quicker response times indicated higher intelligence. This idea laid the foundation for later work on the relationship between information processing speed and intelligence. Studies by early psychologists like Charles Spearman also supported the notion that there was a correlation between sensory discrimination and general intelligence (Wasserman & Kaufman, 2016). In the late-20th century, researchers like Arthur Jensen and Philip Vernon expanded on these ideas by exploring the heritability of reaction times and their correlation with intelligence (Jensen, 2002; Vernon, 1987). Jensen's studies, for instance, found that reaction times were moderately correlated with intelligence test scores and that this relationship was stronger for more complex tasks (Jensen, 2002). These findings suggested that information processing speed might be a fundamental component of cognitive abilities.

Moreover, one of the most influential models in understanding information processing is the Atkinson and Shiffrin model of memory, introduced in 1968. This model conceptualised human cognition as a series of stages through which information flows, each with distinct properties (Atkinson & Shiffrin, 1968; Baddeley, 2010). The model highlights three memory systems: sensory memory, short-term memory, and long-term memory. Sensory memory briefly retains incoming sensory information, while short-term memory acts as a temporary storage for information under active processing. Long-term memory, in contrast, serves as a more permanent repository of knowledge. This model emphasized the importance of attention and rehearsal in transferring information from sensory to short-term memory and ultimately to long-term memory (Atkinson & Shiffrin, 1968). By framing cognitive processing as a systematic flow of information, the Atkinson model provided a theoretical basis for studying the mechanisms underlying information processing speed (Bouchrika, 2024).

Today, the study of information processing speed encompasses various cognitive tasks and employs advanced technologies such as neuroimaging and computer modelling (E.g. Li et al., 2024; Ma et al., 2024). Researchers examine how quickly individuals can process information across different contexts and tasks, from simple reaction times to complex decision-making scenarios (Xue et al., 2010). This research has broad applications, including understanding developmental changes in cognitive processing, diagnosing and treating cognitive impairments, and optimising human performance in various fields (De Boeck & Jeon, 2019; Nettelbeck & Burns, 2010). In summary, the history of information processing speed highlights the evolution of methods and theories from the 19th century to the present day.

The Biological Basis of Working Memory and Information Processing Speed

Research by Goldman-Rakic (1992) highlighted the role of the prefrontal cortex (PFC) in maintaining and manipulating information in working memory. This provides a biological basis for the theoretical constructs proposed by cognitive psychologists. Magistro et al. (2015) found that information processing speed is closely linked to the integrity of white matter and the efficiency of neural transmission across the brain. Understanding the biological foundations of both working memory and information processing speed is important for interpreting how these cognitive functions could be connected and how their underlying neural mechanisms influence performance on cognitive tasks.

Working Memory. Biological studies have shown that working memory is dependent on a network of brain regions. These regions specifically include the prefrontal cortex (PFC) and the hippocampus (Liu et al., 2018). Functional imaging studies and electrophysiological recordings in animals and humans show that these areas are crucial for maintaining and manipulating information in working memory (Stretton et al., 2012). Activity decay and sustained activation are key processes in working memory, with neurotransmitters such as dopamine playing a crucial role in modulating PFC activity, which are essential for working memory tasks (Polizzotto et al., 2020).

Advances in neuroimaging have explained the structural connectivity between the PFC and other brain regions involved in working memory (Cao et al., 2021). From a neuroscientific standpoint, the prefrontal, cingulate, and parietal cortices are among the fronto-parietal brain regions that are activated by working memory activities. The parietal cortex functions as the "workspace" (Chai et al., 2018, p.3) for sensory or perceptual processing, whereas the anterior cingulate cortex acts as an "attention controller" (Chai et al., 2018, p.3) that assesses the need for adjustment based on task demands. The dorsolateral prefrontal cortex (DLPFC) is crucial to executive control tasks because it integrates information for decision-making, maintains, and manipulates/retrieves stored information (Chai et al., 2018). Research has now connected working memory to subcortical regions such as the cerebellum and midbrain (Chai et al., 2018). Furthermore, subcortical structures like the basal ganglia, specifically the caudate and thalamus, are important during different phases of working memory tasks. These regions are involved in enhancing focus on relevant information and suppressing distractors (Deldar et al., 2020). The cerebellum, traditionally associated with motor control, has also been implicated in higher-order cognitive functions, including working memory, as evidenced by impairments in attention-related working memory in patients with cerebellar lesions (Gottwald et al., 2004;

Ziemus et al., 2007). These findings support Baddeley's (2000) multicomponent model by linking the central executive to the dorsolateral prefrontal cortex (DLPFC), a region essential for decision-making, attention control, and the manipulation of stored information. The visuospatial sketchpad, responsible for handling visual and spatial information, corresponds to the parietal cortex, which functions as a sensory "workspace" (Chai et al., 2018, p.3) for perceptual processing. Similarly, the episodic buffer's role in integrating and temporarily storing multimodal inputs aligns with activity in regions like the posterior parietal cortex, which are involved in synthesizing sensory and cognitive information. Advances in neuroimaging further reveal the interconnected nature of these systems, highlighting the structural connectivity between the prefrontal cortex (PFC) and other regions within the fronto-parietal network, including the anterior cingulate cortex, which acts as an "attention controller" (Chai et al., 2018, p.3) to adapt processing based on task demands (Cao et al., 2021; Chai et al., 2018).

The persistence of neuronal firing and synaptic mechanisms, such as residual calcium at presynaptic terminals, are vital for working memory processes (Balagué-Marmaña & Dempere-Marco, 2023). This supports Cowan's concept of Activated Long-Term Memory (ALTM; Mongillo et al., 2008; Rose et al., 2016). This theory suggests that working memory is not a separate system but a subset of long-term memory that temporarily holds activated items for cognitive tasks (Cowan, 2019). However, in Norris's (2019) critique of Cowan's ALTM, he argues that ALTM alone cannot support the computations required for short-term and working memory. Norris (2019) emphasises the necessity of a separate short-term memory (STM) system to handle tasks like storing novel representations and performing variable binding, which ALTM cannot adequately address. In contrast, Cowan (2019) suggests that STM could be seen as the front end of long-term learning. Norris (2019) believes this reclassification lacks computational clarity and does not eliminate the need for a distinct STM system (Norris, 2019). Thus, Cowan's theory of ALTM is still a subject of debate, but there is some neurological evidence for it (Norris, 2019).

Neurobiological and environmental factors interact to influence working memory functioning across developmental stages (Tucker-Drob et al., 2013). During childhood, working memory capacity progressively increases up to adolescence, reflecting the maturation of neural circuits and the improvement of executive functions (Goddings et al., 2021; Reynolds et al., 2022). The expansion of working memory capacity in middle and late childhood is likely due to increased processing speed and improved inhibition of irrelevant information, driven by changes in myelination and synaptic pruning in the cortex. Working memory typically peaks in early adulthood, around the age of 30, and then gradually declines (Hartshorne & Germine, 2015). This study focuses on adults aged 18-25, whose working memory may not yet have reached its peak. This is important for interpreting the study's results, as the working memory performance in this age group, while still maturing, provides valuable insight into the relationships between working memory and processing speed. This will be discussed further in the Discussion section of the report.

Processing Speed. The biological underpinnings of information processing speed are closely tied to the integrity of myelin and the structure of white matter in the brain (Li et al., 2022). As individuals age, there is a notable decline in information processing speed, which is significantly influenced by changes in myelin integrity and white matter microstructure (Lu et al., 2011; Bott et al., 2017).

Myelin is essential for the rapid transmission of electrical signals along nerve fibres (Susuki, 2010). Age-related myelin breakdown is a critical factor contributing to cognitive decline (Gong et al., 2023). Research by Lu et al., (2011) indicates that myelin integrity is particularly important in late-myelinating regions of the brain, such as the frontal lobes and the genu of the corpus callosum. These regions are more vulnerable to age-related changes, which can significantly impact cognitive processing speed (Lu et al., 2011). Diffusion tensor imaging studies have provided substantial evidence linking white matter microstructure to cognitive performance (Madden et al., 2012). Lower fractional anisotropy, an indicator of white matter health, in frontal brain regions has been linked with slower reaction times and decreased processing speed in older adults (Salami et al., 2012). These findings underscore the importance of maintaining myelin integrity to preserve information processing speed and cognitive function in aging populations (Bott et al., 2017). The degradation of myelin with age can be attributed to the increased vulnerability of later-myelinating oligodendrocytes, which are responsible for forming myelin sheaths (Stadelmann et al., 2019). These cells are more susceptible to metabolic stress and other age-related factors, leading to a reduction in myelin lamellae and overall myelin density (Stadelmann et al., 2019). This process results in slower neural transmission and decreased cognitive performance (Stadelmann et al., 2019). Additionally, the decline in myelin integrity has been shown to precede and potentially mediate the deterioration of higher-order cognitive functions, such as memory and executive function, which are heavily reliant on fast and efficient information processing (Kerchner et al., 2012).

In clinical populations, such as survivors of paediatric brain tumours, reductions in white matter volume and integrity are associated with significant deficits in processing speed (Mash et al., 2023). These deficits are thought to stem from treatments like surgery and radiation therapy, which can cause lasting damage to white matter structures (Mash et al., 2023). The concept of Sluggish Cognitive Tempo describes the cognitive profile of these individuals, characterised by slow information processing and attentional difficulties (Peterson et al., 2021). This framework highlights the broad impact of compromised myelin integrity on various cognitive domains, particularly processing speed.

Research into the biological aging of the brain, including the brain-age gap estimate (brainAGE), explains the relationship between white matter health and cognitive decline (Elliott et al., 2021). BrainAGE, which measures the difference between an individual's chronological age and their brain age as estimated by neuroimaging, is linked to cognitive performance and the pace of biological aging. Individuals with an older brainAGE exhibit poorer cognitive function and faster cognitive decline, which are associated with reduced myelin integrity and white matter microstructure degradation (Elliott et al., 2021).

Genetic factors also play a role in influencing information processing speed. For instance, certain polymorphisms in genes related to white matter health and myelination processes can affect cognitive processing speed (Li et al., 2022). The presence of these genetic variants can predispose individuals to faster cognitive decline and reduced processing speed in later life, emphasising the interplay between genetic predisposition and environmental factors in determining cognitive outcomes (Bott et al., 2017).

Overall, myelin integrity and white matter microstructure plays a key role in supporting information processing speed. Information processing speed improves significantly during childhood and adolescence, peaking in early adulthood. This peak is driven by the maturation of neural systems, including increased myelination and synaptic efficiency, which supports faster cognitive processing (Salthouse, 2009). Since the sample for the current study comprises healthy young adults, optimal information processing speed is expected.

Cognitive Theories of Working Memory

As previously noted, working memory is a key aspect of human cognition, essential for manipulating and temporarily storing information required for higher-order cognitive processes such as language comprehension, learning, and reasoning (Baddeley, 1992). Theories of working memory have evolved significantly over the past few decades, reflecting advances in cognitive psychology and neuroscience (Coolidge & Wynn, 2020). These aim to explain the mechanisms underlying the capacity and functionality of working memory, exploring how information is maintained and manipulated over short periods.

Atkinson and Shiffrin's Multi-Store Model (1968) marked a pivotal development in the understanding of memory architecture. As described earlier, this model proposed that memory comprises three distinct stores: the sensory register, a short-term store, and a long-term store. According to this model, information flows sequentially through these stores, with short-term memory serving as a crucial gateway to long-term memory. The model underscored the limited capacity and transient nature of short-term memory, emphasising its integral role in processing information for longer-term storage (Atkinson & Shiffrin, 1968). In 1966, Saul Sternberg introduced another influential model, focusing on the retrieval processes within short-term memory. His additive factor method revealed that the time required to retrieve an item from short-term memory increases linearly with the number of items stored, suggesting a serial exhaustive search process. This insight was instrumental in advancing our understanding of retrieval mechanisms and the role of processing speed within short-term memory (Estes, 2014; Sternberg, 1966).

Building on these ideas, Baddeley and Hitch (1974) proposed the Multicomponent Model, which posits that short-term memory, or working memory as it later became named, is a multifaceted system comprising a central executive control system and several distinct subsystems. These storage subsystems include the phonological loop and visuospatial sketchpad. The phonological loop, with its passive phonological store and active articulatory control process, is essential for the processing and storage of auditory-verbal information (Baddeley & Hitch, 1974; Schaeffner et al., 2020). Similarly, the visuospatial sketchpad handles the storage and processing of visual and spatial information (Logie, 2003).

The introduction of the episodic buffer by Baddeley in 2000 further refined this model by explaining how information is integrated into long-term memory through interactions between the central executive and subsidiary stores (Baddeley, 2000). Despite its widespread empirical support, the Multicomponent Model of Working Memory (2000) has faced critiques for its simplicity and limitations in explaining complex real-world cognition (Demir, 2021; Engle & Kane, 2004). The section below details the components of Baddeley’s (2000) model, refined from the Baddeley and Hitch model (1974), which posits specialised, interconnected modular components, and explains why this model was adopted as the theoretical basis for the current study.

Baddeley’s (2000) Working Memory Model

Phonological Loop. The phonological loop was first proposed by Baddeley and Hitch in 1974. It is a key component of the working memory model and is essential for the manipulation and temporary storage of verbal information. This system allows individuals to hold onto auditory information, such as words or numbers, for a short period while also rehearsing it internally to prevent decay (Baddeley, 2003). The loop is crucial not only for language comprehension and learning but also for tasks such as problem-solving and mathematical calculations where verbal mediation is involved (Viesel-Nordmeyer et al., 2022).

The phonological loop is made up of two main parts: the phonological store and the articulatory rehearsal process. The phonological store, often referred to as the ‘inner ear,’ is responsible for holding onto auditory information for a few seconds (Alderson-Day & Fernyhough, 2015). This component is localised in the left supramarginal gyrus of the parietal lobe, which plays an important role in the short-term retention of verbal material (Graves et al., 2008; Perrachione et al., 2017). The articulatory rehearsal process, known as the ‘inner voice,’ refreshes the stored information through subvocal repetition (Alderson-Day & Fernyhough, 2015). This process involves Broca’s area in the left inferior frontal gyrus and BA 44 and 6 in the frontal cortex, which are engaged during tasks involving the maintenance and active manipulation of verbal information (Paulesu et al., 1993; Perrachione et al., 2017; Sridhar et al., 2023).

Studies utilising functional MRI have shown that phonological tasks, such as repeating non-words or maintaining verbal sequences, result in increased activation in these brain regions. This activation underscores the importance of the phonological loop in auditory processing and verbal memory (Chein et al., 2003; Sridhar et al., 2023). Furthermore, lesion studies provide further evidence for the loop’s critical role. Damage to the left hemisphere, particularly in areas associated with the phonological loop, often leads to impairments in phonological working memory, as observed in patients with conditions such as aphasia and other language disorders (D’Esposito & Postle, 2015; Sridhar et al., 2023). The phonological loop is fundamental, not only for everyday tasks like reading and repeating sequences, but also for more complex cognitive functions, including language acquisition and the development of literacy skills in children (Baddeley, 2003; Repovš & Baddeley, 2006).

Visuospatial Sketchpad. The visuospatial sketchpad is an essential component of working memory. It manipulates and temporarily stores visual and spatial information. It comprises of two subcomponents: the visual cache, which passively holds visual data, and the inner scribe, which actively processes spatial information and aids in the rehearsal of visuospatial content. This system is essential for tasks such as navigating through a city or visualising objects (Repovš & Baddeley, 2006; Miyake et al., 2001). The visuospatial sketchpad is primarily localised in the right hemisphere, involving regions such as the occipital lobe, parietal cortex, and frontal areas (Alderson-Day & Fernyhough, 2015). Studies have pinpointed specific areas linked to this function, including the right infero-lateral prefrontal cortex, lateral pre-motor cortices, right inferior parietal cortex, and dorsolateral occipital cortices (Ren et al., 2019; Sridhar et al., 2023). The posterior parietal cortex and the intraparietal sulcus are particularly important for spatial working memory. Both playing a key role in tasks that require the retention and manipulation of spatial information (Xu & Chun, 2006). Neuroimaging studies support these findings, showing increased activation in the superior and posterior parietal cortex during mental rotation tasks, highlighting the involvement of these regions in visuospatial processing (Sridhar et al., 2023). Despite these findings, additional research is required to completely comprehend the integration of the visuospatial sketchpad with other cognitive processes (Baddeley, 2003; Sridhar et al., 2023). Lesion studies provide additional evidence of the sketchpad's significance. Damage to the posterior parietal cortex can impair the capacity to mentally transform and manipulate visual representations, leading to deficits in tasks that depend on visuospatial memory (Buiatti et al., 2011). Similarly, according to Sridhar et al. (2023), lesions in the occipital cortex can hinder the ability to complete tasks involving the creation and alteration of mental images, emphasising the significance of these regions in visuospatial working memory.

Central Executive. The central executive is another important element of working memory, serving as the control centre that manages and coordinates cognitive processes (Shallice, 2002). Unlike the phonological loop and visuospatial sketchpad, which handle specific types of data, the central executive does not retain data itself but instead manages attention and allocates resources to these subsystems (Baddeley, 2003). Neuroimaging studies have identified the involvement of the prefrontal cortex, particularly the dorsolateral prefrontal cortex (DLPFC), and the anterior cingulate cortex in executive functions related to attention control and decision-making (Jung et al., 2022). The central executive system has a dual network control. The dual network control involves both the cingulo-opercular network and the frontoparietal network (Yu et al., 2023). The cingulo-opercular network, which includes the dorsal anterior cingulate cortex and anterior insula, is hypothesised to have a role in sequential regulation over the working memory process. The frontoparietal network, which encompasses the DLPFC, frontal eye field, and intraparietal sulcus, may be more important in moment-to-moment processing and control (Sridhar et al., 2023; Yu et al., 2023). The central executive's ability to coordinate the phonological loop and visuospatial sketchpad is essential for complex cognitive tasks, such as problem-solving, reasoning, and multitasking (Baddeley, 2003; Menon & D’Esposito, 2021). This interaction allows for the integration of verbal and visual information, supporting more sophisticated cognitive operations. The precise neural mechanisms underlying this interaction involve specific brain regions that are activated depending on the task's demands. For instance, the DLPFC is heavily engaged during tasks requiring the manipulation of information held in the phonological loop or visuospatial sketchpad (Alderson-Day & Fernyhough, 2015). Overall, the central executive is vital in regulating and integrating the varied aspects of working memory, ensuring that cognitive processes are efficiently managed and executed.

Episodic Buffer. The episodic buffer, introduced by Baddeley (2000), is an essential component of working memory that integrates information across different modalities. It serves as a multidimensional store, combining various features into coherent episodes or chunks (Sridhar et al., 2023). This component acts as a link between the central executive, long-term memory, and other parts of working memory, unifying information from these sources (Baddeley et al., 2010). Neuroanatomically, the episodic buffer is not confined to one area in the brain. Research suggests potential associations with the hippocampus, which plays a key role in memory formation, and the inferior lateral parietal cortex, involved in integrating sensory information (Alderson-Day & Fernyhough, 2015). However, it likely operates as part of a broader network that includes the prefrontal cortex, which is crucial for managing and coordinating cognitive processes, and the parietal cortex, which supports spatial and sensory integration. This network enables the episodic buffer to draw on multiple neural systems, allowing it to integrate and store multimodal information effectively (Baddeley et al., 2010). The episodic buffer also connects the central executive's attentional control with the content-specific processing of the phonological loop and visuospatial sketchpad. This integration is vital for organising and retrieving complex episodes, supporting tasks like reasoning, problem-solving, and memory formation (Gelastopoulos et al., 2019). The interaction between the episodic buffer and other working memory components underscores its role in facilitating flexible and adaptive cognitive functions.

Criticisms. Baddeley's model has also received critique on several fronts. Initially, the model's strict differentiation between short-term memory (STM) and long-term memory (LTM) was criticised for being overly simplistic as neuropsychological evidence revealed that both phonological and semantic coding could occur in STM, contrary to the model's assumptions (Baddeley & Hitch, 2019; Demir, 2021). Additionally, the model lacked a realistic mechanism for serial ordering, which is crucial for tasks involving serial recall. The original 'tape loop' concept, which compares the phonological loop to a tape recorder that stores and replays auditory information in a linear sequence, proved inadequate in explaining errors in serial recall, such as transpositions or omissions (Baddeley & Hitch, 2019). This limitation highlighted the need for a more nuanced understanding of how serial order is maintained in working memory.

The role of the phonological loop in language comprehension was also questioned, with research suggesting that comprehension might rely more on long-term memory and automatic processes rather than the loop itself (Vallar & Papagno, 2017). Furthermore, the central executive, described as the control system of working memory, has been criticised for its lack of detailed mechanisms. While it is understood to coordinate attention and manage the flow of information between subsystems, the model does not provide a clear explanation of how it operates or how it interacts with other components, leaving its functional architecture somewhat vague (Baddeley & Hitch, 2019). In light of these criticisms, Cowan's (2005) model offers an alternative perspective on the nature of working memory.

Cowan's (2005) Embedded-Processes Model

Cowan's (2005) embedded-processes model offers a compelling alternative to traditional models of working memory, like Baddeley's (2000) Working Memory Model. Unlike Baddeley's (2000) model, which proposes distinct subsystems within working memory (e.g., the phonological loop, visuospatial sketchpad, and episodic buffer), Cowan's (2005) model conceptualises working memory as a temporary activation of long-term memory representations managed by the focus of attention, integrating long-term memory and attention into a single, cohesive framework that highlights its fluid and dynamic nature (Adams et al., 2018; Cowan, 2005). This concentration of attention has a limited capacity, often storing only four pieces of information at a time. The model suggests that all information processed in working memory is part of a single, integrated system, where attention plays an important role in maintaining and manipulating information (Cowan, 2005, 2014). This differs from Baddeley's model (2000), where various types of information are processed in separate, specialised subsystems (Adams et al., 2018). One of the key strengths of Cowan's model (2005) is its ability to explain working memory updating, a process central to tasks such as the *n*-back test used in the current study. The *n*-back test requires continuous monitoring and updating of the information held in working memory, which aligns well with Cowan's emphasis on the role of attention in dynamically managing the contents of working memory (Adams et al., 2018; Frost et al., 2021).

In this context, Cowan's (2005) model suggests that the focus of attention is responsible for updating the information by bringing relevant items into the forefront of working memory from long-term memory stores while discarding outdated information. This process reflects the model's emphasis on the interaction between long-term memory and attention, with working memory serving as a flexible and adaptive system that responds to the demands of the task at hand. Cowan's model (2005) offers a comprehensive framework that captures the dynamic and adaptive nature of working memory and places a significant emphasis on the role of attention in managing and updating the contents of working memory. In this model, attention actively selects relevant information from long-term memory and discards irrelevant items, which makes working memory processing highly dynamic and integrated (Cowan, 2005, 2014). In contrast, Baddeley's model, while also acknowledging the importance of attention, assigns this role primarily to the central executive, which oversees the operation of multiple distinct subsystems such as the phonological loop and visuospatial sketchpad (Baddeley, 2003; Persuh et al., 2018).

Neuroimaging studies have identified several key brain regions that underpin these processes (Chein, 2003; Yoon et al., 2016). The dorsolateral prefrontal cortex (DLPFC) is central to the executive functions that govern attention. This attention is essential for bringing specific long-term memory representations into an activated state that can be used to perform cognitive tasks (Yoon et al., 2016). The inferior parietal cortex plays a critical role in attentional scanning. It functions as a domain-general mechanism that shifts and engages attention across various activated memory representations, facilitating their maintenance in working memory (Behrmann et al., 2004). Additionally, Broca's area, traditionally associated with language and rehearsal in Baddeley's model (2000), is reinterpreted in Cowan's theory (2005). In the latter, it is seen as a region involved in both phonological processing and the broader attentional processes that support working memory. This reinterpretation aligns with findings that Broca's area is activated not only during tasks requiring verbal rehearsal but also during tasks involving attentional control and phonological processing. This reflects its versatile role in the embedded-processes model. Overall, this neuroanatomical evidence supports Cowan's (2005) view of working memory as a fluid and dynamic system. It is deeply intertwined with long-term memory, where attention serves as the key mechanism for maintaining and manipulating information (Chein, 2003).

Furthermore, Chai et al. (2018) found that working memory may be maintained through residual calcium at presynaptic terminals, supporting the concept of activated long-term memory. This aligns with Cowan's (2005) idea that non-cued items, previously thought inaccessible, can be stored in a latent state and later reactivated via the focus of attention. This evidence challenges the traditional view of continuous neural activity in working memory and suggests that more complex, activity-silent synaptic mechanisms play a key role which makes working memory a dynamic and flexible system (Chai et al., 2018).

Baddeley's (2000) multicomponent model and Cowan's (2005) embedded-processes model offer complementary perspectives. While Baddeley's (2000) model provides a structured framework with distinct components, Cowan's (2005) model emphasises a more fluid interaction within a unified system guided by attention. Both models contribute to understanding the complex nature of working memory and its underlying mechanisms, as evidenced by neuroimaging and behavioural studies and therefore provide useful theoretical frameworks for the current study (Adams et al., 2018; Albouy et al., 2019; Chai et al., 2018; Lim et al., 2022).

Theories of Information Processing Speed

As mentioned previously, information processing speed refers to the efficiency with which individuals conduct mental operations and respond to stimuli, encompassing various cognitive tasks such as perception, encoding, and response generation, thus playing a crucial role in overall cognitive functioning (Ebaid et al., 2017; Harvey, 2019; Holdnack et al., 2016). It is considered a fundamental aspect of the cognitive system's architecture, as it develops and evolves throughout an individual's lifetime (Kail & Salthouse, 1994).

Atkinsons and Shiffrin's (1968) Information Processing Theory

The Information Processing Theory, proposed by Atkinson and Shiffrin (1968), suggests that all information is processed sequentially in the same series of stages such as encoding, storage, and retrieval. According to this theory, sensory input is transformed into meaningful information through attention, perception, and memory processes, but this theory does not consider the pace of information processing. In the current study, information processing speed is tapped with the Symbol Digits Modality Test (SDMT). In this test, participants engage in a series of cognitive processes to complete the task (Ryan et al., 2020). Initially, sensory information, represented by visual symbols paired with numbers, is processed by the perceptual system. Subsequently, the encoded information is temporarily stored in working memory as participants generate responses. Finally, the motor system is activated to produce appropriate verbal responses corresponding to the presented symbols (Chen et al., 2020).

While theories of working memory and information processing provide valuable insights into cognitive functions, they also present challenges and limitations. The following section will explore how these constructs are measured behaviourally, offering a practical perspective on their application in research and assessment.

Measures of Working Memory and Information Processing Speed

Neuropsychological assessments play an important role in understanding the interplay between working memory and information processing speed. These two constructs are closely interconnected, as faster processing speed can facilitate the encoding, manipulation, and retrieval of information in working memory tasks (Lengenfelder et al., 2006). In this study, three tests were utilised to assess working memory, while one test was used to evaluate processing speed. Next, a deeper explanation of each test followed.

Digit Span Test

It consists of three subtests: Digit Span Forwards, Digit Span Backwards, and Digit Span Sequencing. The Digit Span Forwards test primarily focuses on attention and the ability to store information, making it a test of attention and short-term memory. It involves verbal stimuli, where the respondent is presented with a sequence of digits (e.g., '4, 7, 2, 9') and must repeat the sequence in the exact same order. This task taps into the phonological loop part of Baddeley's (2000) theory, which is responsible for the storage of auditory-verbal information (Gray et al., 2017). The test requires the respondent to repeat the correct sequence verbally, which engages their auditory-verbal memory system (Gray et al., 2017; Hilbert et al., 2015; Schaeffner et al., 2020). However, there is an ongoing debate about the cognitive resources involved in backward digit recall and digit sequencing. This is because backward digit recollection and sequencing tasks involve executive control, requiring manipulation and spatial considerations. This raises questions about whether the Digit Span subtest is purely verbal or if it also utilises visuospatial resources (St Clair-Thompson & Allen, 2012). Despite this debate, the Digit Span test remains widely used in neuropsychological assessments as a measure of verbal working memory (Hilbert et al., 2015; Leung et al., 2011).

In clinical neuropsychology, the Digit Span subtest is utilised to differentiate between cognitive abilities in healthy and impaired populations. Research has demonstrated distinct performance differences on the Digit Span Backwards subtest between individuals that are cognitively healthy and mildly cognitive impaired individuals or individuals with dementia (Eppig et al., 2012; Idowu et al., 2020). This subtest, particularly the backward condition, involves higher cognitive demands due to the requirement for manipulation and organisation of information, thus providing a more accurate measure of working memory capacity (Lumpkin & Sheerin, 2018; Schaeffner et al., 2020).

The Digit Span Sequencing condition, introduced in the newest version of the WAIS (Wechsler, 2008a), further enhances the assessment by requiring participants to recall digits in ascending order. This condition involves continuous cognitive comparison and manipulation, making it a more complex task. The sequencing condition not only evaluates storage and manipulation but also the ability to correctly order information, adding depth to the assessment of working memory (Wechsler, 2008b). Performance on the Digit Span Sequencing subtest can differentiate between cognitively healthy and impaired groups more effectively than the Forwards and Backwards conditions alone (Lumpkin & Sheerin, 2018; MacDonald et al., 2001).

Symbol Span Test

The Symbol Span subtest is a component of the Wechsler Memory Scale-Fourth Edition (WMS-IV, 2009a). This subtest was created as an image-based (visual) counterpart to the Digit Span subtest which is number-based. The symbol span subtest measures visuospatial working memory rather than verbal working memory (Wechsler, 2009a). This subtest assesses immediate memory for both symbols and their spatial locations, thus restricting the activation of the phonological loop during the task. The Symbol Span test is an integral component of the WMS-IV, as it involves the temporary storage and manipulation of visual and spatial information, tapping into the visuospatial sketchpad and central executive in Baddeley's (2000) model of working memory (Wechsler, 2009a). There is a modest correlation ($r = 0.47$) between the Symbol Span test and the Digit Span test, reflecting the central executive processing tapped by both subtests (Young et al., 2012).

Performance on the Symbol Span subtest, which requires participants to recall geometric symbols in the correct order and spatial arrangement, may be more effective in identifying new and emerging cognitive deficits than comparable verbal working memory measures. This is because visuospatial processing, being less automated and less ingrained in daily cognitive routines compared to verbal processing, places greater cognitive demands on individuals (Emrani et al., 2019; Tang et al., 2021). Interestingly, even in nonverbal tasks like the Symbol Span subtest, individuals often assign verbal labels to nonverbal stimuli, implicating the involvement of verbal cognitive operations. This reliance on verbal strategies may further increase cognitive demands, making such tasks particularly sensitive to detecting subtle impairments (Seabra et al., 2025; Taylor et al., 2016).

***n*-Back Task**

The *n*-back task, developed by Gevins and Cutillo (1993), is widely utilised in research to measure working memory (Meule, 2017). It operates by presenting participants with a continuous stream of items (e.g., letters, numbers, or spatial locations) and requiring them to indicate when the current item corresponds to the one that appeared n-steps prior in the sequence, where n can represent 1,2,3 or even 4. For instance, in a 2-back task, participants must respond when the current item is the same as the one presented two rounds before. This task requires maintaining and updating information in working memory, as well as monitoring the sequence of presented stimuli. This continuous monitoring and updating process is thought to engage the central executive component of working memory (Salminen et al., 2012; Wilhelm et al., 2013). Additionally, the *n*-back task's reliance on rapid processing and accurate response selection highlights its sensitivity to information processing speed (Miller et al., 2009). Despite its widespread use, some researchers argue that the *n*-back task may not effectively measure working memory capacity but instead information processing speed. For example, Miller et al., (2009) investigated if the *n*-back task is a valid measure of working memory in a sample with a mean age of 60, including both Parkinson's disease (PD) patients and healthy controls. The findings revealed that *n*-back accuracy did not correlate with the Digit Span Backward, a traditional working memory measure, but did show a significant correlation with processing speed, particularly the Trail Making Test Part A. This is particularly notable since processing speed is known to decline significantly in the Parkinson's population (Cholerton et al., 2021). Moreover, individuals with Parkinson's disease made more errors on the *n*-back task compared to the control group, suggesting that the *n*-back task may be more sensitive to deficits in processing and motor speed rather than purely reflecting working memory capacity.

Furthermore, in a study conducted by Jaeggi et al. (2010), using a sample with a mean age of 29.09 years, the *n*-back task and the reading span task were administered to assess working memory. The study discovered that the *n*-back task is only marginally associated to tasks typically used as complex working memory capacity tests, such as the reading span task, with correlation coefficients ranging from $r = .10$ to $r = .24$. This weak correlation suggests that the *n*-back task and reading span task may tap into different sub-components of working memory. The *n*-back task appears to rely more on processes based on familiarity and recognition whereas complex working memory span tasks like the readings span task emphasise active recall. Additionally, the study noted that the *n*-back task showed higher correlations with recognition tasks than with complex span tasks, and that modified variations of the original *n*-back task, which incorporate recall processes, tend to show stronger correlations (r = .55) with working memory measures like the operation span task. However, the mixed reliability results of the *n*-back task make it challenging to make definite conclusions about its concurrent validity (Jaeggi et al., 2010).

These findings collectively suggest that while the *n*-back task is a useful tool in cognitive research, it may not be a definitive measure of working memory capacity. Instead, its stronger correlation with processing speed and familiarity-based tasks highlights its potential utility in assessing these cognitive functions (Jaeggi et al., 2010; Miller et al., 2009; Redick & Lindsey, 2013).

Overall, the *n*-back task's validity as a pure measure of working memory remains debated. While it taps into important executive functions like attentional switching and updating, its weaker correlations with complex span tasks raise questions about its efficacy in assessing comprehensive working memory abilities (Miller et al., 2009). Therefore, researchers should carefully consider these limitations when interpreting *n*-back task performance in relation to working memory (Gajewski et al., 2018). In order to investigate this issue, in addition to working memory measures, the current study included a measure of information processing speed, the Symbol Digits Modalities Test.

Symbol Digits Modalities Test

The Symbol Digits Modality Test (SDMT) is a widely used tool for assessing cognitive impairment, particularly related to slowed information processing (Smith, 2007). Its value lies in its ability to measure several key cognitive domains, including attention, perceptual speed, motor coordination, visual scanning, working memory, and lexical access speed (Kiely et al., 2014). Notably, the SDMT is highly reliable in measuring perceptual processing speed, a cognitive ability that tends to decline with age, making it particularly useful in studies of age-related cognitive deterioration (Salthouse, 1996). This broad assessment of cognitive functions makes the SDMT sensitive to neurocognitive changes, making it a valuable tool for evaluating the efficacy of therapies and tracking disease progression over time (Benedict et al., 2017).

The SDMT requires participants to match symbols with corresponding numbers within a time limit, testing both visual scanning and motor coordination. Its dual format, offering both written and oral versions, allows it to be used across diverse settings and populations. For example, individuals with motor impairments can use the oral version, ensuring that physical disabilities do not affect cognitive performance results (Smith, 2007). Research has confirmed the SDMT's sensitivity to brain dysfunction.

Demographic factors, such as biological sex and socioeconomic status (SES), can influence working memory and information-processing ability (Vonk et al., 2020). In this study, we will examine how these two factors affect the relationship between working memory and processing speed.

Demographic Factors

This section examines the role of demographic variables, specifically biological sex and socioeconomic status (SES), in influencing cognitive task performance. Both variables were selected due to their links to working memory and information processing speed. Biological sex has been shown to influence cognitive performance, with differences observed between males and females, particularly in tasks related to working memory and processing speed (Loprinzi & Frith, 2018; Ivan et al., 2022). SES, on the other hand, has been chosen due to its potential impact on access to resources that influence cognitive development and performance (Rakesh et al., 2024). These variables are included to investigate how they may interact with cognitive abilities and to explore potential differences in performance across different demographic groups. The following sections will provide an overview of how each demographic factor is linked to cognitive functions and the specific tests used in this study

Biological Sex

Despite growing biological sex equality, biological sex differences still influence cognitive task performance, particularly working memory and information processing speed (Steffl et al., 2019). In this study biological sex refers to the classification assigned at birth based on an individual's physical and biological characteristics, such as chromosomes, hormones, and reproductive anatomy (National Institutes of Health, 2023).

Elosúa et al., (2017) showed that men and women exhibit distinct patterns in cognitive functions. Men tend to perform better than women in visuospatial tasks across different age groups and cognitive conditions. For instance, Elosúa et al., (2017) found that in patients with mild cognitive impairment (MCI), men achieved significantly higher results than women in visuospatial working memory tasks. This difference is also notable in the Corsi Block-Tapping test, where men with MCI performed better than women, indicating a biological sex-based disparity in visuospatial abilities for patients with MCI (Blokland et al., 2011). Additionally, a meta-analysis by Voyer et al. (2021) examined sex differences in verbal working memory across various age groups in healthy individuals, including the 18 to 29 age group. For this age group, task-specific differences were identified, with males showing an advantage in complex span and simple span tasks, which involve higher cognitive load and the manipulation of information. In contrast, females demonstrated an advantage in free recall tasks, where information is recalled in any order. No significant sex differences were observed in the cued tasks. These results suggest that sex differences in verbal working memory may fluctuate based on the nature of the task. Interestingly, Voyer et al. (2021) also found an overall male advantage in Visuospatial working memory across the lifespan when comparing different age categories.

Furthermore, Elosúa et al. (2017) reported that in verbal span tasks, such as the Digit Span and Semantic Fluency tests, there were no notable performance differences between healthy men and women and even among those with Alzheimer's disease (AD) or MCI. This finding suggests that biological sex does not significantly impact verbal working memory performance in these populations. The influence of biological sex on cognitive decline also varies by cognitive domain (Laws et al., 2016). Women with AD have been found to experience greater overall cognitive deterioration compared to men, particularly in visuospatial skills, although this is not consistently observed across all studies (Laws et al., 2016). Research by Gerstorf (2006) indicates that higher education levels in female AD patients might mitigate visuospatial deficits. This might suggest that educational background could interact with biological sex to influence cognitive outcomes (Gerstorf et al., 2006). Blasiman and Was (2018) further explored how task difficulty and individual differences impact working memory performance, noting that men and women might use different strategies to manage cognitive load, which can influence their performance outcomes.

Furthermore, in a study on biological sex differences in processing speed, it was found that biological sex differences in SDMT performance were not statistically significant (Sheridan et al., 2006). However, when examining correlations separately by biological sex, education had a significant impact on SDMT scores for women, with higher levels of education correlating with better performance on both written and oral administrations of the test. This effect was not observed in men, suggesting that educational attainment may play a more substantial role in influencing SDMT scores among women than men. Similarly, Ryan et al. (2020) found that although there were no significant overall biological sex differences in SDMT performance, socio-demographic factors, including age, education, and biological sex, moderated performance outcomes. Notably, women generally outperformed men except in sub-groups of highly educated males, indicating that education level may be a key factor in explaining differences in SDMT performance. Overall, both studies suggest that while biological sex alone does not significantly influence SDMT performance, education may have a more pronounced effect on women's performance, potentially compensating for any underlying differences.

Given the differential performance of females and males on working memory tasks based on the modality—verbal or visuospatial—it is essential to investigate biological sex differences in these cognitive domains. The findings suggest that while biological sex differences are evident in certain cognitive tasks, such as visuospatial working memory, they may not be as pronounced in others, such as verbal working memory or information processing speed. Therefore, further research is necessary to explore these nuances and to better comprehend how biological sex interacts with different cognitive modalities.

In addition to biological sex, SES is another important demographic factor that can influence cognitive performance. The following section will explore how SES impacts working memory and information processing speed, and how it interacts with biological sex to shape cognitive outcomes.

Socioeconomic Factors

Socioeconomic Status (SES) encompasses various aspects of an individual's social and economic standing, typically measured by family income, educational attainment, and parental occupation (Leonard et al., 2015). This multifaceted construct significantly impacts an individual's environment, influencing resource availability, degree of stress, and possibilities for cognitive development opportunities (Eid Abo Hamza et al., 2024). Understanding how SES influences cognitive functions like working memory and processing speed is essential for addressing educational and developmental disparities.

Low SES has been repeatedly linked to circumstances that may jeopardise the brain's anatomical and functional development, affecting cognitive processes like working memory and processing speed (Rakesh et al., 2024). For instance, children from low SES backgrounds often face poor nutrition, hindered access to educational opportunities, and higher exposure to stress and violence, which can negatively influence brain development (Duncan et al., 2017; Hamza et al., 2024). Several studies have identified specific neuroanatomical differences in children from low SES backgrounds, particularly in areas associated with executive functions and working memory (Noble et al., 2015). For example, Noble et al. (2015) found that the relationship between income and brain surface area is logarithmic, indicating that small differences in income can lead to significant differences in brain surface area among individuals from the lowest income families. This suggests that SES may influence brain structures important for working memory performance (Hackman et al., 2014; Lurie et al., 2024; Noble et al., 2015). Neuroanatomical variances, especially in areas crucial for executive function and language, have been observed in children from low SES backgrounds (Mackey et al., 2015; Noble et al., 2015). Empirical evidence shows an association between lower SES with poorer working memory performance. Rosen et al. (2018) found that children aged 6 to 19 years from lower SES backgrounds had significantly poorer working memory (Rosen et al., 2018). Similarly, Evans and Schamberg (2009) found an inverse relationship between childhood poverty and working memory performance in young adults, suggesting long-term cognitive impacts of early socioeconomic disadvantages (Evans & Schamberg, 2009). Another study by Evans et al. (2021) supported these findings, highlighting that young adults who experienced prolonged socioeconomic disadvantages exhibited lower working memory performance (Evans et al., 2021).

One proposed mechanism for the impact of SES on cognitive function is the role of stress. Lower SES environments often entail higher levels of persistent stress, which can impair neuroplasticity and cognitive development (Duncan et al., 2017; Evans, 2004). Beilock and DeCaro (2007) demonstrated that individuals with increased working memory capacities only performed better than those with lower capacities under low-stress conditions, indicating that stress can disproportionately affect those already at a cognitive disadvantage (Beilock & DeCaro, 2007). This finding is consistent with other research on the negative impacts of stress on working memory (Naninck et al., 2015; Lukasik et al., 2019; Shields et al., 2016).

Processing speed, another important cognitive function, is also influenced by SES. A study by Fry et al. (2017) found that young adults (aged 16-19) who experienced poverty or homelessness exhibited slower processing speeds in comparison to their peers who are not disadvantaged (Fry et al., 2017). This finding highlights the broader cognitive impacts of SES beyond working memory alone.

Interestingly, there is disagreement about whether SES may influence working memory and processing speed. Lower SES is associated with a range of environmental factors like poor nutrition and heightened stress, all impacting brain development and cognitive functions such as working memory and processing speed (Adler & Rehkopf, 2008; Evans, 2004; Hackman et al., 2010). Despite these challenges, individuals from low SES backgrounds may develop specialised cognitive skills, such as resourcefulness, potentially enhancing attention, memory, and learning (Ellis et al., 2017; Young et al., 2018).

While the majority of research highlights the negative impacts of low SES on cognitive development, some studies suggest a more nuanced view. Ellis et al. (2017) proposed that children raised in turbulent environments might acquire specialised cognitive skills tailored to their specific contexts (Ellis et al., 2017). For example, Young et al. (2018) found that adults who grew up in turbulent environments performed better on working memory tasks that require updating, suggesting that adaptive responses to environmental stressors may enhance certain cognitive functions (Young et al., 2018). In addition to these adaptive cognitive abilities, individuals from lower SES backgrounds often develop greater resourcefulness and resilience due to the necessity of navigating challenging environments with limited resources. This resourcefulness can manifest in various ways, such as enhanced problem-solving skills, creativity, and the ability to make efficient use of available resources. These skills are particularly crucial for adapting to and overcoming daily challenges and can contribute to cognitive flexibility and innovation (Ellis et al., 2017; Young et al., 2018).

The relationship between SES, working memory and processing speed is complex and multifaceted (Lurie et al., 2024). While low SES is generally associated with poorer cognitive performance, particularly in environments characterised by chronic stress and limited resources, there are instances where adaptive cognitive abilities emerge in response to these challenges (Ellis et al., 2017; Young et al., 2018). Therefore, it’s important to explore the association between SES and measures of working memory and processing speed.

Rationale and Aims of the Study

Research in cognitive psychology has focused on critical areas underlying general cognitive functioning, particularly working memory and information processing speed (Chai et al., 2018; van der Fels et al., 2015). Working memory is essential for learning, decision-making, and reasoning and has garnered substantial attention (Alloway & Copello, 2013; Baddeley, 1992). Similarly, information processing speed, marked by the rapid ability to process information, is intricately linked to the execution of higher-order cognitive tasks (Lichtenberger & Kaufman, 2012). Furthermore, information processing speed is linked to the effective functioning of the central nervous system (Covey et al., 2011; Salthouse, 1996). This connection is frequently acknowledged as a central factor contributing to challenges in executing complex cognitive measures across various age groups (Salthouse, 1996; Salthouse & Ferrer-Caja, 2003).

Working memory and processing speed each require accurate assessments of these abilities to conduct research that is valid, diagnose cognitive deficits and understand individual cognitive variations (Mahendran et al., 2015). The *n*-back test (Gevins & Cutillo, 1993), the Symbol Span subtest (WMS-IV; Wechsler, 2009a), and the Digit Span subtest (WAIS-IV-SA; Wechsler, 2014) are working memory tests that are commonly used in clinical and research contexts. However, there is ongoing debate about what the *n*-back test actually measures and whether it is possible to separate working memory and processing speed influences (Andrade, 2002). Related to this, conflicting views persist regarding the suitability of the *n*-back test as a measure of working memory (Jaeggi et al., 2010). Therefore, this study examined the relationship between three measures of working memory (the *n*-back test, the Digit Span test, and the Symbol Span test) and the Symbol Digit Modality Test (SDMT), a test of information processing speed. Furthermore, by examining these relationships, the study also investigated the concurrent and construct validity of the *n*-back test. The purpose of construct validity is to evaluate whether test scores are an accurate assessment of a particular construct, whereas concurrent validity is a measure's ability to accurately identify or diagnose an individual's current behaviour or status in terms of specified abilities or attributes (Roodt & Foxcroft, 2000; Murphy & Davidshofer, 2014).

Research Questions

This study aims to determine the relationships between the *n*-back, Digit Span, Symbol Span, and Symbol Digit Modality tests. Thus, the study will investigate the following questions

1. Is there a statistically significant relationship between the *n*-back, Digit Span, Symbol Span, and Symbol Digits Modality tests?
2. If there is a statistically significant relationships between the above tests, is the *n*-back test more strongly related to the working memory tests or to the processing speed test (SDMT)?
3. Are demographic factors (such as biological sex and socioeconomic status) of the participants significantly related with performance on each of the tests?

The following chapter will discuss the methods and materials used in this study.

Chapter 2: Method

This study investigates the relationship between working memory and information processing speed by evaluating the relationships between four commonly used cognitive tests. It specifically explores the potential associations between the *n*-back test, the Digit Span test, the Symbol Span test, and the Symbol Digit Modality Test (SDMT). By studying these relationships, the study contributes to the continuing discussion over the construct validity of the *n*-back test. This chapter discusses the study's design, sample and sampling, instruments, procedure, and ethical considerations.

Research Design

This research was conducted in two distinct phases, each addressing a specific aspect of the investigation. In the first section, participants completed the *n*-back, Digit Span, and Symbol Span tests, as well as the Symbol Digit Modality test. The focus of the first part of the study was on the behavioural data (i.e., scores) collected from these tests. The second section examined the impact of demographic variables, including biological sex and socioeconomic status (SES), on performance on these cognitive tests. Methodologically, the study adopted a post-positivist critical realism paradigm, acknowledging the influence of social conditioning on knowledge construction and the inherent subjectivity in research (Dobson, 2002). This paradigm emphasised the need to address researcher biases and acknowledged the imperfect nature of reality comprehension (Ryan, 2022; Trochim, 2020). The study employed a non-experimental, quantitative approach, utilising both correlational and cross-sectional designs to examine the relationships among the tests. A correlational design identified and measured the relationships between variables without manipulation from the researchers, aiming to determine the strength and direction of associations between variables (Curtis et al., 2016). Because data for each participant was gathered at a specific point in time, this study was also categorised as cross-sectional (Setia, 2016).

Sample and Sampling

The sample consisted of seventy participants selected through a non-probability convenience sampling method (Edgar & Manz, 2017). Thirty-nine participants were students from the Psychology Department at the University of the Witwatersrand. The remaining thirty-one participants, all young adults aged 18-25, were recruited via social media platforms in Pretoria, with some of these participants being further recruited through a snowball sampling method. No participants were excluded, as all their data could be collected. The age range of

18-25 was selected because it represents a period of peak cognitive abilities in young adults, and the sample was easily accessible through university networks and social media platforms (Hartshorne & Germine, 2015; Salthouse, 2000). The sample included thirty-nine Black participants, thirty White participants and one Coloured participant. Biological sex distribution included twenty-four males and forty-six females. Furthermore, participants' language backgrounds were as follows: thirty-three were multilingual, and thirty-seven were bilingual. However, language proficiency was not directly assessed. All participants were either currently pursuing or had completed a degree, ensuring they were test-wise and proficient in using computers and completing questionnaires. Since all participants had studied in English and were computer literate, they were considered adequately skilled in both the language and computer abilities necessary for completing the cognitive assessments, which were delivered in English, and some were computer-based tasks (specifically the *n*-back task).

Instruments

A demographic questionnaire was administered first to gather essential background information on participants, such as age, biological sex, socioeconomic status, and educational background. This information was important for examining how these demographic variables might influence performance on the cognitive tests. The selection of the cognitive instruments was guided by their established reliability and validity in assessing cognitive functions. Each participant completed a series of tests designed to evaluate different aspects of working memory and information processing speed. The instruments included the Digit Span Test, Symbol Span Test, *n*-back Test, and Symbol Digits Modality Test (SDMT). The following sections provide a comprehensive overview of each instrument, including their purpose, administration procedures, and psychometric properties.

Demographic Questionnaire

The self-reported demographic questionnaire (see Appendix A) captured data about the participants' sex, age, and educational background as well as the educational background and number of caregivers present when they grew up. The questionnaire also documented participants' self-reported vision, hearing, language and/or learning impairments, and neurological disorders. Neurological disorders, which can affect working memory and memory processing abilities, served as an exclusion criterion. The Demographic questionnaire also included the Living Standards Measure (SAARF, 2001). The LSM is used to assess socioeconomic status (SES). Participants responded to a series of true and false questions, with their SES score calculated by summing the total number of items they indicated as present in their lives. The lowest possible SES score was 0, indicating very low SES, while the highest score was 23, representing high SES. The questionnaire took approximately 15 minutes to complete. The information gained from this questionnaire helped to address the third research question: Were the relationships between the four tests related to the demographic factors (such as biological sex and socioeconomic status) of the participants?

Working Memory Measures

Participants completed a series of well-established working memory tests from the WAIS-IV-SA (Wechsler, 2014) and WMS-IV (Wechsler, 2009a). The following section provides a description of the three tests.

Digit Span Subtest (WAIS-IV; Wechsler, 2008a). The Digit Span Subtest, a component of the Wechsler Adult Intelligence Scale - Fourth Edition, South African standardisation (WAIS-IV-SA; Wechsler, 2014), is a commonly used task to measure verbal working memory abilities and is designed for individuals aged 16 years and older. Divided into three conditions, this subtest assesses verbal short-term memory and working memory abilities. In the Digit Span Forward task, participants heard a sequence of random numbers and were asked to recall them in the same order. Conversely, the Digit Span Backwards task required participants to recall a sequence of random numbers in reverse order, while the Digit Span Sequencing task involved recalling the numbers in ascending order. The numbers ranged from two to nine digits. The subtest comprised of eight sets, each containing two trials. Participants earned one point for every correctly recalled sequence, with a maximum possible raw score of 48 points. If a participant provided incorrect responses on both trials of the same item, the task was discontinued. The test took approximately fifteen minutes to complete. The WAIS-IV (Wechsler, 2008a) was standardised on a South African population, leading to the development of the WAIS-IV-SA (Wechsler, 2014). The normative sample for the WAIS-IV-SA was selected using a matrix designed by JvR Psychometrics, ensuring that the sample reflected the demographic proportions of the 2011 South African census (Wechsler, 2014). The final norm sample consisted of 433 individuals, with 49% male and 51% female, and a mean age of 28.41 years. The majority of the participants had a matric certificate. The age group of 20-24 years was specifically examined for psychometric properties because the current study's sample had a mean age of 21.48 years. The reliability for the 20-24 age group, as reported in the WAIS-IV-SA manual, was 0.88 for the Digit Span subtest. The reliability scores for each component of the Digit Span subtest were 0.84 for Digit Span Forward, 0.88 for Digit Span Backward, and

0.77 for Digit Span Sequencing in this age group. To assess the validity of the WAIS-IV-SA, effect sizes, including Cohen's d, were calculated and compared to the validated WAIS-IV (US version; Wechsler, 2008a). The analysis revealed medium to large effect sizes across all subtests, indicating that the WAIS-IV-SA is a valid assessment tool (Wechsler, 2014).

Symbol Span Subtest (WMS-IV; Wechsler, 2009a). Visuospatial working memory, or the capacity to retain and manage visual information in working memory, is assessed by the Symbol Span subtest (Wechsler, 2009a). A total of 26 items, ranging from one to seven linearly ordered symbols, were presented to the participants. The page containing the target symbols was taken down and substituted with a page that had foil and target symbols on it after five seconds of viewing. The previous display's symbols had to be recognised by the participants in the proper sequence from left to right. According to Emrani et al. (2019), this subtest evaluated memory for both the correct symbols and where they were in the sequence. One practice trial was provided in the Symbol Span subtest. One point was given for correctly recognising the symbols out of order, two points were provided for correctly identifying the symbols in the right sequence, and zero points were given for inaccurate or missing answers. In the event that participants made corrections, the updated replies were noted. After four consecutive incorrect scores (one or zero points), the test was discontinued. A maximum raw score of 50 points was produced by adding the total scores for each item. It took about fifteen minutes to finish the subtest. The Wechsler Memory Scale, Fourth Edition (WMS-IV) is widely used to assess memory functions in individuals aged 16 to 90. The WMS-IV was co-normed with the WAIS-IV using a normative sample of 1,400 examinees. The examinees consisted of 900 individuals who completed the Adult Battery and 500 who completed the Older Adult Battery (Wechsler, 2009a). The sample was stratified by biological sex, race/ethnicity (based on the 2005 US Census), and education level to ensure a representative distribution.

The WMS-IV demonstrates strong psychometric properties, with internal consistency reliability coefficients ranging from .93 to .97 and test-retest reliability for the adult battery indexes ranging from .77 to .95 (Wechsler, 2009a). The Symbol Span subtest within the WMS-IV measures visuospatial working memory and shows strong test-retest reliability (.83), although subsequent studies have found slightly lower reliability (.72) (Dzikon, 2020; Holdnack & Drozdick, 2010). Research suggests that the Symbol Span requires greater cognitive effort than verbal memory tasks and may be more sensitive in detecting emerging cognitive impairments, with performance reflecting a broader range of neurocognitive operations. Although the WMS-IV South African version is not available, the Symbol Span subtest is appropriate to use in South Africa because nonverbal visuospatial working memory is less influenced by language and cultural differences (Dutra et al., 2022).

***n*-Back task (Gevins & Cutillo, 1993).** The *n*-back task is frequently used in experimental studies to evaluate executive functions like updating and attentional switching as well as working memory load (Gajewski et al., 2018). In this study, OpenSesame (version 3.3.11; Mathôt et al., 2012) was used to administer a digital version of the *n*-back task, where participants viewed digits presented sequentially on a 17-inch monitor (Arial font, size 58; black background with white text; resolution: 1024 x 768 pixels). Participants in this activity had to select if the digit displayed on the screen matched the digit displayed in the previous 'n' trials (e.g., 1-digit back, 2-digit back, 3-digit back, etc.). Number 7 was absent since it has two syllables. Thus, only the numbers 1, 2, 3, 4, 5, 6, 8, and 9 were available.

Participants were instructed to press the "F" key on the keyboard (marked with a sticker as "S" for "same") when the current digit matched the one shown 'n' trials earlier. They pressed the "J" key (labeled "D" for "different") if the digit did not match the one presented 'n' trials before. This study included three working memory load conditions: 1-back, 2-back, and 3-back tasks. For instance, if the sequence of digits was 5, 9, 3, 2, 9, and 2, and "n" was set to "3," the correct response would be to press "S" when the second "9" appears, as it matches the digit shown three trials earlier.

Instructions were presented vocally and on screen for each of the *n*-back situations, using a similar strategy for each participant. Participants performed the 1-Back, 2-Back, and 3-Back tasks in that order. Participants completed 25 practice runs to ensure they understood the instructions for each *n*-back condition. In order to pass, they had to score at least 85% in the 1-Back practice condition (there were 25 stimuli in each block), 75% in the 2-Back practice condition (there were 25 stimuli in each block), and 70% in the 3-Back practice condition (there were 25 stimuli in each block). Up to three tries, or three "blocks," were allowed in each practice round to satisfy the requirements. The experiment was stopped if the conditions for the practice run were not fulfilled. Participants were sent to the experiment and instructed to react as fast and accurately as they could when they achieved the necessary level of accuracy in the practice round or rounds.

Using OpenSesame software (Mathôt et al., 2012), individual numbers were presented in a fixed position at the middle of the screen (500 ms), followed by an interstimulus delay (250 ms) indicated by a green cross. For every load condition, there were five blocks of 25 stimuli (i.e., 125 trials per condition). To lessen mental fatigue, participants were instructed to fixate on a green fixation cross in the middle of the computer screen during the 10-second intervals that occurred between each of the five blocks. Unlike the practice run, the participants in the experimental tasks moved on to the next block regardless of their accuracy in the previous block or blocks. Each block's stimuli were placed at random. For each *n*-back condition, recorded data comprised accuracy, average reaction time, and response correctness in addition to an overall average. Each experimental condition lasted roughly fifteen minutes, for a total of 45 minutes. Lastly, there were no limitations placed on the tactics the participants used (such as vocal rehearsing) during the task.

Information Processing Speed Measure

This section describes the instrument used to evaluate information processing speed in this study. The selected test, the Symbol Digits Modality Test (SDMT), is widely recognised for its effectiveness in measuring cognitive processing speed and was chosen for its established reliability and validity.

Symbol Digits Modalities Test (SDMT; Smith, 1973). The SDMT is a commonly used instrument that assesses both processing and motor speed in individuals aged 8-91 (Ebaid et al., 2017; Sherman et al., 2020). For this study, the paper-pencil version was used (a computerised version also exists). Participants are required to replace digits with corresponding abstract symbols by referring to a key, as swiftly as they can (Ryan et al., 2020).

The reference key is composed of nine abstract symbols, each matched with a number ranging from 1 to 9 (Smith, 1973). This task requires participants to quickly match each symbol with its corresponding number, assessing both processing speed and the ability to switch between visual and numeric information efficiently. Participants will be given 90 seconds to pair the numbers and the abstract symbols (Benedict et al., 2017). The score is the number of correctly coded objects, ranging from 0 to 110 in 90 seconds. It took the participants about five minutes to complete the entire test (Smith, 1973). Benedict et al. (2017) validated the SDMT as a reliable measure of cognitive processing speed in individuals with multiple sclerosis (MS), specifically in a population aged 18 to 65 years. Their findings showed strong correlations between SDMT performance and MRI metrics like brain atrophy and lesion burden, solidifying the test as an accurate indicator of cognitive impairments. A 4-point or 10% change in SDMT scores was found to be clinically significant, especially in detecting cognitive decline associated with MS relapses.

The reliability of the SDMT was further demonstrated by a normative sample of 80 adults, comprising 32 males and 48 females, with a mean age of 34.8 years (SD = 11.32). Each participant completed both the written and oral versions of the SDMT twice, with a 29-day gap between the two test administrations. Test-retest reliability for the written version, which will be used in this study, was found to be 0.8, confirming the test's strong psychometric properties (Sherman et al., 2020; Smith, 1973). The SDMT's validity was assessed by comparing non-clinical samples to clinical ones. A group of 206 undergraduate and graduate students from the University of Michigan completed the written version, and their mean scores were compared to those of clinical samples. The clinical group's scores were significantly lower, further establishing the SDMT's ability to detect cognitive impairments (Smith, 1973). The SDMT is a robust and versatile tool for measuring cognitive impairment and processing speed, and its perceived cultural neutrality makes it suitable for use across diverse populations without significant bias (Kiely et al., 2014). This cultural neutrality and the test's strong validity in assessing information processing speed are key reasons for its inclusion in the present study.

Procedure

An initial participant information sheet outlining the details of this study was sent to potential participants who expressed interest in taking part (see Appendix B). Interested individuals received an email with a survey-link. Participants then completed an online demographic questionnaire using the secure application Research Electronic Data Capture (REDCap) as part of the first phase of data collection (Harris et al., 2009). Upon completing the survey, participants used the Doodle booking system to select a convenient time and day for their in-person sessions. The second phase of the study involved face-to-face completion of the cognitive tests. Data collection took place in two settings to ensure a more diverse sample and increased participant numbers. The first setting was the Neuroscience Research Laboratory in the Emthonjeni Building on the University of the Witwatersrand's East Campus. The second setting was the Gesonde Self Sentrum in Pretoria, where similar lab conditions (well-lit and quiet rooms) were simulated. To prevent fatigue, data was collected in two sessions separated by a fifteen minute break. In the first session, participants completed the Digit Span and Symbol Span subtests, as well as the Symbol Digits Modality Test, using pencil and paper. While the pencil-and-paper tests were always administered together, a counterbalanced design helped mitigate the effects of fatigue and test order (Breakwell et al., 2020). Thus, the participants completed the sessions in different orders. The order of the test administration was noted. Additionally, each participant's preferred participation time (e.g., morning or afternoon) was recorded. All tasks were given in English with standardised instructions. Participants were urged to ask for clarity or help if they did not understand the tasks, and practice examples for each activity were provided to ensure understanding of the instructions and objectives. Each slot, consisting of two test sessions and a break, totalled approximately 90 minutes.

Ethical considerations

Before data collection commenced, ethics clearance was obtained from the Human Research Ethics Committee (HREC Non-medical) (see Appendix C). The following ethical principles were respected in the study: Participation in this study was optional, and participants could withdraw at any time without penalty. Participants did not receive an incentive to participate in the study. All participants received an information sheet (See Appendix B: participant information sheet) that explained the purpose of the study and provided them with information about the process of the study. Furthermore, participants were required to complete a consent form (Appendix D). As all participants were over eighteen, formal consent was obtained. The consent form was made available through the REDCap online platform. Since the data collection took place face-to-face, complete anonymity for the participants was not possible. However, confidentiality was assured using participant identifier codes, ensuring their anonymity once the data was captured. Additionally, all personal information was kept confidential and stored securely on password-protected devices. No individual results were reported; only group results were calculated and analysed. The information that connected participants' codes to their real names was only available to me and my supervisor, Kate Cockcroft, and was necessary in case the data needed to be double checked.

Participants were informed that the collected data would be used in a research report, for further analysis, and possible conference papers and/or journal articles. The data collected was kept secure on a password-protected removable external hard drive/flash stick accessible only to the researcher and her supervisor. Participants were informed that they could access the study's findings upon request. The information letter provided an email address, and participants were encouraged to contact the researcher at the end of the year to request a copy of the completed research report. The data was securely stored on a password-protected removable external hard drive/flash drive accessible only to the researcher and her supervisor. The data will be stored indefinitely, and any future use beyond the outlined purposes will be subject to review and approval by the HREC.

Data Analysis

The IBM SPSS Statistics Data Editor (version 29) package was utilised to analyse all data collected in this research study. Descriptive statistics, including histograms for each variable, were used to summarise and depict the raw scores of the working memory and processing speed tests. Skewness and kurtosis were computed to assess the normality of variable distributions. Although some data indicated a non-normal distribution, means were used instead of medians for consistency in reporting results. Both parametric and non-parametric tests were employed, depending on normality assumptions. Non-parametric methods were primarily used when applicable, but in some cases, robust non-parametric analyses were unavailable, so parametric tests were used instead. While the median is more robust in the presence of skewed data or outliers, the mean still remains a widely used and informative measure of central tendency when paired with appropriate statistical methods to account for non-normal distributions (Laerd Statistics, 2018).

Furthermore, correlational analyses were conducted to explore the relationships between working memory, processing speed, and demographic factors. Multiple regression analyses were run to examine the predictive power of these variables on performance on the *n*-back test. To further investigate whether demographic factors moderate the relationship between processing speed and working memory performance, a moderation analysis was conducted using the PROCESS macro (Hayes, 2013) in SPSS. Hierarchical moderated regression analyses, the Mann-Whitney U test, and ANOVA were also employed to examine the role of demographic variables in cognitive performance. Finally, multiple regression analyses assessed whether the Digit Span and Symbol Span subtests, along with demographic factors, predicted *n*-back performance, addressing the study's second and third research questions. A more detailed discussion of these analyses will be provided in the next chapter.

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Chapter 3: Results

This study used a variety of commonly used cognitive tests to investigate the concepts of working memory and information processing speed. The main aim was to determine the relationship between three measures of working memory—the *n*-back test, the Digit Span subtest, and the Symbol Span subtest—and the Symbol Digits Modality Test, which assesses information processing speed. The objective was to ascertain whether the *n*-back test is more closely related to the processing speed measure or if it draws from the same (or comparable) underlying cognitive processes as the recognised measures of working memory. This study also investigated whether demographic characteristics such as biological sex and socioeconomic background predicted variation in performance on various cognitive measures. Understanding these influences is important because cognitive abilities are shaped by a combination of biological and environmental factors (Tucker-Drob et al., 2013). Identifying such effects can provide insight into potential disparities.

The theoretical and conceptual frameworks for working memory and information processing speed were discussed in previous chapters. Chapter 1 covered an investigation of the potential correlations between the *n*-back, Digit Span, Symbol Span, and Symbol Digits Modality tests, as well as the reason for integrating demographic data. Chapter 2 described the study's non-experimental, cross-sectional research design, as well as the specific methods employed to investigate the research topics.

This chapter presents the study's outcomes. First, descriptive data were generated to provide an overview of the sample's sociodemographic profile. Second, correlation analyses were conducted to investigate preliminary relationships between working memory and processing speed measures, thereby answering the first research question: Does the *n*-back task correlate more strongly with working memory tests (Digit Span and Symbol Span) or processing speed tests (Symbol Digits Modality Test)?

Analyses were conducted to examine the role of demographic factors in cognitive performance. As mentioned earlier hierarchical moderated regression, the Mann-Whitney U test, and ANOVA were used to explore these relationships. Multiple regression analyses addressed the second and third research questions by assessing whether the Digit Span and Symbol Span subtests, along with demographic factors, predicted *n*-back performance.

Descriptive Statistics

This section provides an overview of the data used in the analysis, starting with a detailed description of the variables and the approach taken to assess their suitability for parametric testing. Following this, the sociodemographic profile of the participants is presented to offer context for the sample. Finally, the performance outcomes on the cognitive tasks, including the Digit Span, Symbol Span, SDMT, and *n*-back tests, are discussed to give a comprehensive understanding of the key variables analysed in the study.

Determining Parametric Analysis Suitability

Data eligibility for parametric analysis was determined by analysing three crucial assumptions: random independent sampling, the absence of extreme outliers, and an approximately normal distribution of test results (Field, 2018). Even though this study used a convenience sample of participants, efforts were taken to randomise the order in which the working memory assessments were given. Each participant took the tests only once to ensure the independence of their observations.

The cognitive tests produced continuous scores, which are essential for parametric analysis. The Digit Span subtest included three conditions—Forwards, Backwards, and Sequencing. Each condition had a maximum possible score of 16 points, with a total of 48 points. Similarly, the Symbol Span subtest had a maximum possible score of 50 points, the *n*-back test had a maximum score of 75 points across conditions, and the Symbol Digits Modality Test had a maximum score of 110 points. Boxplots were generated for all cognitive measures to check for potential outliers, as extreme values could skew the results, particularly in small samples (Field, 2018). Although minor outliers were detected, none were considered extreme enough to significantly impact the analysis. Outliers were carefully evaluated, as excluding them without justification can distort the analysis (Gress et al., 2018).

The normality of the cognitive variables was assessed using skewness, kurtosis, and the Kolmogorov-Smirnov test to determine the suitability of parametric statistical methods for data analysis. The Kolmogorov-Smirnov test was chosen due to the larger sample size (n=70), as it is more appropriate for detecting deviations from normality in such cases (Mishra et al., 2019). For the Digit Span subtests—Digit Span Forwards, Digit Span Backwards, and Digit Span Sequencing—skewness and kurtosis values were close to zero, indicating near-symmetric distributions (Appendix E). Specifically, Digit Span Forwards had skewness of -.138 and kurtosis of -.255; Digit Span Backwards had skewness of .076 and kurtosis of -.247; and Digit Span Sequencing had skewness of .266 and kurtosis of .015. The Kolmogorov-Smirnov test results indicated that Digit Span Total ($p = .200$) did not significantly deviate from normality, while Digit Span Forwards ($p = .050$) was at the significance threshold, suggesting marginal deviation. In contrast, Digit Span Backwards ($p < .001$) and Digit Span Sequencing ($p = .004$)

demonstrated significant deviations, indicating non-normal distributions for these subtests. Similarly, the Symbol Span subtest displayed acceptable skewness (-.488) and kurtosis (-.303) values, with a non-significant Kolmogorov-Smirnov result (p = .200), suggesting approximate normality. The SDMT variable also demonstrated acceptable skewness (.093) and kurtosis (.265), with a non-significant Kolmogorov-Smirnov result (p = .077), indicating a normal distribution. These results support the use of parametric tests for Digit Span Total, Digit Span Forwards, Symbol Span, and SDMT, while caution is advised for Digit Span Backwards and Digit Span Sequencing due to their significant deviations from normality.

The *n*-back test results revealed varying degrees of normality across conditions and the total scores. The 1-back accuracy score showed significant deviation from normality, with high negative skewness (-1.588) and kurtosis (3.660), supported by a significant Kolmogorov-Smirnov result (p < .001), indicating a non-normal distribution. Similarly, the 2-back accuracy score exhibited pronounced non-normality, with skewness of -1.773 and kurtosis of 6.477, and a significant Kolmogorov-Smirnov test (p = .005). In contrast, the 3-back accuracy score was closer to a normal distribution, with skewness (.054) and kurtosis (-.493) near zero and a non-significant Kolmogorov-Smirnov test (p = .200). The total accuracy across *n*-back conditions showed skewness (-0.477) and kurtosis (-.057) values near zero, with a non-significant Kolmogorov-Smirnov test result (p = .200). For the reaction times across the *n*-back conditions, skewness and kurtosis were within acceptable limits, with non-significant Kolmogorov-Smirnov values for 1-back (p = .200), 2-back (p = .028), and 3-back (p = .098) reaction times. The total reaction time across *n*-back tasks displayed skewness (.547) and kurtosis (-.095) within acceptable limits; however, the Kolmogorov-Smirnov test was significant (p = .027). The socioeconomic status (SES) variable demonstrated negative skewness (-.834) and mild kurtosis (.452), indicating a slight leftward skew in the distribution, with more participants clustered toward the higher end of the SES scale. The Kolmogorov-Smirnov test was also significant (p = .046), which means it is not normal and suggests that the data deviates from a normal distribution.

Based on these results, most variables, including the Digit Span Total, Digit Span Forwards, Symbol Span, and SDMT, demonstrated approximate normality. However, significant deviations from normality were observed in the Digit Span Backwards, Digit Span Sequencing, key *n*-back accuracy scores, and the socioeconomic status variable. Given these findings, non-parametric methods (where available) were applied for variables showing non-normal distributions, particularly the *n*-back accuracy and socioeconomic status measures, to ensure the robustness of the statistical analyses. Parametric methods were used for variables that exhibited normal distributions.

The sociodemographic information of the participants

The sociodemographic profile of the participants (Table 1) in this study offers a comprehensive overview of their backgrounds. The sample consisted of 70 participants who were predominantly females (67.1%). The mean age of the sample was 21.48 years (SD = 2.00). The majority of participants (92.9%) reported attending primary school. Regarding parental marital status, a significant proportion of participants' parents were married (40%).

In terms of parental education, there was a clear trend toward higher education since a substantial percentage (61.4%) of participants' mothers had completed tertiary education, and a similar percentage (61.4%) of fathers had done the same. Most participants (61.4%) reported having two caregivers. Lastly, the language competency of participants showed a nearly even split, with 52.9% identifying as bilingual and 47.1% as multilingual. These sociodemographic characteristics highlight the demographic and background factors that characterise the sample, particularly in terms of education, family structure, and language proficiency.

Table 1

The sociodemographic profile of the participants.

Demographic variable	Frequency	Percent (%)
Biological Sex		
Female	47	67.1
Male	23	32.9
Primary School Attendance		
No	5	7.1
Yes	65	92.9
Parent Marital Status		
Divorced/separated	19	27.1
Living together as husband and wife	7	10.0

Demographic variable	Frequency	Percent (%)
Married	28	40.0
Other	6	8.6
Widow/widower	10	14.3
Parent education (Mother)		
Less than primary school completed	1	1.4
Other	1	1.4
Primary school completed	3	4.3
Secondary school completed	22	31.4
Tertiary school completed	43	61.4
Less than primary school completed	1	1.4
Parent education (Father)		
Less than primary school completed	2	2.9
Other	3	4.3
Primary school completed	2	2.9
Secondary school completed	20	28.6
Tertiary school completed	43	61.4
Less than primary school completed	2	2.9
Number of Caregivers		
>2	11	15.7
1	16	22.9

Demographic variable	Frequency	Percent (%)
2	43	61.4
Language Competency		
Bilingual	37	52.9
Multilingual	33	47.1

The socioeconomic status (SES) of the participants was assessed using a scale ranging from 1 (low) to 23 (high). The mean SES score was 15.66 (SD = 4.35), indicating that, on average, participants tended to fall in the middle to upper-middle range of the socioeconomic spectrum. Despite this, there were participants in the sample from lower SES backgrounds, allowing for some SES diversity. This range may provide valuable insights when examining the relationships between socioeconomic status and cognitive performance.

Descriptive Statistics for the Cognitive Variables

The primary aim of the statistical analysis was to evaluate the *n*-back test's construct validity by determining whether it correlates more strongly with other working memory measures (Digit Span and Symbol Span) or with the information processing speed measure (Symbol Digits Modality Test). Table 2 provides descriptive statistics for these cognitive tests across the sample of 70 participants. Raw scores were used for all measures.

Table 2

Descriptive Statistics for Cognitive Tests.

Working Memory Tests	N	Minimum	Maximum	Mean	Std. Deviation
Digit Span Subtest					
Forwards	70	4	15	10.03	2.31
Backwards	70	3	12	7.64	1.87
Sequencing	70	4	13	7.76	1.72
Digit Span Total	70	15	36	25.43	4.72

Working Memory Tests	N	Minimum	Maximum	Mean	Std. Deviation
Symbol Span Subtest	70	6	38	24.71	7.37
***n*-Back Task**					
1-Back Test Accuracy	70	57	75	70.91	3.40
1-Back No Response	70	0	3	.71	.950
1-Back Test RT	70	458.77	1330.39	754.63	172.17
2-Back Test Accuracy	70	31	75	64.33	6.95
2-Back No Response	70	0	10	.70	1.5
2-Back Test RT	70	406.28	1313.67	781.66	209.73
3-Back Test Accuracy	70	45	74	59.80	7.06
3-Back No Response	70	0	5	.46	1.03
3-Back Test RT	70	425.10	1304.04	770.96	198.0
n-Back Test Accuracy	70	159	222	195.04	13.2
n-Back No Response	70	0	17	1.87	2.58
n-Back Test RT	70	489.92	1171.02	769.08	165.15
Processing Speed Measure	N	Minimum	Maximum	Mean	Std. Deviation
SDMT	70	20	82	51.79	11.88

Notes. RT – Reaction Time in Milliseconds. SDMT – Symbol Digits Modalities Test. Digit Span accuracy refers to the number of correct responses. N=70.

The Digit Span subtest allows a maximum score of 16 per condition, resulting in a combined total score of 48. The most variability was observed in the Forwards condition (SD = 2.31). This suggests differences in participants' passive storage capabilities.

The Backwards (SD = 1.87) and Sequencing (SD = 1.72) conditions displayed lower variability, possibly reflecting the similar working memory demands involved in these tasks, where participants must actively manipulate information rather than merely store it. These results align with the expectation that Digit Span Forwards is less demanding on working memory, as it primarily assesses simple storage, while Backwards and Sequencing involve more complex manipulation processes (St Clair-Thompson & Allen, 2012; Weiss et al., 2016). Furthermore, the Symbol Span subtest had an average score of 24.71 (SD = 7.37) out of a possible 50, showing moderate variability. This similarity in average performance and variability between the visuospatial working memory task (Symbol Span) and the verbal working memory tasks (Digit Span) is consistent with the expectation that Symbol Span also taps into working memory processes, albeit through a non-verbal format (Park & Jon, 2018). However, this will be further explored when looking at the correlations.

Lastly, for the *n*-back test, accuracy scores decreased as task difficulty increased, which is expected given the increased working memory demands of each condition. Specifically, participants achieved the highest accuracy in the 1-back condition (M = 70.91, SD = 3.40) and the lowest in the 3-back condition (M = 59.80, SD = 7.06). Reaction times also increased with task difficulty, suggesting that participants took longer to respond as they engaged in higher levels of cognitive control and working memory. Next, we will proceed to inferential statistics to investigate the relationships between these cognitive measures in greater depth.

Inferential Statistics

This section presents the inferential statistical analyses performed to address the research questions. The primary aim was to determine whether the *n*-back test correlates more strongly with working memory measures (Digit Span and Symbol Span) or with the processing speed measure (Symbol Digits Modality Test) in order to evaluate the construct validity of the *n*-back test. Kendall's rank correlation coefficients (commonly referred to as Kendall's tau) were calculated to assess the relationships between these cognitive tests. Additionally, multiple regression analyses were conducted to explore the extent to which the working memory and information processing speed tests predicted performance on the *n*-back test. The results of these analyses provide insight into the predictive value of the cognitive tests and the role of demographic factors in influencing cognitive performance.

Correlational Analyses

Correlation is usually regarded as descriptive (and not inferential) of the patterns of relationships. Since the assumption of normality was not met for several key variables, a non-parametric correlation was used to examine the relationships between working memory and processing speed measures. Kendall's rank correlation coefficient was chosen over Spearman's correlation coefficient because the former not only handles non-normal data, but it also provides a more reliable measure of correlation, particularly in datasets with smaller sample sizes or numerous tied ranks (Laerd Statistics, 2018). Kendall's rank correlation coefficient offers better statistical power and consistency in such cases, making it well-suited for analysing the nuanced relationships in this study, such as those between *n*-back accuracy scores and socioeconomic status. Additionally, it is less sensitive to outliers, further enhancing its robustness compared to Spearman's correlation coefficient (Arndt et al., 1999; Laerd Statistics, 2018).

Table 3 shows the Kendall's rank correlation, conducted to investigate whether the *n*-back test correlated more strongly with working memory measures (Digit Span and Symbol Span subtests) or with the processing speed measure (Symbol Digits Modality Test). The Kendall's rank correlation was also used to assess whether demographic factors, such as SES, were significantly related to performance on any of the cognitive tests.

Table 3

Kendall's Rank Correlations Between Cognitive Test Performance and the Interval Demographic Variable (N=70)

	Digit (F)	Digit (B)	Digit (S)	Digit T	SS	SDMT	1-BA	1-RT	2-BA	2-BRT	3-BA	3-BRT	N-BA	N-BRT	SES
Digit (F)	--														
Digit (B)	.391**	--													
Digit (S)	.313**	.380**	--												
Digit T	.677**	.667**	.611**	--											
SS	.222*	.191*	.110	.222**	--										
SDMT	.165	.274**	.168	.236**	.122	--									
1-BA	-.043	-.027	-.011	-.042	.054	-.004	--								
1-BRT	.022	.050	.120	.059	-.086	.134	-.168*	--							
2-BA	.149	.134	.224*	.187*	.035	.294**	.085	-.011	--						
2-BRT	-.042	.009	.038	-.005	-.032	-.057	.176*	.425**	-.084	--					
3-BA	.077	.113	.115	.128	-.037	.292**	.135	-.026	.403**	-.060	--				
3-BRT	-.018	-.047	-.034	-.057	-.091	-.106	.104	.310**	.073	.519**	.019	--			
N-BA	.100	.115	.151	.143	.007	.280**	.301**	-.093	.627**	-.064	.718**	.025	--		
N-BRT	-.027	.015	.038	.003	-.066	-.054	.074	.564**	-.017	.755**	-.048	.641**	-.057	--	
SES	.057	.126	.148	.130	.078	.351**	-.091	.240**	.204*	.124	.194*	.115	.166*	.156	--

Notes. N=70; RT = Reaction Time in Milliseconds; SES = Socioeconomic Demographic Questionnaire Score; n-back = Total reaction time and correct answers for the n-back test (N1-3); Digit (F/B/S/T) = Digit Span Forward, Backward, Sequencing, Total; SS = Symbol Span; SDMT = Symbol Digits Modalities Test; 1/2/3-BRT = Average RT for 1/2/3-Back; 1/2/3-BA = Accuracy for 1/2/3-Back; N-BA = Total n-back correct; N-RT = Average n-back RT. $^{*}p < .05$; $^{**}p < .01$.

Table 3 showed strong positive correlations among the Digit Span subtests, demonstrating their shared reliance on working memory processes. Digit Span Forward correlated significantly with Digit Span Backward, τ (70) = .391, *p* < .001, and Sequencing, τ (70) = .313, *p* < .001. Similarly, Backward and Sequencing were strongly correlated, τ (70) = .380, *p* < .001. These intercorrelations confirm that the Digit Span subtests measure overlapping components of working memory, with Digits Forward focusing on passive storage and Backward and Sequencing involving more complex manipulation (Lumpkin & Sheerin, 2018). As expected, the Digit Span Forward and Backward subtests were also significantly correlated to the Symbol Span test. Even though the Symbol Span test is a measure of visuospatial working memory and Digit span a test of verbal working memory both tap into similar working memory processes (Young et al., 2012). However, the Digit Span sequencing subtest was not significantly correlated. This could potentially be due the fact that the sequencing subtest requires updating and monitoring which is not required to the same extent in the Symbol Span test (Holdnack, 2019).

For the *n*-back test, intercorrelations among its conditions revealed a progressive increase in shared variance as task complexity increased. The 1-back accuracy score had weak, non-significant correlations with 2-back accuracy, τ (70) = .085, *p* = .328, and 3-back accuracy, τ (70) =.135, *p* =.119, suggesting that performance in simpler tasks is not related to performance in more complex tasks. However, a moderate and significant correlation between 2-back and 3-back accuracy, τ (70) =.403, *p* < .001, indicates shared working memory demands in the higher complexity conditions. Similarly, reaction times in milliseconds (RT) across the *n*-back conditions demonstrated consistency, with significant correlations between 1-back and 2-back RT, τ (70) = .425, *p* < .001, and between 2-back and 3-back RT, τ (70) = .519, *p* < .001. These findings suggest that while simpler tasks like 1-back are less related to performance in complex tasks.

In Table 3 the only significant relationship found between the *n*-back task and the working memory tests were between 2-back accuracy and Digit Span sequencing. This could, once again, be due to the fact that both of these tests require active updating and monitoring (Holdnack, 2019).

To address whether the *n*-back test is more strongly related to working memory or processing speed measures, correlations between SDMT and *n*-back scores were analysed. While the total *n*-back accuracy score (N-BA) showed a significant correlation with SDMT, τ (70) = .280, *p* < .001, individual *n*-back conditions provided greater insight. SDMT scores were significantly correlated with 2-back accuracy, τ (70) = .294, *p* < .001, and 3-back accuracy, τ

(70) = .292, $p < .001$, indicating that processing speed is particularly relevant for more complex *n*-back tasks. No significant correlations were observed between SDMT and 1-back accuracy, τ (70) = -.004, $p = .959$, or *n*-back reaction times across conditions. These results suggest that the *n*-back test, particularly in the more demanding 2-back and 3-back conditions, relies more on information processing speed.

To explore the influence of SES, correlations with cognitive performance were analysed. SES demonstrated a significant positive correlation with processing speed, as measured by SDMT, τ (70) = .351, $p < .001$, suggesting that participants from higher SES backgrounds generally processed information more quickly. Furthermore, SES was significantly correlated with accuracy in the 2-back condition, τ (70) = .204, $p = .018$, and the 3-back condition, τ (70) = .194, $p = .023$, indicating that higher SES may provide an advantage in tasks with higher working memory demands. Interestingly, SES also showed a positive correlation with 1-back reaction time, τ (70) = .240, $p = .004$, suggesting that participants from higher SES backgrounds might approach simpler tasks more cautiously or strategically, potentially reflecting a different approach to cognitive problem-solving. Furthermore, SES did not show any significant correlations with any of the working memory tests.

Demographic Variables

A Mann-Whitney U test was conducted to assess differences in performance of biological males and biological females (a dichotomous variable) on the cognitive tests, namely the *n*-back test, Digit Span, Symbol Span, and Symbol Digits Modality Test. The Mann-Whitney U test was chosen over the point-biserial correlation because the former is a non-parametric test that assesses differences between two independent groups, making it ideal for this comparison (biological males versus biological females; Laerd Statistics, 2013). Additionally, it does not require the assumption of normality, which was necessary due to the non-normal distribution of some cognitive test scores in this dataset. Unlike the point-biserial correlation, which only measures the strength of the relationship between a dichotomous and continuous variable, the Mann-Whitney U test is specifically designed to identify statistically significant differences between groups (biological sex in this case) on continuous or ordinal variables (Laerd Statistics, 2013; Schutte & Axelrod, 2011). This made it an appropriate choice for these analyses. The results of these analyses are presented in Table 4.

Table 4

Mann-Whitney U Test Results Comparing Cognitive Task Performance by Biological Sex.

	Digit (F)	Digit (B)	Digit (S)	Digit T	SS	SDMT	1-BA	1-NR	1-RT	2-BA	2-NR	2-RT	3-BA	3-NR	3-RT	N-BA	3-NR	N-RT	SES
Mann-Whitney U	488.5	370.0	468.0	411.5	501.5	418.5	437.5	529.5	402.0	391.0	514.0	448.0	295.5	387.0	454.0	329.0	436.0	420.0	434.0
Z	-.656	-2.16	-.922	-1.617	-.488	-1.527	-1.29	-.154	-1.732	-1.873	-.394	-1.157	-3.068	-2.467	-1.082	-2.646	-1.34	-1.51	-1.34
Asymp. Sig. (2-tailed)	.512	.031*	.356	.106	.625	.127	.194	.878	.083	.061	.694	.247	.002**	.014*	.279	.008**	.179	.132	.182

a. Grouping Variable: Biological Sex.

*Notes. N=70; RT = Reaction Time in Milliseconds; SES = Socioeconomic Demographic Questionnaire Score; n-back = Total reaction time and correct answers for the n-back test (N1-3); Digit (F/B/S/T) = Digit Span Forward, Backward, Sequencing, Total; SS = Symbol Span; SDMT = Symbol Digits Modalities Test; 1/2/3-BRT = Average RT for 1/2/3-back; 1/2/3-BA = Accuracy for 1/2/3-back; N-BA = Total n-back correct; N-RT = Average n-back RT; *p< .05; **p<.01*

Mann-Whitney U tests revealed significant biological sex differences in performance across several cognitive tasks. For the overall *n*-back accuracy, males scored significantly higher than females (U = 329.00, z = -2.65, p = .008), reflecting stronger performance across some of the *n*-back conditions. Specifically, In the 3-back accuracy scores, males performed significantly better than females (U = 295.50, z = -3.07, p = .002). Furthermore, for the 3-back no-response condition, females exhibited significantly more non-responses compared to males (U = 387.00, z = -2.47, p = .014), which may suggest differences in task engagement or response strategies under high working memory load. For the Digit Span Backwards (Digit B) subtest, a significant difference was observed (U = 370.00, z = -2.16, p = .031), with males achieving higher scores than females. These results indicate that differences in performance between biological sex may emerge depending on the specific demands of the task.

The Effect of Test Order

A Mann-Whitney U test was conducted to compare performance on the working memory tests based on the order in which the tests were administered. Total scores were used to conduct these analyses.

In one condition, participants completed the Digit Span, Symbol Span, and Symbol Digits Modalities Test (SDMT) in a first session, followed by the *n*-back test in a second session after a break. In the second condition, participants began with the *n*-back test before completing the SDMT, Digit Span, and Symbol Span tests. This variation was implemented to allow for the statistical control of any differences in test order, should they emerge, as order effects such as fatigue or practice could potentially influence performance outcomes (Süss & Schmiedek, 2000). As the data did not match normality assumptions, a Mann-Whitney U test was used to compare participants' total scores on the working memory and processing speed assessments based on the order in which they were administered. The Kolmogorov-Smirnov test, skewness, and kurtosis values, as well as visual inspection of Q-Q plots and histograms, revealed that the scores for the working memory tests were not normally distributed. This indicated that the Mann-Whitney U test was the best option (Laerd Statistics, 2013). The results are presented in Table 5.

Table 5

Mann-Whitney U Test Results Comparing Cognitive Task Performance by Test Order.

	Digit T	SS	SDMT	N-BA	N-RT
Mann-Whitney U	449.000	488.500	459.000	558.000	556.000
Z	-1.670	-1.194	-1.548	-.360	-.384
Asymp. Sig. (2-tailed)	.095	.232	.122	.719	.701

a. Grouping Variable: Test Order

Notes. Digit T: Digit Span Total. SS: Symbol Span total. SDMT: Symbol Digits Modalities Test. N-BA: Total n-back correct. RT: Reaction Time measured in Milliseconds. N=70.

From Table 5, the Mann-Whitney U tests revealed no statistically significant differences in performance between the two test order groups across the Digit Span Total, Symbol Span, SDMT, *n*-back Accuracy, and *n*-back Total Average Reaction Time (all p-values > .05). Therefore, the order in which the tests were administered did not significantly influence performance on these cognitive tasks.

Differences Across SES Groups

The SES variable, originally a continuous variable ranging from 1-23 (where 1 is considered low SES and 23 is considered high SES), was grouped into three categories to enhance interpretability between SES levels and cognitive test scores. While discretisation is often considered a downgrading of measurement, it can provide unique insights by enabling researchers to examine relationships across clearly defined categories, such as SES levels. This approach aligns with research practices that use discretisation to explore meaningful patterns and associations that may not be as clear as in continuous data (Kim & Frisby, 2018; Maslove et al., 2013). However, conclusions must be made with caution as discretisation can lead to oversimplification and loss of information in data sets (Jin et al., 2008). The SES scores were divided into three groups based on their range: scores from 1 to 8 were categorised as low SES, scores from 9 to 16 as medium SES, and scores from 17 to 23 as high SES. Below in table 6 it shows the mean SES score for each of the SES categories.

Table 6

Mean SES Scores by SES Category

SES Category	Mean Score
Low	5.8
Medium	13.44
High	19.30

In order to assess whether there were significant differences in cognitive test scores across SES groups, a parametric test was used. Although the SES variable itself was found to be skewed, the assumptions of parametric tests like ANOVA primarily require that the dependent variables, in this case, the cognitive test scores, are normally distributed within each group of the independent variable (SES; Field, 2018). Since the normality assumption applies to the dependent variables and they were found to be approximately normal (Appendix F), ANOVA was deemed appropriate. ANOVA was used instead of t-tests because it allows for the comparison of more than two groups (low, medium, and high SES) simultaneously, whereas t-tests are limited to comparing only two groups at a time (Kim, 2014).

The key assumptions of ANOVA include the normality of the dependent variables within each SES group, the homogeneity of variances (i.e., the variance of cognitive scores should be similar across SES groups, tested using Levene's test), and the independence of observations (i.e., the data points within each group must be independent of each other; Field, 2018). For all the cognitive tests listed (Digit Span Total, Symbol Span, SDMT, *n*-back Test Accuracy, and *n*-back Test Total Average Reaction Time), the *p*-values for Levene's Test > .05, indicating that the assumption of homogeneity of variances has been met across the SES groups. Furthermore, each test could only be completed once, and they were each taken independently of each other thus the assumption for independence of observations have also been met. As all assumptions were reasonably met, ANOVA was used to determine whether there were statistically significant differences in cognitive performance across the SES groups.

Table 7

ANOVA Results for Cognitive Test Performance Across Socioeconomic Status (SES) Groups.

1-way ANOVA		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
Digit Span Total	Between Groups	74.9	2	37.48	1.72	.19
	Within Groups	1462.19	67	21.82		
	Total	1537.14	69			
Symbol Span	Between Groups	145.27	2	72.64	1.35	.27
	Within Groups	3605.02	67	53.81		
	Total	3750.29	69			
SDMT	Between Groups	1761.55	2	880.77	7.40	.001*
	Within Groups	7974.24	67	119.02		
	Total	9735.79	69			
***n*-Back Test Accuracy**	Between Groups	870.53	2	435.26	2.58	.083
	Within Groups	11314.35	67	168.87		
	Total	12184.87	69			
***n*-Back Test Total Average Reaction Time (ms)**	Between Groups	152623.79	2	76311.89	2.96	.059
	Within Groups	1729348.83	67	25811.18		
	Total	1881972.62	69			

Notes. SDMT = Symbol Digits Modalities Test; ms = measured in milliseconds; N=70.

The ANOVA results presented in the table compared cognitive test scores across three SES groups for various cognitive tasks. The analysis revealed a significant effect of SES on the Symbol Digits Modality Test (SDMT), $F(2, 67) = 7.40$, $p = .001$, suggesting that participants' processing speed could vary across SES groups. To determine where the specific difference between groups lie the Tukey HSD post hoc test was used.

The Tukey HSD post hoc test was chosen because the assumption of homogeneity of variances was met, as indicated by Levene's test ($p>.05$). This test is well-suited for comparing all possible pairs of SES groups while controlling for Type I error and ensuring reliable interpretation of group differences across several means (Field, 2018). The Tukey HSD post hoc test revealed significant differences in cognitive performance across SES groups for certain measures. Specifically, for the SDMT, participants in the high SES group scored significantly higher than those in the low SES group ($p=.002$), with a mean difference of M=17.59.

However, for the *n*-back Test Total Average Reaction Time, although the post hoc test suggested a significant difference (p = .048) between the high and low SES groups, this result cannot be interpreted as meaningful because the omnibus ANOVA test for this variable was not significant (p = .059). Since post hoc tests should only be conducted if the overall ANOVA is significant, the observed difference in reaction times cannot be reliably attributed to SES group differences (Laerd Statistics, 2018). No other comparisons across SES groups for the remaining cognitive tests showed statistically significant differences.

Regression Analyses

This section presents the simple and multiple regression analyses conducted to investigate the relationships between *n*-back performance and various predictor variables. Simple linear regression was applied to examine how individual cognitive measures, such as working memory (measured by the Digit Span and Symbol Span tests) and processing speed (measured by the Symbol Digits Modality Test), predicted performance on the *n*-back test. Multiple regression analyses were then employed to explore whether a combination of cognitive predictors, including working memory, processing speed, and demographic factors (such as socioeconomic status and biological sex), could better explain the variance in *n*-back performance.

Multiple Regression Analysis. Multiple regression analyses were conducted to determine whether Digit Span Forwards, Backwards, Sequencing, and SDMT scores accounted for variability in *n*-back test accuracy, average reaction time, and no-response scores. The assumptions of multiple linear regression were extensively examined (Appendix G). First, the dependent variable must be measured on a continuous scale, which was satisfied in this study. The independent variables, Digit Span Forwards, Sequencing, and the SDMT, included only continuous predictors, which is appropriate for regression analysis. For the second assumption to be met, there needs to be a linear relationship between the independent and dependent variables. This was assessed using scatterplots, confirming that the assumption was met. Next, the research design ensured the independence of observations by requiring each participant to complete each working memory test only once, thereby eliminating repeated measurements. Homoscedasticity, the fourth assumption, was tested by plotting standardized residuals against predicted values, which confirmed appropriate homogeneity. Finally, residual normality was assessed using both a histogram and a Q-Q plot of standardized residuals, both of which suggested that the residuals were approximately normally distributed (Field, 2018).

To assess potential outliers, diagnostic outputs such as standardised residuals, Cook’s distance, leverage points, and Mahalanobis distance were computed. While three outliers were flagged, no observations were excluded, as they were considered rightful values of the distribution. These flagged values had Cook's Distance greater than the calculated threshold, but all were still smaller than 1, indicating that they were not highly influential data points. Additionally, their leverage points were not considered to be outliers, further supporting the decision to retain these observations in the analysis. Lastly, multicollinearity was assessed, and no strong intercorrelations ($r \geq .80$) were found between Digit Span Forwards, Sequencing, and SDMT, confirming that multicollinearity was not an issue in this model for predicting *n*-back Accuracy (Field, 2018).

Multiple Regression Analysis for *n*-back test Accuracy. The first multiple regression was conducted to examine the predictors of *n*-back test accuracy. Five variables—Digits Forward (F), Digits Backward (B), Digits Sequencing (S), Symbol Span, and SDMT—were included to evaluate their individual contributions to predicting *n*-back accuracy. The results are shown in Table 8.

Table 8

Results of Multiple Regression Analysis for n-back test Accuracy.

Variable	B	SE	β	*p*	95% CI	
					LB	UB
Digit (F)	-.161	.801	-.028	.841	-1.762	1.439
Digit (B)	-.363	1.072	-.051	.736	-2.506	1.780
Digit (S)	1.237	1.067	.160	.250	-.894	3.369
Symbol Span	-.029	.224	-.016	.896	-.477	.418
SDMT	.383	.141	.343	.008	.102	.664

Notes. Digit span F/B/S = Forwards/Backwards/Sequencing; B = unstandardised Beta; SE = standard error; β = standardised beta coefficient; CI = confidence interval; LB = lower bound; UB = upper bound. N=70.

The analysis revealed that the predictor SDMT had a statistically significant effect on the dependent variable, *n*-back Test Accuracy (β=.343, t=2.725t, *p*=.008), indicating that it contributes significantly to the prediction of the outcome variable. The overall model explained 14.1% of the variance (R^2=.141), but the adjusted R^2 was modest at .073. Despite this, the model's overall significance was not reached F(5, 64) = 2.094, *p* = .078, suggesting that while SDMT is a strong individual predictor, the combination of predictors does not significantly explain the variability in the outcome variable at the $p<0.05$ threshold.

Simple Linear Regression Predicting *n*-back Accuracy from SDMT. Since the multiple regression analysis showed that SDMT had a statistically significant effect on the dependent variable, *n*-back Test Accuracy (β = .343, t = 2.725, *p* = .008), but the overall model did not reach significance, a simple regression analysis was performed to further examine the contribution of SDMT to the prediction of *n*-back accuracy. This follow-up analysis aimed to isolate the predictive power of SDMT without the influence of additional predictors, providing a clearer understanding of its individual effect on the outcome variable. To investigate whether SDMT scores predicted variance in *n*-back Accuracy, the assumptions of simple linear regression were assessed. SDMT, measured as a continuous variable, satisfied the first assumption. A linear relationship between SDMT and *n*-back Accuracy was confirmed through scatterplots, and independence of observations was ensured by the study design, with each participant completing the tasks only once. Homoscedasticity and normality of residuals were checked using residual plots and histograms, both of which showed no major violations.

Diagnostic outputs for outliers, such as Cook's distance and leverage points, revealed no highly influential data points, supporting the inclusion of all observations in the analysis. Multicollinearity was not a concern as only SDMT was included as the predictor (Field, 2018). The results are shown in Table 9.

Table 9

Results of Simple Linear Regression Predicting n-back Accuracy from Symbol Digits Modality Test (SDMT)

Variable	B	S. E	β	*p*	95% CI	
					LB	UB
SDMT	.391	.127	.349	.003	.137	.644

Notes. B = unstandardised Beta; SE = standard error; β = standardised beta coefficient; CI = confidence interval; LB = lower bound; UB = upper bound. N=70.

The results in Table 9 showed that SDMT significantly predicted *n*-back Test Accuracy scores. The model was statistically significant ($F(1, 68) = 9.445$, $p = .003$) and explained 12.2% of the variance in *n*-back Accuracy scores ($R^2 = .122$). The unstandardised coefficient for SDMT ($B = .391$, $p = .003$) indicates that for every one-unit increase in SDMT, the *n*-back Test Accuracy score increases by .391 units. The standardised coefficient ($\beta = .349$) confirms that SDMT has a moderate positive relationship with the outcome variable. This result contrasts with the multiple regression analysis (Table 9), where SDMT was significant, but the overall model was not. One possible explanation is that the inclusion of additional predictors in the multiple regression model reduced power due to the loss of degrees of freedom. Furthermore, SDMT was significantly correlated with Digit Span Backwards ($r = .352$, $p = .001$) and Digit Span Forwards ($r = .302$, $p = .006$; these coefficients are the Pearson's results produced by the regression), suggesting some overlap in constructs. However, collinearity diagnostics indicated that multicollinearity was not a concern. These findings suggest that correlations between SDMT and other predictors may have diluted its unique predictive power in the multiple regression model.

Simple Linear Regression Predicting *n*-back Accuracy from SDMT. Since the simple linear regression analysis indicated that SDMT significantly predicted overall *n*-back test accuracy, further simple regression analyses were conducted to determine which specific aspect of the *n*-back task was significantly predicted by SDMT. This follow-up investigation aimed to isolate the contribution of the SDMT to each *n*-back condition (1-back, 2-back, and 3-back) so that the predictive power of the SDMT could be investigated across several cognitive loads. Before performing the simple regression analyses to identify which *n*-back subtest was significantly predicted by SDMT, key assumptions were evaluated. Scatterplots (Appendix G) confirmed a linear relationship between SDMT and each subtest (1-back, 2-back, and 3-back). Independence of observations was ensured by the study design, with each participant completing the tasks once. Homoscedasticity was checked through residual plots, and normality of residuals was confirmed using histograms. Since SDMT was the only predictor, multicollinearity was not a concern. Finally, diagnostic checks, including Cook's distance and leverage values, indicated no highly influential outliers. Thus, no data points were excluded (Field, 2018). Table 10 below shows the first linear regression of the *n*-back subtests.

Table 10

Results of Simple Linear Regression Predicting 1-back Accuracy from Symbol Digits Modality Test (SDMT)

Variable	B	SE	β	*p*	95% CI	
					LB	UB
SDMT	.002	.035	.008	.947	-.067	.072

Notes. B = unstandardised Beta; SE = standard error; β = standardised beta coefficient; CI = confidence interval; LB = lower bound; UB = upper bound. N=70.

The results in Table 10 show that the model was not statistically significant, $F(1, 68) = 0.005$, $p = .947$, so the SDMT was not a significant predictor of 1-back accuracy.

Table 11

Results of Simple Linear Regression Predicting 2-back Accuracy from Symbol Digits Modality Test (SDMT)

Variable	B	SE	β	*p*	95% CI	
					LB	UB
SDMT	.189	.067	.323	.006	.055	.323

Notes. B = unstandardised Beta; SE = standard error; β = standardised beta coefficient; CI = confidence interval; LB = lower bound; UB = upper bound. N=70.

Table 11 shows the results of a simple linear regression examining whether SDMT significantly predicted 2-back test accuracy. The model was statistically significant, *F*(1, 68) = 7.904, *p* = .006, explaining 10.4% of the variance in 2-back accuracy scores (R^2 = .104).

Table 12

Results of Simple Linear Regression Predicting 3-back Accuracy from Symbol Digits Modality Test (SDMT)

Variable	B	SE	β	*p*	95% CI	
					LB	UB
SDMT	.199	.068	.336	.004	.064	.335

Notes. B = unstandardised Beta; SE = standard error; β = standardised beta coefficient; CI = confidence interval; LB = lower bound; UB = upper bound. N=70.

The results in Table 12 show that a simple linear regression was conducted to examine whether SDMT significantly predicted 3-back test accuracy. The model was statistically significant, *F*(1, 68) = 8.637, *p* = .004, explaining 11.3% of the variance in 3-back accuracy scores (R^2 = .113).

Multiple Regression Analysis for *n*-back Reaction Time (in milliseconds). The next multiple regression was performed to examine the predictors of *n*-back Total Reaction Time. This analysis included the same five predictors—Digits Forwards (F), Digits Backwards (B), Digit Sequencing (S), Symbol Span, and SDMT—to assess their contribution to explaining variability in average reaction time on the *n*-back test. The results are shown in Table 13.

Table 13
Results of Multiple Regression Analysis for n-back Reaction Time (ms)

Variable	B	SE	β	*p*	95% CI	
					LB	UB
Digit (F)	-.944	10.682	-.013	.930	-22.283	20.395
Digit (B)	-1.597	14.299	-.018	.911	-30.162	26.968
Digit (S)	6.863	14.223	.071	.631	-21.550	35.275
Symbol Span	-1.574	2.987	-.070	.600	-7.541	4.392
SDMT	-.598	1.875	-.043	.751	-4.344	3.148

Notes. B = unstandardised Beta; SE = standard error; β = standardised beta coefficient; CI = confidence interval; LB = lower bound; UB = upper bound; Digit F/B/S: Forwards, Backwards, Sequencing. N=70.

The multiple regression analysis in Table 13 revealed no significant predictors of *n*-back Total Average Reaction Time (ms)**,** and the model as a whole was not statistically significant $F(5,64) = .142, p = .982$).

Multiple Regression Analysis for *n*-back No Response. The next multiple regression was performed to examine the predictors of *n*-back Total No Response. This analysis included the same five predictors—Digit Span Forwards, Digit Span Backwards, Digit Span Sequencing, Symbol Span, and SDMT—to assess their contribution to explaining variability in no responses on the *n*-back test. The results are shown in Table 14.

Table 14

Results of Multiple Regression Analysis for n-back No Response (N=70)

Variable	B	SE	β	*p*	95% CI	
					LB	UB
Digit (F)	-.080	.165	-.072	.629	-.410	.250
Digit (B)	.166	.221	.120	.457	-.276	.608
Digit (S)	.134	.220	.089	.544	-.305	.574
Symbol Span	.023	.046	.066	.618	-.069	.115
SDMT	-.012	.029	-.055	.684	-.070	.046

Notes. B = unstandardised Beta, SE = standard error, β = standardised beta coefficient, CI = confidence interval, LB = lower bound, UB = upper bound. Digit F/B/S: Forwards, Backwards, Sequencing. N=70.

The multiple regression analysis in Table 14 did not yield any significant findings. The overall regression model for *n*-back Test Total No Response was not statistically significant ($F(5, 64) = .401$, $p = .846$), accounting for only 3% of the variance ($R^2 = .030$).

Multiple Regression Analysis for Cognitive Tests. Another multiple regression analysis was undertaken to determine whether Digit Span and Symbol Span scores significantly predict performance in SDMT, exploring the extent to which these variables contribute to the variance in SDMT scores. The results can be found in Table 15.

Table 15

Results of Hierarchical Multiple Regression Analysis for Symbol Span and Digit Span Total Predicting SDMT performance.

Model	Variable	B	SE	β	*p*	95% CI	
						LB	UB
1	Digit Span Total	.930	.284	.370	.002	.364	1.496
2	Digit Span Total	.868	.302	.345	.005	.266	1.471
	Symbol Span	.119	.193	.074	.538	-.266	.505

Notes. B = unstandardised Beta, SE = standard error, β = standardised beta coefficient, CI = confidence interval, LB = lower bound, UB = upper bound. DS total: Digit Span Total. N=70.

The analysis showed that Model 1, which included only Digit Span Total as a predictor, significantly predicted SDMT performance ($F(1, 68) = 10.752$, $p = .002$), explaining 13.7% of the variance ($R^2 = .137$). The unstandardised coefficient for Digit Span Total ($B = .930$, $p = .002$) indicates that for every one-unit increase in Digit Span Total, SDMT scores increase by .930 units. In Model 2, Symbol Span was added as an additional predictor, but the model improvement was not significant ($\Delta R^2 = .005$, $F(1, 67) = .383$, $p = .538$). Although Model 2 also significantly predicted SDMT performance overall ($F(2, 67) = 5.519$, $p = .006$), Symbol Span did not contribute significantly to the prediction ($B = .119$, $p = .538$).

These findings suggest that Digit Span Total is a significant predictor of SDMT performance, while Symbol Span does not provide additional explanatory power when included. The next step was to examine each Digit Span subtest (Forwards, Backwards, and Sequencing) individually to determine their unique contributions to predicting SDMT performance. A hierarchical regression was chosen for this analysis because the Kendall's rank correlations indicated that only Digit Backwards significantly correlated with SDMT. This approach allowed for the systematic inclusion of each subtest to assess their incremental predictive power while controlling for the influence of the other variables (Field, 2018). The results of this regression can be seen in Table 16 below.

Table 16

Results of Hierarchical Regression Analysis for Predicting SDMT Performance Using Digit Span Subtests.

Model	Variable	B	SE	β	*p*	95% CI	
						LB	UB
1	Digit (B)	2.229	.720	.352	.003	.793	3.666
2	Digit (B)	2.035	.850	.321	.019	.338	3.731
	Digit (S)	.407	.928	.059	.663	-1.446	2.260
3	Digit (B)	1.605	.912	.253	.083	-.216	3.426
	Digit (S)	.229	.935	.033	.808	-1.638	2.095
	Digit (F)	.855	.678	.166	.212	-.499	2.209

Notes. B = unstandardised Beta, SE = standard error, β = standardised beta coefficient, CI = confidence interval, LB = lower bound, UB = upper bound. Digit B/S/F: Backwards, Sequencing, Forwards. N=70.

The hierarchical regression analysis revealed that Digit Backwards significantly predicted SDMT performance in Model 1 ($F(1, 68) = 9.587$, $p = .003$), accounting for 12.4% of the variance ($R^2 = .124$), with a positive association indicated by its unstandardised coefficient ($B = 2.229$, $p = .003$). In Model 2, the addition of Digit Sequencing did not significantly improve the model ($\Delta R^2 = .003$, $p = .663$), and Digit Sequencing was not a significant predictor ($B = .407$, $p = .663$). Model 3, which included Digit Forwards, showed that while the overall model was significant ($F(3, 66) = 3.780$, $p = .014$), the addition of Digit Forwards did not provide a significant improvement ($\Delta R^2 = .021$, $p = .212$), and neither Digit Forwards ($B = .855$, $p = .212$) nor Digit Sequencing ($B = .229$, $p = .808$) contributed uniquely. These findings highlight Digit Backwards as the strongest predictor of SDMT performance, with no other subtests offering additional explanatory power.

Moderation Analysis. To investigate the effect of demographic variables on *n*-back accuracy, a moderation analysis was conducted using the PROCESS macro (Hayes, 2013) in SPSS. This analysis was performed because both the simple and multiple regressions between SDMT and *n*-back accuracy were significant thus a further exploration of potential moderation effects was warranted. In the moderation analysis, SDMT was included as the predictor, with Sex and SES serving as moderators.

Several assumptions were assessed for this analysis. The dependent variable (*n*-back Accuracy) is continuous, as is the predictor (SDMT), while Sex is dichotomous. The SES variable was used in its original form and was a continuous variable in this analysis. Independence of observations was ensured by the study design, where each participant completed the tasks only once. There is a linear relationship between SDMT and *n*-back Accuracy for each level of Sex as well as for SES, confirmed through scatterplots. Homoscedasticity, indicating equal error variances across levels of SES and Sex, was evaluated by plotting residuals against predicted values. There was no multicollinearity among predictors, as confirmed using Tolerance and VIF values. Additionally, no significant outliers, leverage points, or influential points were identified using Cook’s Distance, and residuals were approximately normally distributed, as assessed using the Shapiro-Wilk test. These assumptions ensure the validity of interpreting the moderating effects of SES and Sex on the relationship between SDMT and *n*-back accuracy (Field, 2018).

Table 17

Results of Moderation Analysis Examining the Effect of SDMT, Sex, and SES on n-back Test Accuracy.

Variable	B	SE	*p*	95% CI	
				LB	UB
SDMT	-.1823	.5013	.7174	-1.1838	.8192
Sex	10.3966	14.6116	.4793	-18.7936	39.5868
Interaction 1	-.0624	.2688	.8172	-.5995	.4747
SES	-1.7291	1.2470	.1704	-4.2202	.7620
Interaction 2	.0387	.0251	.1281	-.0115	.0889

Notes. Interaction 1: SDMT and Biological Sex; Interaction 2: SDMT and SES; B = unstandardised Beta, SE = standard error, CI = confidence interval, LB = lower bound, UB = upper bound. N=70.

Table 17 presents the results of the moderation analysis examining whether the relationship between SDMT and *n*-back Test Accuracy was moderated by biological sex and SES. The overall model was significant (R^2 = .2221, F(5, 64) = 3.6545, *p* = .0057), explaining 22.21% of the variance in *n*-back Accuracy. However, neither the interaction between SDMT and Sex (B = -.0624, *p* = .8172) nor the interaction between SDMT and SES (B = .0387, *p* = .1281) reached statistical significance. The combined effect of both interactions was also not significant (R^2 change = .0289, F(2, 64) = 1.1896, *p* = .3110). These findings indicate that neither Sex nor SES moderates the relationship between SDMT and *n*-back accuracy. The effect of SDMT on *n*-back Test Accuracy remained consistent regardless of the levels of the moderators.

The results in this chapter provide a comprehensive overview of the relationships between cognitive performance and demographic factors. Key findings indicate that processing speed, as measured by the SDMT, significantly predicts *n*-back accuracy. Additionally, SES emerged as an important demographic variable, with higher SES associated with improved processing speed and better performance on complex cognitive tasks. While demographic moderators such as sex and SES did not significantly alter the relationship between SDMT and *n*-back performance, the results suggest nuanced contributions of cognitive and demographic variables to overall performance. In the upcoming chapter the results will be discussed in depth drawing upon findings from previous studies.

Chapter 4: Discussion

This chapter presents the findings of the study, focusing on the relationships between the *n*-back task, Digit Span subtest, Symbol Span subtest, and the Symbol Digit Modality Test (SDMT). The data analysis assessed whether the *n*-back task is more strongly associated with measures of working memory or information processing speed, contributing to the ongoing debate about its construct validity. Additionally, the chapter explores how demographic factors, such as biological sex and socioeconomic status (SES), influence performance across these cognitive assessments.

The chapter is organised to address the research questions systematically. Specifically, it examines: (1) whether there is a statistically significant relationship between the *n*-back, Digit Span, Symbol Span, and Symbol Digit Modality tests (2) If such relationships exist, whether the *n*-back task is more strongly associated with working memory measures (Digit Span and Symbol Span tests) or with the processing speed measure (SDMT) (3) How demographic factors, such as biological sex and SES, influence performance across these cognitive tests.

The findings from Chapter 3 reveal several significant correlations among the cognitive measures. Interestingly, the *n*-back task showed limited significant correlations with working memory measures. Specifically, there was only a significant positive correlation between 2-back accuracy and the Digit Sequencing subtest, a verbal working memory measure. No significant correlations were found between the *n*-back tasks and the Symbol Span or other Digit Span subtests, indicating that the *n*-back task's relationship with working memory may be limited and potentially primarily tied to verbal working memory.

As expected, the Symbol Span test, a visual working memory measure, was significantly correlated with Digit Span Forward and Digit Span Backward, reflecting these tests' shared reliance on working memory processes. These correlations can be explained using Baddeley's Multicomponent Model (2000) of Working Memory. While the Symbol Span subtest primarily relies on the visuospatial sketchpad to encode and recall visual sequences, the Digit Span subtests engage the phonological loop to process and maintain verbal information (Baddeley, 2000). Despite these modality-specific subsystems, both tests depend on the central executive for directing attention, managing cognitive demands, and coordinating information across subsystems. The observed correlations highlight the shared involvement of the central executive and the episodic buffer, which integrate and manipulate information across modalities, enabling successful task performance (Baddeley, 2000).

The SDMT was also significantly correlated to total *n*-back accuracy, specifically the 2-Back Accuracy, 3-Back Accuracy. This suggests a potential overlap between what the SDMT measures and the cognitive demands of the *n*-back task.

Regression analyses further indicated that the SDMT was a stronger predictor of *n*-back performance than the working memory tests, suggesting that the *n*-back test taps into processing speed to a greater extent than working memory. Of the demographic factors included in this study, SES was significantly correlated with SDMT performance, 1-Back Reaction Time, 2-Back Accuracy, and 3-Back Accuracy, highlighting its predictive power and association with variations in performance across these specific tasks. Additionally, biological sex was significantly correlated with Digit Span Backward Subtest, 3-Back Accuracy, 3-Back No Response.

In interpreting these results, consideration is given to the study's theoretical framework and previous research findings. Key patterns, implications, and the degree to which these results align with cognitive models, such as Baddeley's (2000) multicomponent working memory model and Cowan's (2005) embedded-processes model, are discussed in this chapter. This discussion highlights the broader relevance of the findings to the field of cognitive assessment and make suggestions for future research. Each of the findings is discussed in detail in the sections that follow.

The Relationship Between the *n*-back, Digit Span, Symbol Span, and Symbol Digit Modality Tests

Examining the relationships between these cognitive measures is important to understanding their interconnectedness and the specific constructs they assess. As described in the first chapter, the *n*-back task, Digit Span, and Symbol Span subtests are regarded as standard measures of working memory, whereas the SDMT taps information processing speed. The *n*-back task (Gevins & Cutillo, 1993) is a popular cognitive measure that assesses working memory by asking participants to watch a continuous stream of stimuli (digits in the current study) and identify when the present stimulus matches the one delivered "n" steps previously (Jacola et al., 2014; Meule, 2017). In a 2-back task, for example, participants must determine if the current stimulus is the same as the one from two trials ago. This task requires constant updating and manipulation of information stored in working memory, involving both the central executive and storage components specified in Baddeley's (2000) Multicomponent Model of Working Memory (Salminen et al., 2012). The *n*-back task gradually becomes more difficult as the value of "n" rises because participants must retain a larger number of stimuli in their working memory while simultaneously processing new ones. This requires the ability to maintain attention, inhibit irrelevant information, and dynamically update stored representations. Therefore, higher levels of "n" introduce more cognitive load, placing greater demands on both the capacity and efficiency of working memory systems. As a result, performance typically declines with increasing "n", reflecting the task's sensitivity to working memory limits (Salminen et al., 2012; Wilhelm et al., 2013). This was seen in this study's results as well. The mean accuracy score (correct responses) for the 1-back trial was M=70.91 (SD = 3.404) whereas the mean score (correct responses) for the 3-back trial was M=59.80 (SD = 7.058).

The particular elements of working memory tested by the *n*-back task are still debated. Some research revealed moderate to substantial correlations between the *n*-back task and complex measures of working memory (E.g. Shamosh et al., 2008). However, other research such as Jaeggi et al. (2010) discovered stronger relationships between the *n*-back task and simple span tasks. This inconsistency supports the ongoing debate surrounding the *n*-back task's validity.

The current study investigated the working memory processes involved in the *n*-back task, comparing them to those measured by the Digit and Symbol Span subtests. Given that the *n*-back task is thought to reflect working memory capacity under increasing processing demands, it was predicted that the task would show significant correlations with the Digit Span subtest's Backward and Sequencing conditions, in addition to the Symbol Span subtest. All of these tests are indicators of complex working memory (Wilhelm et al., 2013). To demonstrate construct validity as a working memory measure, the *n*-back task should correlate significantly with tasks that require information manipulation and processing rather than those that focus solely on storage and rehearsal (Kane et al., 2007).

The findings from this study revealed limited support for the *n*-back task as a direct measure of working memory. Notably, there was only one significant correlation between the *n*-back task and the measures of working memory which challenges the view of the *n*-back task as a working memory-heavy test. The only significant correlation between the *n*-back task and the working memory tests was between 2-Back Accuracy and Digit Span Sequencing. This finding suggests that Digit Span Sequencing shares certain working memory processes. Digit Span Sequencing also showed significant correlations with Digit Span Forward, Digit Span Backward, and Symbol Span, this is however expected as all these measures are measures of working memory so they should tap into the same constructs and thus be significantly correlated. However, the unique correlation with 2-Back Accuracy suggests that Digit Sequencing may also assess an additional process, potentially updating (Frost et al., 2021).

This aligns with Cowan's (2005) embedded-processes model, which posits that updating occurs through the focus of attention dynamically managing information by retrieving relevant items, discarding outdated information, and keeping task-relevant content activated in working memory (Cowan, 2005).

The addition of Digit Span Sequencing as a subtest in the WAIS-IV (Wechsler, 2008a), absent in previous versions that only included Digit Forward and Backward, was intended to expand the construct of working memory assessment (Jennifer & Sheerin, 2019). Unlike Forward and Backward, Digit Span Sequencing introduces a requirement to reorganise information in real time, aligning with the cognitive demands of tasks like the 2-Back that also rely on monitoring and updating (Adams et al., 2018; Frost et al., 2021; Holdnack, 2019). This supports the idea that Digit Span Sequencing taps into more dynamic aspects of working memory beyond simple storage or manipulation (Holdnack, 2019). Further research may be necessary to explore the specific role of updating in both Digit Span Sequencing and its relationship with tasks like the *n*-back.

Furthermore, the 2-Back Accuracy scores and 3-Back Accuracy scores were significantly correlated with the SDMT, while 1-Back Accuracy was not. This aligns with the findings of Jaeggi et al. (2010), who demonstrated that performance on higher-load *n*-back tasks, such as 2-Back and 3-Back, is more closely related to cognitive functions like processing speed and fluid intelligence. Jaeggi et al. (2010) argued that higher-load tasks impose greater demands on executive functions, particularly attentional control and working memory updating, which are critical for tasks requiring rapid information processing. The correlation observed between SDMT and higher *n*-back loads in the present study supports this view, as the SDMT also requires fast cognitive processing, efficient attention shifting, and response speed (Benedict et al., 2017). Since Jaeggi's study used a comparable sample of university students (N = 281, mean age = 21.89 years, SD = 2.53), their findings are particularly relevant when interpreting the relationship between performance on high-load *n*-back tasks and processing speed in young adult populations.

As a task with minimal working memory demands, the 1-back primarily relies on short-term storage and quick recognition of previously presented stimuli (Meule, 2017). Therefore, one might expect it to correlate significantly with Digit Forward, which also emphasises basic short-term storage (Gray et al., 2017; Schaeffner et al., 2020). However, the lack of a significant correlation suggests that the 1-back task is tapping into a different construct. Furthermore, as it does not show a significant relationship with the SDMT, it appears that the 1-back is not strongly associated with processing speed either. Since the 1-back condition is often used as a control condition, this is not completely unexpected. This means that the 1-back task may primarily assess short-term recognition memory rather than more complex cognitive processes such as working memory capacity or processing speed. Its use as a control condition highlights its role in establishing baseline performance, against which tasks with higher cognitive demands, like the 2-back or 3-back, can be compared (Meule, 2017).

The findings of this study provide a nuanced answer to research question 1. Significant relationships were observed between the *n*-back task (specifically 2-back and 3-back) and the SDMT, indicating that processing speed may play a key role in *n*-back task performance. In contrast, the relationships between the *n*-back task and traditional working memory measures (Digit Span and Symbol Span) were limited. Only one significant correlation was found between 2-back accuracy and Digit Span Sequencing. This suggests that while Digit Sequencing may share some cognitive processes with the *n*-back task, it does not fully capture the complexity of *n*-back performance. These findings also align with the results of Miller et al. (2009), who reported that *n*-back accuracy, particularly under higher cognitive load, correlated significantly with the Trail Making Test Part A—a widely recognised measure of processing speed—but not with traditional working memory assessments like Digit Span Backward. This supports the interpretation that the *n*-back task involves processes beyond core working memory, potentially processing speed, which may explain the stronger association with SDMT in this study. The study by Miller et al. (2009) had a sample size of 21 patients with Parkinson's disease and 17 healthy controls, with a mean age of 60 years. Despite differences in age and clinical status, the cognitive processes underlying the *n*-back task and processing speed are likely consistent across populations (Gajewski et al., 2018). The performance on the tasks is not compared across different age groups but rather if the *n*-back shows a significant relationship with processing speed tasks within a specific age group. Therefore, the Miller et al. (2009) findings remain relevant for comparison. The key focus is on the shared reliance of both tasks on processing speed, a cognitive ability applicable to both older adults and young university students (Gajewski et al., 2018).

Multiple regression analyses of Digit Span Forwards, Backwards, Sequencing, and Symbol Span showed that none of these variables were significant predictors of *n*-back accuracy (all $p > .05$). Although these tasks assess different components of working memory, they did not significantly influence *n*-back performance. This aligns with findings by Redick and Lindsey (2013), who reported weak correlations between complex span tasks (e.g., Operation Span and Reading Span) and *n*-back accuracy in university students. Their results suggest that *n*-back tasks rely more on distinct processes, such as continuous updating and attentional control, rather than the storage and processing demands typical of complex span tasks (Redick & Lindsey, 2013). This pattern indicates that the rapid updating and processing speed required by the *n*-back task may be more closely related to SDMT performance than to the working memory measures used in this study. Indeed, a simple linear regression confirmed that SDMT was a significant predictor of *n*-back accuracy ($\beta = .349$, $p = .003$), explaining 12.2% of the variance in this score. This finding is consistent with that of Jaeggi et al. (2010), who observed that *n*-back performance in university students correlated more strongly with tasks involving processing speed and attentional control than with traditional working memory tasks. The stronger predictive power of SDMT highlights the key role of processing speed in tasks that require frequent information updating, such as the *n*-back task. Additional analyses explored SDMT's predictive power for each *n*-back subtest (1-back, 2-back, and 3-back). The SDMT significantly predicted performance on the 2-back and 3-back subtests, but not on the 1-back subtest. This suggests that processing speed may be more important for higher-load tasks, where quick thinking and frequent information updating are essential.

Furthermore, it was also found that the Symbol Span test, which largely evaluates visuospatial working memory, has low predictive power for *n*-back performance. This is most likely due to domain-specific differences, as the digit-based *n*-back task is argued to primarily activate verbal working memory processes (Redick & Lindsey, 2013). This interpretation aligns with the results from a substantial study involving a large sample of young adults (n = 6,274; ages 17-35). In that study it was found that the relationship between the visuospatial- and verbal complex span tasks ($r = .53$) was notably weaker compared to the stronger relationship observed among the complex verbal span tasks ($r = .68$; Redick et al., 2012). The findings highlight the distinction between verbal and visuospatial working memory domains, and thus it is recommended that future studies also incorporate a visuospatial variant of the *n*-back test to better understand its link to tasks like the Symbol Span.

Similarly, although Digit Span Backward and Sequencing involve manipulation of verbal material, neither was a significant predictor of *n*-back accuracy. Despite the fact that the *n*-back task also involves verbal memory due to the presentation of numbers, this indicates that the Digits Backwards and Sequencing tasks' predictive strength is weaker compared to the SDMT (Miller et al., 2009).

These results highlight the *n*-back task as being more heavily influenced by processing speed, as the SDMT, a measure of processing speed, is the strongest predictor of *n*-back performance. This finding directly addresses research question 2.

One potential explanation for why the SDMT is the strongest predictor of *n*-back performance is that the *n*-back task involves multimodal cognitive processes, which may rely more heavily on processing speed. Alternatively, the findings suggest that working memory performance, as assessed by the *n*-back task, is potentially linked to processing speed, pointing to a connection between the two cognitive functions. Nettelbeck and Burns (2010) support this notion, as their research demonstrated that higher processing speed was associated with enhanced working memory abilities in both adults (ages 18-87) and children (ages 8-14).

Demographic Variables and Cognitive Test Performance

This section explores the influence of demographic factors, specifically biological sex and SES, on performance across the cognitive tests used in this study. The focus addresses research question 3: How do demographic factors, such as biological sex and SES, influence performance across these cognitive tests?

The role of Biological Sex

Biological sex differences in working memory tasks are generally minimal or inconsistent, with most studies finding comparable performance between males and females across various tasks (Elosúa et al., 2017; Hill et al., 2014; Lejbak et al., 2011). However, contrary to earlier studies reporting inconsistent biological sex differences, our findings indicate a male advantage specifically in the Digit Span Backward subtest. There were no significant differences observed in the Forward or Sequencing versions. Research shows that while Forward and Backward Digit Span tasks generally do not show consistent biological sex differences across studies, variations in results may arise due to sample characteristics, such as age and educational background (Polunina et al., 2018). Similarly, Hilbert et al. (2015) suggest that Backward Digit Span tasks, which involve active manipulation and higher cognitive load, may reveal subtle biological sex differences depending on task complexity and strategy use. This suggests that although biological sex differences in Backward Digit Span are not universal, they may emerge under specific conditions that increase task demands.

Interestingly, despite the high cognitive load imposed by Digit Span Backwards and Sequencing, no significant biological sex differences were found in the Digit Span Sequencing subtest. In the Digit Span Backward subtest, where a sex difference was found, males outperformed females. This difference may be explained by variations in cognitive strategies and neural network recruitment across the sexes. Research indicates that males tend to activate more parietal regions, associated with spatial and executive processing, while females show greater activation in prefrontal and limbic areas, which are linked to emotional regulation and verbal processing (Hill et al., 2014).

The reliance on different neural networks may account for the observed performance difference in the Digit Span Backward subtest. On the other hand, both biological sexes may adopt similar strategies in Digit Span Sequencing, resulting in comparable outcomes. Although Hill et al. (2014) did not specify the age range of their participants, their study remains relevant due to its large sample size and the use of a meta-analysis, which examined a wide range of different samples. This approach strengthens the generalisability of their findings across diverse populations (Møller & Myles, 2016). Prior research further supports that sex-specific network recruitment may influence working memory performance depending on task complexity and demands (Grissom & Reyes, 2019; Lejbak et al., 2011; Alarcón et al., 2014).

Furthermore, in the current study, males demonstrated significantly higher accuracy in the 3-back condition. One plausible explanation for this performance disparity is that males may have approached the task with greater confidence and decisiveness, resulting in fewer no-responses and consequently higher accuracy scores. In contrast, females exhibited significantly more no-responses in the 3-back no-response condition. A no-response is automatically marked incorrect when participants take too long to respond and this likely contributed to the lower accuracy observed among females.

The greater number of no-responses by females may reflect increased hesitation, which could stem from the engagement of broader neural networks during cognitive tasks, a pattern often observed in females. Neurophysiological studies have reported that females tend to recruit additional brain regions, such as those involved in emotional regulation and higher-order control, when completing demanding tasks (Hill et al., 2014). While this broader activation can be beneficial in certain contexts, it may also result in increased cognitive load and hesitation under high-pressure conditions like the 3-back task, slowing down performance which would have negative implications under timed conditions. In the 3-back task e rapid and confident responses are crucial (Betz et al., 2023). A recent study by Betz et al. (2023) demonstrated that higher cognitive load significantly increases hesitation (N=19, median age 30, 63% males, with all the participants being either students or scientists). This highlights how demanding tasks can disrupt fluent performance when mental resources are heavily taxed. However, the sample size was small and predominately male making it difficult to draw concrete conclusions.

Interestingly, no significant gender differences were found in the processing speed task (SDMT). Sheridan et al. (2006) investigated SDMT performance in a community-based sample of younger to middle-aged adults (ages 21–49) without major medical or psychiatric conditions and found no significant gender differences in either the written or oral administration. While education level did not emerge as a significant factor in their multivariate analysis, further analysis revealed a significant positive correlation between education and SDMT scores, particularly for women. This suggests that higher education may enhance performance on tasks requiring processing speed and cognitive efficiency. However, Sheridan et al. (2006) noted that the lack of significant findings in the multivariate analysis could be attributed to the way education was categorised and the relatively homogeneous nature of their sample in terms of education levels, particularly for men. In the current study, the absence of significant gender differences may similarly be explained by the relatively homogeneous sample of university students, where participants had comparable educational backgrounds, reducing the potential for large variations in cognitive performance related to education.

Where studies have reported male advantages in working memory, these have consistently been in visuospatial tasks, suggesting a sex-based disparity in cognitive domains involving spatial manipulation (Blokland et al., 2011; Voyer et al., 2021). These studies share sample characteristics similar to those in the current study, which focuses on university students. For example, Blokland et al. (2011) conducted a functional magnetic resonance imaging (fMRI) study involving adults ranging in age from 20 to 28 years, with both male and female participants completing spatial variants of the *n*-back task. Their findings revealed that males exhibited greater activation in frontoparietal regions associated with spatial working memory (Kashyap et al., 2011). Similarly, Voyer et al. (2021) conducted a meta-analysis of cognitively healthy individuals (aged 3-86) highlighting male advantages in visuospatial tasks across the lifespan.

Despite the above-mentioned findings, the current study found no significant biological sex differences in the Symbol Span task, a visuospatial working memory measure. Although this contrasts with the findings of a male advantage in visuospatial tasks it does align with findings that suggests education can mitigate biological sex disparities in visuospatial tasks (Piccardi et al., 2016). Working memory performance typically reaches its highest levels during young adulthood (Greene et al., 2020). The lack of observable biological sex differences in both the SDMT and Symbol Span tasks may be attributed to the relatively advanced educational background and age of the participant sample, which could have reduced potential performance gaps.

Overall, the results suggest that, in general, there were no consistent biological sex differences across all cognitive tasks. Some subtle differences emerged in specific high-demand tasks. These findings highlight the importance of task complexity and strategy use in understanding biological sex differences in cognitive performance and suggest that such differences are context-dependent rather than widespread.

The role of Socioeconomic Status

The impact of SES on cognitive development is debated, with some researchers linking lower SES to hindered development and others suggesting it fosters adaptive cognitive strategies. Lower SES is often associated with environmental disadvantages such as poor nutrition, limited access to education, and chronic stress, all of which can negatively impact brain development and cognitive processes (Hackman et al., 2010; Evans, 2004). For instance, Fry et al. (2017) found that young adults who experienced poverty or homelessness exhibited significantly slower processing speeds than their more advantaged peers. In this study, a homeless group (n = 68, aged 16–19 years, 62% male) was compared with a housed group (n = 37, aged 16–19 years, 54% female), with the homeless group demonstrating lower educational attainment and higher rates of substance use. However, a key limitation of this study is the potential confounding effect of substance use, which is known to impair cognitive functioning, particularly processing speed (Herbeck & Brecht, 2013). Since substance use was not controlled for, it remains unclear whether the slower processing speeds observed were a result of socioeconomic disadvantage alone or partially due to substance use. Nonetheless, lower SES environments often expose individuals to higher rates of substance use, creating a complex interaction that may worsen cognitive outcomes (Gerra et al., 2020; Lewis et al., 2018).

In contrast, higher SES environments provide enriched resources and opportunities that promote healthy brain development, particularly in the prefrontal cortex—an area critical for processing speed and attentional control (Brito & Noble, 2014). While low SES is commonly associated with negative cognitive outcomes, some research suggests that it can foster adaptive abilities. For example, Ellis et al. (2017) and Young et al. (2018) found that individuals from unpredictable environments may develop specialised cognitive skills, such as heightened working memory under uncertain conditions, resourcefulness, and resilience, indicating that environmental adversity can sometimes lead to positive cognitive adaptations.

In the current study, no significant relationship was found between SES and working memory performance, consistent with findings from previous research. Engel et al. (2008) examined working memory in a sample of children aged 6 to 7 years and reported no significant differences between low-SES and high-SES groups. Working memory tasks may be more environmentally neutral, as they rely less on knowledge-based skills influenced by environmental factors, making them less sensitive to SES disparities (Cockcroft, 2016). Additionally, the lack of association between working memory and SES remains relatively stable, and thus the results found by Engel et al (2009) are compared, with caution (because of the significantly younger sample), with that of the current study (Hackman et al., 2014).

There are, however, other studies that have found a significant relationship between working memory and SES. For example, Hackman et al. (2014) found that adolescents from lower SES backgrounds (mean age = 15 years, n = 60) exhibited poorer working memory performance, likely due to reduced prefrontal cortex volume. The inconsistency between this study's findings and prior research showing significant SES effects could potentially be explained by the composition of the sample. Specifically, 92.4% of participants in the current study fell within the middle and high SES groups, while only 8.6% were from low SES backgrounds. This disproportionate representation likely reduced the variability in SES, which may have made it difficult to detect meaningful differences.

On the other hand, even though SES did not show any significant relationships with the working memory measures it showed significant relationships with some of the *n*-back subtests as well as with the measure of processing speed. Specifically, SES showed significant positive correlations with the SDMT, 1-back reaction time, 2-back accuracy, and 3-back accuracy, with the SDMT demonstrating the strongest correlation. The SDMT, as a direct measure of processing speed, is particularly sensitive to socioeconomic disparities, reflecting the influence of SES on rapid cognitive processing. These findings are consistent with those of Hackman and Farah (2009), who reviewed SES disparities across executive functioning, language, and memory systems and found that processing speed is closely tied to the development of the prefrontal cortex which can be affected by SES environments. Although Hackman and Farah focused on children and adolescents up to age 18, their findings remain relevant, as the prefrontal cortex continues to mature well into young adulthood (Johnson et al., 2009).

The significant correlations between SES and the more complex *n*-back measures, such as 2-back and 3-back accuracy, likely reflect SES's influence on tasks requiring rapid updating, manipulation, and attentional control (Bowers et al., 2009). Tasks like the 2-back and 3-back place higher demands on working memory and executive function, particularly the ability to update and manipulate information in real-time. These cognitive abilities are closely linked to prefrontal cortex development, which is influenced by environmental factors such as cognitive stimulation and educational opportunities (Hackman et al., 2010). Since processing speed underpins performance in these complex tasks, the observed correlations suggest that SES-related differences in processing speed may mediate performance on *n*-back tasks (Jaeggi et al., 2010). In contrast, 1-back accuracy, which primarily relies on short-term memory and places fewer demands on executive control, did not show a significant correlation with SES, consistent with findings that simpler working memory tasks may be less sensitive to environmental disparities (Meule, 2017).

Finally, because significant correlations were found between processing speed (SDMT) and aspects of *n*-back task performance, a moderation analysis was conducted to determine whether SES or biological sex influenced the relationship between processing speed and *n*-back performance. The results indicated that neither SES nor biological sex significantly moderated the relationship. The mean SES score in the sample was 14.5 (SD = 4.5), with a maximum score of 22, reflecting a relatively high and restricted range of SES. This limited variability may have constrained the ability to detect moderation effects, as moderation analyses are more sensitive when there is substantial variability in the moderator variable (Hayes, 2018).

Thus, while the findings for working memory align with some prior research suggesting its resilience to SES disparities, the strong relationship between SES and processing speed shows the sensitivity of this cognitive function to environmental influences. These results suggest that although SES may not uniformly impact all cognitive domains it might still have an impact on some.

Test order effects

A Mann-Whitney U test was conducted to determine whether the order in which the cognitive tests were administered affected participants' performance on the working memory and processing speed measures (Appendix H). This analysis was necessary to control for potential order effects, such as fatigue or practice, which may influence performance outcomes (Kotnik et al., 2024; Süss & Schmiedek, 2000). The test order manipulation included two conditions: (1) participants completed the Digit Span, Symbol Span, and Symbol Digits Modalities Test (SDMT) first, followed by the *n*-back task after a break, and (2) participants completed the *n*-back task before completing the SDMT, Digit Span, and Symbol Span tests after a break.

These findings suggest that the order in which the cognitive tests were administered did not significantly influence participants' performance. This outcome is consistent with previous research indicating that order effects, such as fatigue or practice, may not always manifest significantly when appropriate counterbalancing and rest periods are implemented during testing. Specifically, Kotnik et al. (2024) conducted a study on 27 university students (M =21.4, SD=2.5) to investigate mental fatigue during prolonged theoretical classes. Their findings revealed that a 20-minute break significantly reduced subjective mental fatigue. This study is relevant to the current research as it highlights the importance of implementing structured rest periods to mitigate fatigue and sustain performance during cognitively demanding tasks. Thus, the inclusion of breaks between the first set and second set of tests in the current study most likely helped to mitigate the effects of cognitive fatigue.

The structured testing approach and the relatively short duration of the tasks used in this study may have further reduced fatigue-related variability in performance. In addition, Lu et al. (2020) emphasised the importance of familiar environments in enhancing cognitive performance. Their study involved a sample of 35 high school students, aged 14 to 18, who completed working memory tasks in both familiar and unfamiliar classroom settings. While the age range differs slightly from the present study's sample of university students aged 18 to 25, both groups represent young populations with relatively high baseline cognitive abilities, which makes the comparison relevant (Craik & Bialystok, 2006). Lu et al. (2020) found that students scored significantly higher in familiar environments, suggesting that unfamiliar settings increased anxiety and occupied cognitive resources. Although the present study utilised an environment unfamiliar to the participants the environment was controlled as much as possible, and it was based on the university campus, which they were familiar with. It was ensured that the testing environment had minimised external distractions and consistent procedures, which may have mitigated the cognitive load typically associated with environmental novelty. Additionally, the sample in the present study consisted of university students, who may have been less affected by unfamiliarity due to their familiarity with cognitive testing environments. This combination of a controlled environment and a familiarised sample likely contributed to the absence of significant order effects observed.

In contrast, previous studies involving older adult populations, such as those by Gilsoul et al. (2024), have reported more pronounced order effects. Gilsoul et al. (2024) examined cognitive fatigue in a sample of 55 participants, including 17 older adults aged 62 to 72 years (M = 65.06, SD = 3.19) and 38 younger adults aged 18 to 30 years (M = 24.18, SD = 2.67). They found that older adults exhibited significant increases in reaction times during a prolonged cognitive task, indicating heightened vulnerability to fatigue compared to younger participants. This variation in performance may be attributed to differences in cognitive resilience, as younger adults generally exhibit higher baseline cognitive abilities and faster recovery from fatigue (Gilsoul et al., 2021; Hartshorne & Germine, 2015). These findings suggest that the superior cognitive resilience of younger university-aged participants likely also contributed to the absence of significant order effects in the present study.

Overall, the lack of significant order effects in this study is possibly due to a combination of factors, including the sample's characteristics, the structured testing approach as well as the breaks included between tests. The findings align with prior research emphasising the importance of structured testing approaches and suggest that familiarity with cognitive testing procedures may enhance performance consistency (Gilsoul et al., 2021; Hartshorne & Germine, 2015; Kotnik et al., 2024; Lu et al., 2020).

Contributions of the Study

This study contributes to the understanding of working memory and processing speed by evaluating the construct validity of the *n*-back task and examining the role of demographic variables in influencing these cognitive processes. In this study it was found that processing speed, measured by the Symbol Digit Modalities Test (SDMT), is more closely associated to *n*-back performance than performance on traditional working memory tests (Digit Span and Symbol Span). This was especially true for higher-load tasks, specifically, performance in the 2-back and 3-back accuracy conditions. Furthermore, the Digit Span Sequencing subtest was significantly related to 2-back accuracy, indicating that both tests might use the cognitive construct of updating and monitoring.

Thus, the findings support the notion that the *n*-back task may not serve predominantly as a measure of working memory but instead involves related cognitive constructs, such as processing speed (Jaeggi et al., 2010; Miller et al., 2009; Salthouse, 1996). The weaker associations between the *n*-back and traditional working memory measures, specifically the Digit Span Backwards and Symbol Span subtests, further challenge its validity as a comprehensive working memory tool (Jaeggi et al., 2010; Alloway & Copello, 2013).

In addition to questioning the *n*-back's construct validity, this study emphasises the importance of considering individual differences in working memory and processing speed research. Gender differences appeared in high-demand tasks. Males scored higher than females in the Digit Span Backward subtest and had better accuracy in the 3-back condition. Females showed more no-responses in the 3-back task, possibly due to increased hesitation under high cognitive load. These findings might suggest potential strategy differences between sexes. However, in the other working memory tests i.e. Digit Span Forwards and Sequencing as well as Symbol Span there were no significant difference in performance between males and females. These findings also add to the existing literature, such as Hilbert et al. (2015), which highlights that task complexity and cognitive strategies can influence sex-based performance differences.

Similarly, the lack of significant correlations between SES and working memory performance suggests that working memory is less affected by environmental differences, meaning that it could be a more consistent ability across different socioeconomic backgrounds (e.g. Cockcroft et al., 2016). Thus, this study contributes to the existing literature by examining the influence of socioeconomic status on cognitive test performance and exploring the impact of gender on cognitive abilities, while also raising critical questions about the construct validity of the *n*-back test.

Limitations and Future Research

When evaluating the results, it is important to take into account the limitations of this study. First, the sample consisted of young-adult university students (M=21.48; SD = 2.00), who were predominantly females (67.1%), recruited through convenience and snowball sampling. The reliance on convenience sampling may have introduced bias by disproportionately including motivated and high-achieving students (Golzar et al., 2022). Most participants reported coming from highly educated households, with 61.4% of participants' mothers and fathers having completed tertiary education. This limited sample diversity restricts the generalisability of the results, particularly to populations with varied socioeconomic and educational backgrounds or older age groups (Scholtz, 2021). Future studies should aim to include more diverse samples in terms of age, gender and parental education to enhance the external validity of the findings and provide a broader understanding of the factors influencing cognitive performance.

Secondly, while SES was examined as a demographic factor, the narrow SES range in the sample likely constrained the ability to fully assess its impact on cognitive performance. Future studies should include participants from broader SES backgrounds and explore whether SES-related disparities affect the relationships between the *n*-back task and the measures of working memory (Digit Span and Symbol Span) and processing speed (SDMT) across different cultural or geographical contexts. Furthermore, the binary classification of biological sex did not account for broader sociocultural influences, and future studies should adopt more inclusive frameworks to better capture the complexity of demographic impacts on cognitive performance.

A notable limitation of the study is the relatively small sample size of 70 participants. While this sample size may be sufficient for preliminary analysis or a pilot study, it may not provide the statistical power required for more robust conclusions, particularly in the context of more complex or multiple analyses (Serdar et al., 2021). A larger sample size would likely improve the precision of the estimates and the generalizability of the findings, enabling more reliable testing of hypotheses and the detection of potential effects (Andrade, 2020). Future studies should aim to recruit larger, more representative samples to enhance the validity of the statistical analyses conducted.

Lastly, the study also relied on a narrow selection of cognitive tasks, comparing the *n*-back test to only two working memory measures (Digit Span and Symbol Span) and one measure of processing speed (SDMT). Including a broader range of working memory and processing speed instruments could provide a more nuanced understanding of the constructs shared with the *n*-back task (Jaeggi et al., 2010). These limitations highlight areas for improvement in future research to build upon the findings of this study.

Conclusion

This study evaluated the construct validity of the *n*-back task by examining its relationships with well-established working memory measures (Digit Span and Symbol Span) and a processing speed measure (Symbol Digits Modalities Test). The results revealed that the *n*-back task was more strongly associated with processing speed than with traditional working memory measures. Specifically, SDMT significantly predicted *n*-back performance, particularly for 2-back and 3-back accuracy. This highlights that processing speed seems to play an important role in *n*-back task performance. Additionally, the only significant correlation between the *n*-back task and working memory measures was found between 2-back accuracy and Digit Span Sequencing. However, none of the measures of working memory were significant predictors of the *n*-back task. This finding further supports the idea that while there is some overlap in cognitive processes between 2-back and Digit Span Sequencing (potentially monitoring and updating), the *n*-back task primarily taps into processing speed rather than working memory.

Demographic analyses showed that SES significantly correlated with SDMT, 1-back reaction time, 2-back accuracy, and 3-back accuracy, while no significant correlations were found between SES and the working memory measures. Biological sex differences emerged in high-demand tasks, with males performing better in the Digit Span Backward subtest and the 3-back accuracy condition, while females exhibited more no-responses under high cognitive load. The lack of significant test order effects further supports the robustness of the findings.

This study highlights the *n*-back task's dependence on processing speed, thus raising concerns about its validity as a pure measure of working memory. Researchers must interpret *n*-back data with caution and consider relying on other well-established tests of working memory, such as Digit Span and Symbol Span, for a more accurate assessment of working memory capacity.

Future research should include more diverse samples in terms of SES, age, and educational backgrounds, and incorporate a broader range of cognitive tasks to better understand the constructs assessed by the *n*-back task. Despite its limitations, this study provides valuable insights into the cognitive processes underlying *n*-back performance. In conclusion, while the *n*-back task offers a useful measure of cognitive functioning, its construct validity as a working memory tool remains questionable, and alternative, more established assessments should be used.

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Appendix A: Demographic Questionnaire

CODE | | | | |

Gender: | M | | F | Date of Birth: | D | D | | M | M | | Y | Y | Y | Y |

Home Language(s): ___________________________

School Language(s): ____________________________________

Current Degree &

Faculty: ____

Previous degrees or qualifications:

____

Current year of study (1st, 2nd, 3rd):

____

(4) On a scale from zero to ten, please select how much the following factors contributed to you learning :

Interacting with friends	(click here for pull-down scale)	Language tapes/self instruction	(click here for pull-down scale)
Interacting with family	(click here for pull-down scale)	Watching TV	(click here for pull-down scale)
Reading	(click here for pull-down scale)	Listening to the radio	(click here for pull-down scale)

(5) Please rate to what extent you are currently exposed to in the following contexts:

Interacting with friends	(click here for pull-down scale)	Listening to radio/music	(click here for pull-down scale)
Interacting with family	(click here for pull-down scale)	Reading	(click here for pull-down scale)
Watching TV	(click here for pull-down scale)	Language-lab/self-instruction	(click here for pull-down scale)

(6) In your perception, how much of a foreign accent do you have in ?

(click here for pull-down scale)

(7) Please rate how frequently others identify you as a non-native speaker based on your accent in :

(click here for pull-down scale)

How many years have you been at university?

____

Did you ever fail a grade at school? If so, which one?

____

Did you ever require an intervention from a language specialist?

____

Did you attend pre-primary school?

____

Educational and occupational status of your parents or primary caregivers:

Mother: Level of Education		**Father: Level of Education**	
No schooling		No schooling	
Less than primary school completed		Less than primary school completed	
Primary school completed		Primary school completed	
Secondary school not completed		Secondary school not completed	
Secondary school completed		Secondary school completed	
Tertiary education completed		Tertiary education completed	
Other		Other	
Current occupation:		Current occupation:	

Marital status of primary caregivers:

Married	
Living together as husband and wife	
Widow/widower	
Divorced/separated	
Other	

Number of caregivers in the household in which you spend the most time (please tick):

0	
1	
2	
>2	

Living Standards Measure:

Please answer the following questions according to your circumstances while growing up, and not in your current student accommodation if these are different.

Question	Answer	
1. I have the following in my household:		
TV set	TRUE	FALSE
VCR	TRUE	FALSE
DVD player	TRUE	FALSE
M-Net/DStv subscription	TRUE	FALSE
Hi-fi/music centre	TRUE	FALSE
Computer / Laptop	TRUE	FALSE
Vacuum cleaner/floor polisher	TRUE	FALSE
Dishwashing machine	TRUE	FALSE
Washing machine	TRUE	FALSE
Tumble dryer	TRUE	FALSE
Home telephone (excluding a cell)	TRUE	FALSE
Deep freezer	TRUE	FALSE
Fridge/freezer (combination)	TRUE	FALSE
Electric stove	TRUE	FALSE
Microwave oven	TRUE	FALSE
Built-in kitchen sink	TRUE	FALSE
Home security service	TRUE	FALSE
3 or more cell phones in household	TRUE	FALSE
2 cell phones in household	TRUE	FALSE
Home theatre system	TRUE	FALSE
2. I have the following amenities in my home:		
Tap water in house/on plot	TRUE	FALSE
Hot running water from a geyser	TRUE	FALSE
Flush toilet in/outside house	TRUE	FALSE
3. There is a motor vehicle in our household	TRUE	FALSE
4. I am a city dweller	TRUE	FALSE
5. I live in a house, cluster or town house	TRUE	FALSE
6. I live in a rural area outside Gauteng and the Western Cape	TRUE	FALSE
7. There are no radios, or only one radio (excluding car radios) in my household	TRUE	FALSE
8. There is no domestic workers or household helpers in household (both live-in & part time)	TRUE	FALSE

Appendix B: Participant Information Sheet

Psychology
School of Human & Community Development
University of the Witwatersrand
Private Bag 3, Wits, 2050
Tel: 011 717 4503
Fax: 011 717 4559

Study title: Determining the Relationship between the *n*-Back Test, Symbol Span subtest, Digit Span subtest and Symbol Digits Modality Test.

Hello,

I am a student in the Department of Psychology, at Wits University, and we would like to invite you to participate in my research examining the relationship between measures of working memory and processing speed.

Details of the Study. The first part of the study can be conducted online at your convenience. The activities will include: (1) reading through this information sheet (5-10 minutes); (2) completing the informed consent form (3 minutes), and (3) completing a biographic and language experience questionnaire (30 minutes).

The second part of the study will take place in the Neuroscience Research Laboratory, Department of Psychology, Wits, East Campus. This second part will be divided into two sessions, which will take place on the same day. In these sessions, participants will complete a series of brief paper and pencil assessments, as well as a computerised memory test. Each session will take approximately 50-90 minutes. If you decide to participate in the first session, participation in the second session is not compulsory, although your participation will be greatly appreciated.

Risks. There are no foreseeable risks associated with this study. Participants may experience fatigue. However, to prevent this the participants will take a break between sessions.
Benefits. Participation in this study requires an investment of your time, which we greatly appreciate. There are no direct benefits associated with participation.
Confidentiality and Anonymity. The data obtained from this study will not be linked to any academic results nor be traceable to participants, as it will be collected with an anonymous participant number only. Anonymity is guaranteed in any resulting publications and presentations. All data will be kept confidential in anonymised, password-protected files, and stored on an external hard drive, and only the researchers will have access to the questionnaires and corresponding data. The results of this research will not be used to examine individual performance; only group performance will be analysed.
Withdrawal from this Study. Participation is entirely voluntary, and you are not obliged to be involved in this study. If you do decide to participate, you have the right to withdraw from the study at any time, and this will not be held against you in any way. If you choose to withdraw, any collected data will be destroyed and will not be used in subsequent analyses.
Research Outputs. The results of this study will be disseminated through a research report, publications and conference papers. Participants may request further information about the

study, although individual feedback on performance will not be available as the collected data will be anonymous. Data may be used for possible secondary analyses.

Contact Details

- If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor on the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), by telephone at +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za. Any issues will be treated in confidence and investigated fully, and you will be informed of the outcome.

- Principal Investigator | Please contact Professor Kate Cockcroft (Kate.cockcroft@wits.ac.za / 011 717 4511) if you require further information about this study or feedback on the progress of this research.

Thank you for taking the time to read this information sheet. If you are satisfied with the information provided and are interested in participating in the study, please contact Joanette Cameron (2722972@students.wits.ac.za).

Date: 21/04/2024

Appendix C: Ethical Clearance

UNIVERSITY OF THE
WITWATERSRAND,
JOHANNESBURG

SCHOOL OF HUMAN AND COMMUNITY DEVELOPMENT ETHICS COMMITTEE CONSTITUTED UNDER THE UNIVERSITY HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)

CLEARANCE CERTIFICATE	**PROTOCOL NUMBER: MAPSYC-24-01**
PROJECT TITLE:	Determining the relationship between the *n*-Back Test, Symbol Span subtest, Digit Span subtest and Symbol Digits Modality Test.
INVESTIGATOR	Cameron Johanna
SCHOOL/DEPARTMENT OF INVESTIGATOR	SHCD/Psychology
DATE CONSIDERED	10 June 2024
DECISION OF THE COMMITTEE	Approved unconditionally
RISK LEVEL	Minimal Risk
EXPIRY DATE	31 December 2026
ISSUE DATE OF CERTIFICATE	01 July 2024

CHAIRPERSON Aline Ferreira Correia
(Prof. Aline Ferreira Correia)

cc: Prof. Kate Cockcroft (Supervisor)

DECLARATION OF INVESTIGATOR

To be completed in duplicate and **ONE COPY** returned to the Chairperson of the School/Department ethics committee.

I/we fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure be contemplated from the research procedure as approved, I/we undertake to submit an amendment of the protocol to the Committee.

Signature ______________ 07,07,2024

Appendix D: Participant Consent Form

Psychology
School of Human & Community Development
University of the Witwatersrand
Private Bag 3, Wits, 2050
Tel: 011 717 4503 Fax: 011 717 4559

Project: Determining the Relationship between the *n*-Back Test, Symbol Span subtest, Digit Span subtest and Symbol Digits Modality Test.
Researchers: Professor Kate Cockcroft, Ms Joanette Cameron

I ……………………………………………………… agree to participate in this research project. The research has been explained to me and I understand what my participation will involve. I agree to the following:

(Please cross the relevant options below).

I have read the participant information letter and my questions have been answered to my satisfaction.	YES	NO
I acknowledge that participation is entirely voluntary.	YES	NO
I am aware that I can withdraw from the study at any time. I do not need to provide a reason, and this will not be held against me.	YES	NO
My data will remain anonymous (participants will be represented as a 'code number').	YES	NO
I agree that the data from this study may be used for secondary analyses, publication and/or conference presentations and in all instances my name and any personal information will remain anonymous and confidential.	YES	NO

…………………………………… (Signature)
…………………………………… (Name of Participant)
…………………………………… (Date)

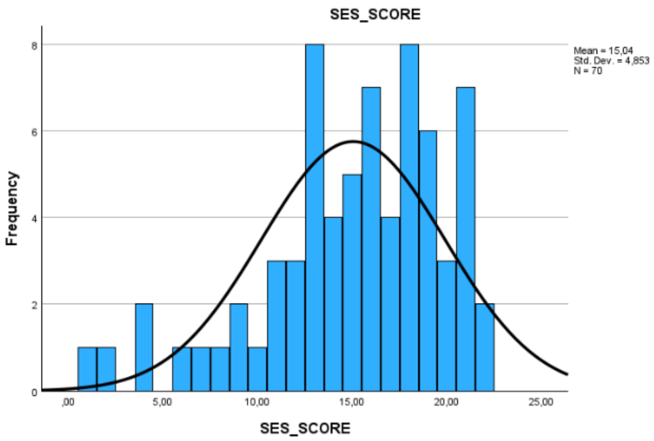
Appendix E: Normality Outputs

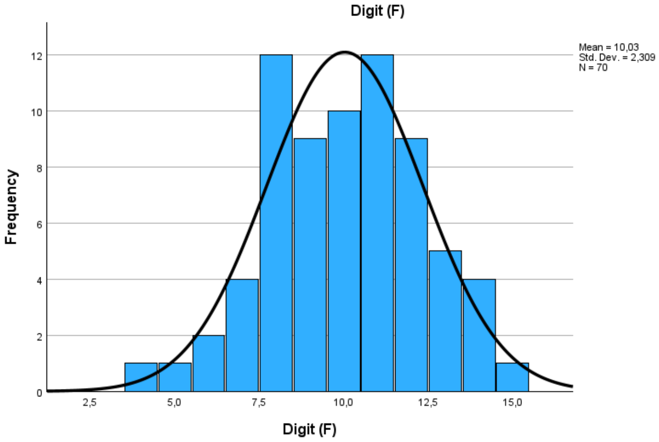
Table 1

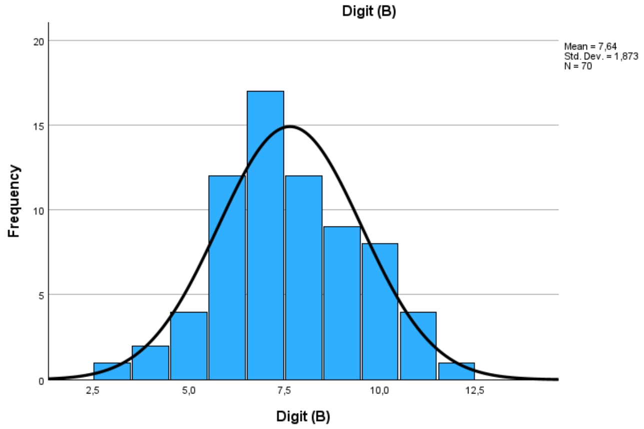
Normality Outputs for Cognitive and Demographic Variables

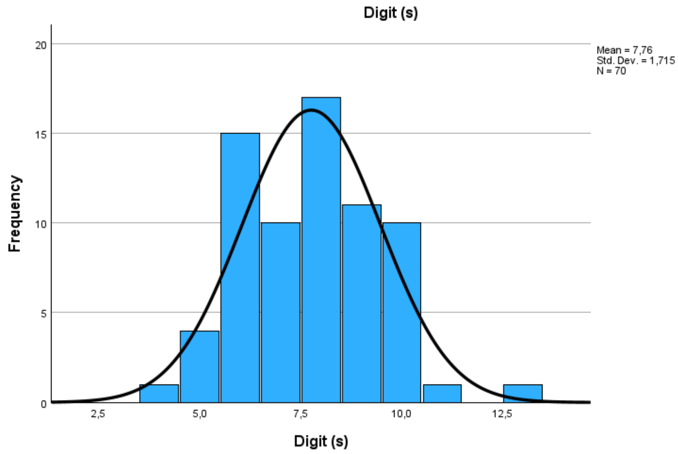
Variable	Skewness	Kurtosis	Kolmogorov-Smirnov
Digit Span Forwards	-.14	-.26	.11
Digit Span Backwards	.08	-.25	.15
Digit Span Sequencing	.27	.02	.13
Digit Span Subtest (Total)	.08	-.34	.07
Symbol Span Subtest	-.49	-.30	.09
1-Back Accuracy	-1.59	3.66	.15*
1-Back Average Reaction Time	.89	1.24	.09
2-Back Accuracy	-1.77	6.48	.13*
2-Back Average Reaction Time	.51	-.35	.11
3-Back Accuracy	.05	-.49	.08
3-Back Average Reaction Time	.56	-.25	.10
n-Back Test Accuracy	-.48	-.06	.09
n-Back test Total Average Reaction Time	.55	-.10	.11
Symbol Digits Modalities Test	.09	.27	.10
Socioeconomic Status	-.93	.65	.11*

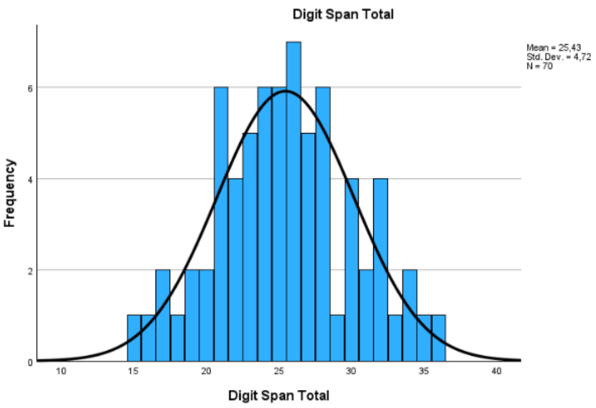
*Notes. *p<.05*

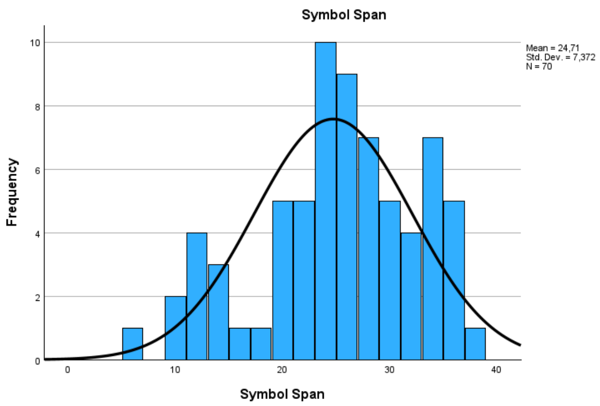

SES_SCORE
Frequency
Mean = 15,04
Std. Dev. = 4,853
N = 70
SES_SCORE

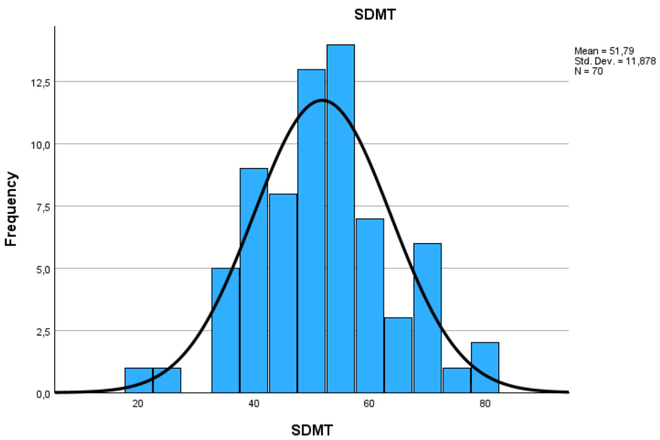

Digit (F)
Frequency
Mean = 10,03
Std. Dev. = 2,309
N = 70
Digit (F)

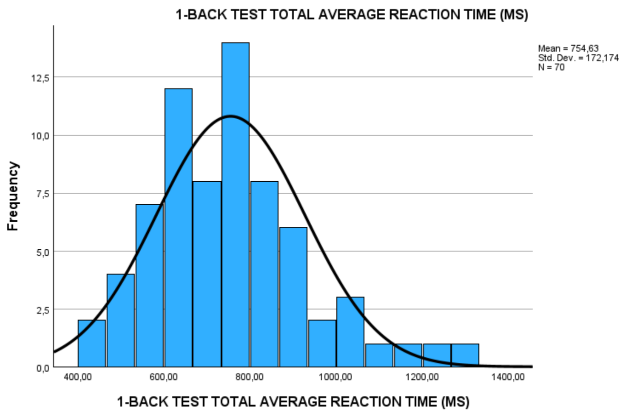

Digit (B)
Frequency
Mean = 7,64
Std. Dev. = 1,873
N = 70
Digit (B)

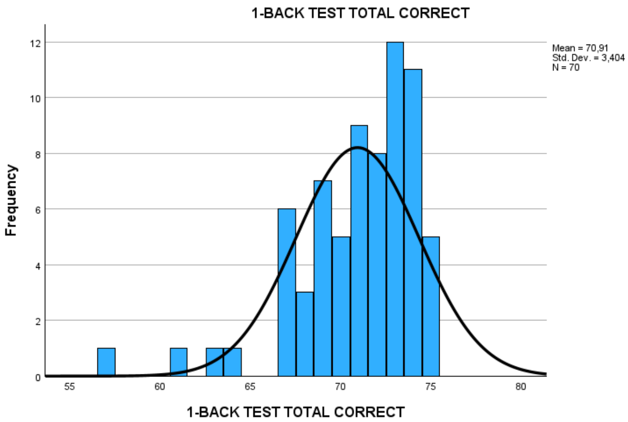

Digit (s)
Frequency
Mean = 7,76
Std. Dev. = 1,715
N = 70
Digit (s)

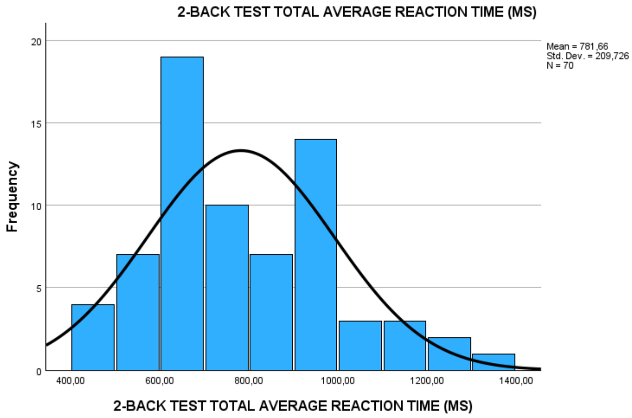

Digit Span Total
Frequency
Mean = 25,43
Std. Dev. = 4,72
N = 70
Digit Span Total

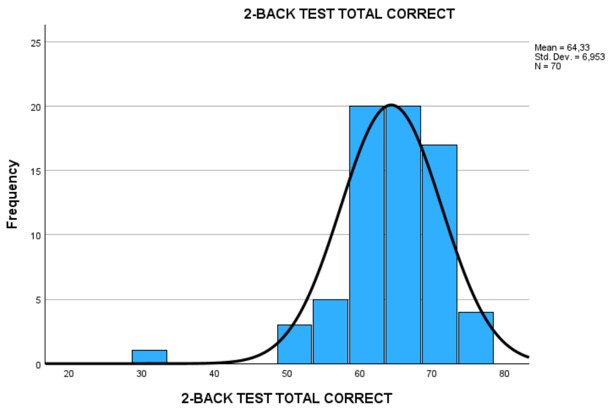

Symbol Span
Frequency
Mean = 24,71
Std. Dev. = 7,372
N = 70
Symbol Span

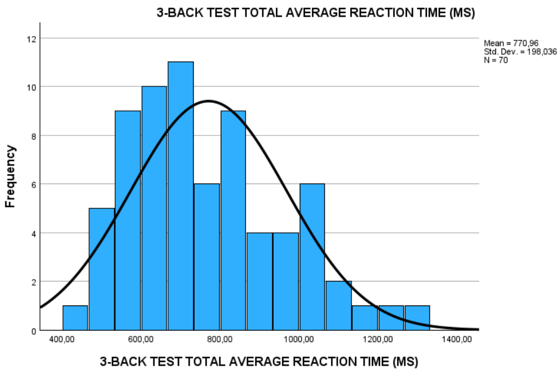

SDMT
Frequency
Mean = 51,79
Std. Dev. = 11,878
N = 70
SDMT

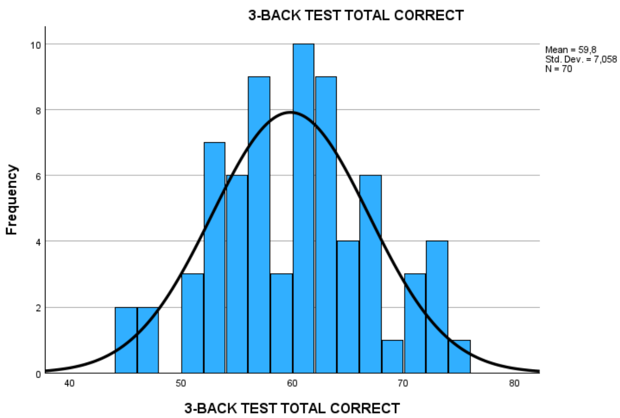

1-BACK TEST TOTAL AVERAGE REACTION TIME (MS)
Frequency
Mean = 754,63
Std. Dev. = 172,174
N = 70
1-BACK TEST TOTAL AVERAGE REACTION TIME (MS)

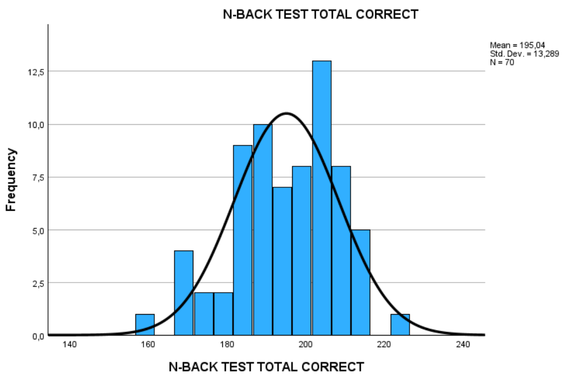

1-BACK TEST TOTAL CORRECT
Mean = 70,91
Std. Dev. = 3,404
N = 70
Frequency
1-BACK TEST TOTAL CORRECT

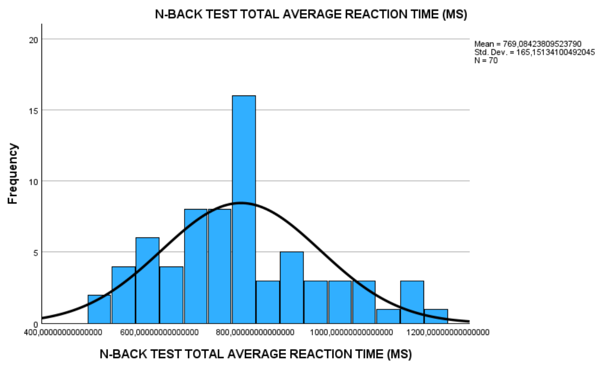

2-BACK TEST TOTAL AVERAGE REACTION TIME (MS)
Mean = 781,66
Std. Dev. = 209,726
N = 70
Frequency
2-BACK TEST TOTAL AVERAGE REACTION TIME (MS)


2-BACK TEST TOTAL CORRECT
Mean = 64,33
Std. Dev. = 6,953
N = 70
Frequency
2-BACK TEST TOTAL CORRECT


3-BACK TEST TOTAL AVERAGE REACTION TIME (MS)
Mean = 770,96
Std. Dev. = 198,036
N = 70
Frequency
3-BACK TEST TOTAL AVERAGE REACTION TIME (MS)


3-BACK TEST TOTAL CORRECT
Mean = 59,8
Std. Dev. = 7,058
N = 70
Frequency
3-BACK TEST TOTAL CORRECT


N-BACK TEST TOTAL CORRECT
Mean = 195,04
Std. Dev. = 13,289
N = 70
Frequency
N-BACK TEST TOTAL CORRECT


N-BACK TEST TOTAL AVERAGE REACTION TIME (MS)
Mean = 769,08423809523790
Std. Dev. = 165,15134100492045
N = 70
Frequency
N-BACK TEST TOTAL AVERAGE REACTION TIME (MS)

Appendix F: ANOVA Assumptions

Table 1
Levene's Test for Homogeneity of Variances for Cognitive Test Scores Across SES Groups (N=70).

		Levene Statistic	df1	df2	Sig.
Digit Span Total	Based on Mean	.23	2	67	.80
	Based on Median	.41	2	67	.67
	Based on Median and with adjusted df	.41	2	66.87	.67
	Based on trimmed mean	.24	2	67	.79
Symbol Span	Based on Mean	1.46	2	67	.24
	Based on Median	1.41	2	67	.25
	Based on Median and with adjusted df	1.41	2	65.52	.25
	Based on trimmed mean	1.42	2	67	.25
SDMT	Based on Mean	.05	2	67	.95
	Based on Median	.05	2	67	.95
	Based on Median and with adjusted df	.05	2	66.87	.95
	Based on trimmed mean	.05	2	67	.95
n-Back Test Total Accuracy	Based on Mean	.68	2	67	.51
	Based on Median	.82	2	67	.44
	Based on Median and with adjusted df	.82	2	65.36	.44
	Based on trimmed mean	.70	2	67	.50
n-Back Test Total Average Reaction Time (ms)	Based on Mean	.73	2	67	.49
	Based on Median	.48	2	67	.62
	Based on Median and with adjusted df	.48	2	63.8	.62

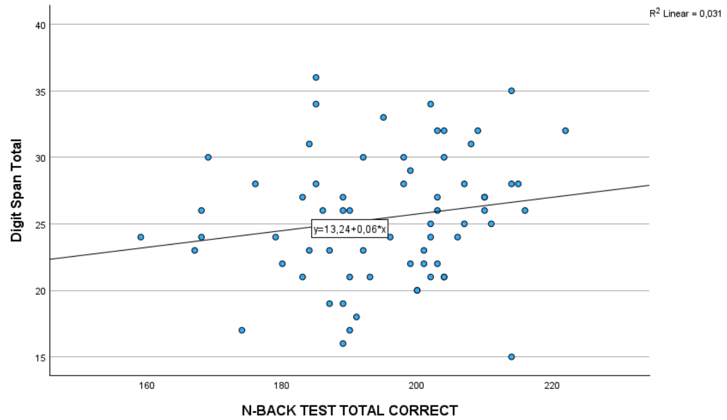
		Levene Statistic	df1	df2	Sig.
	Based on trimmed mean	.66	2	67	.521

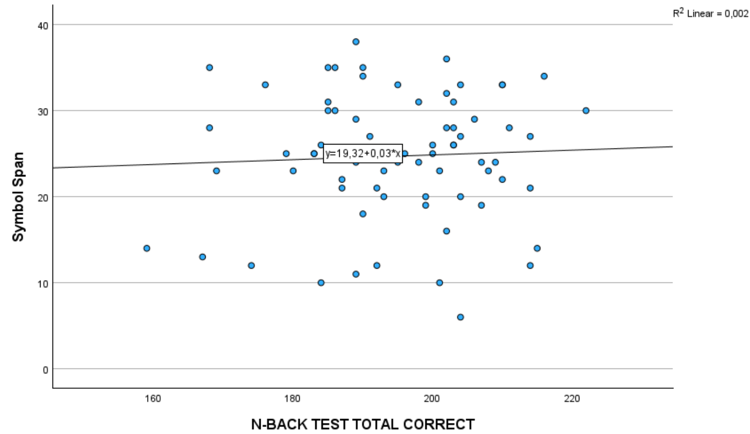
Notes. ms – Milliseconds. SDMT- Symbol Digits Modalities Test.

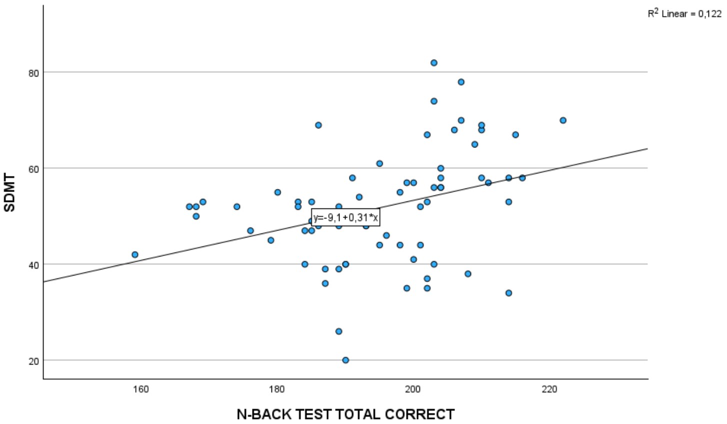
Appendix G: Assumption Testing for Regression

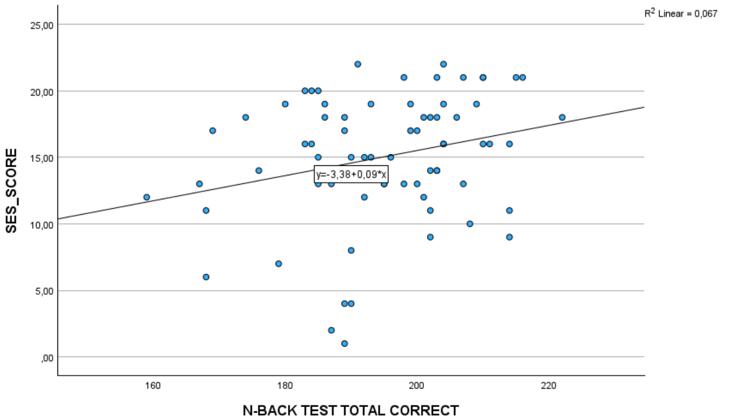
Note that for the regression analysis n-Back total correct and n-Back accuracy was used interchangeably here.

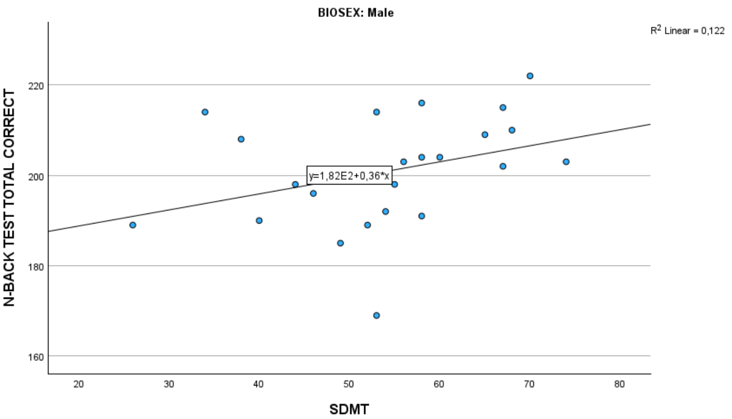
Linear Relationships between the variables

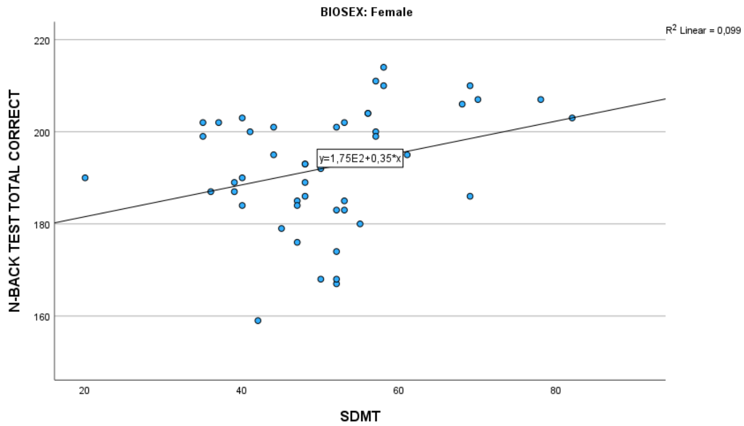




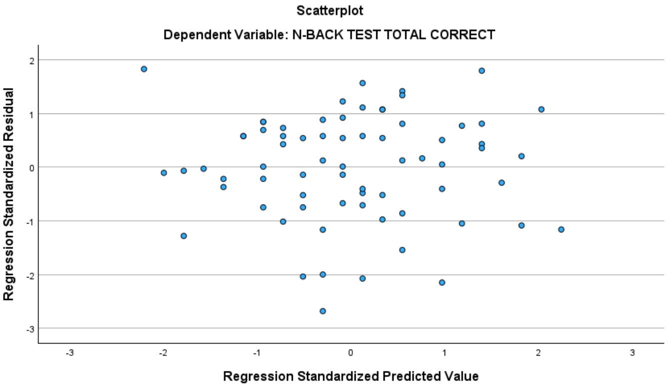




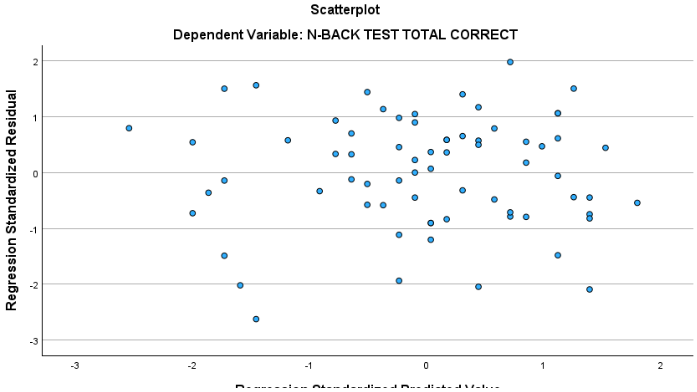




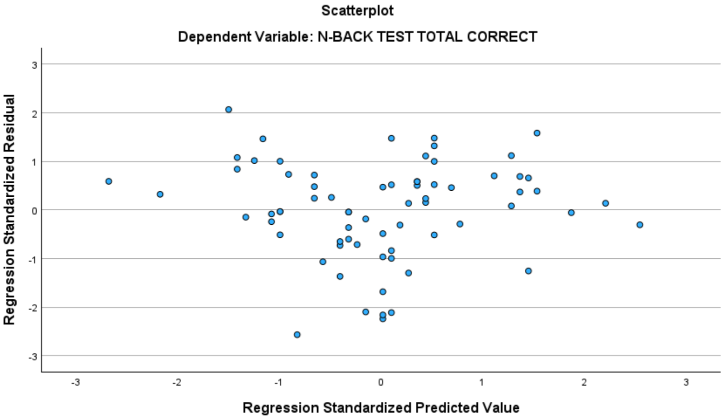
Checking for Homoscedasticity



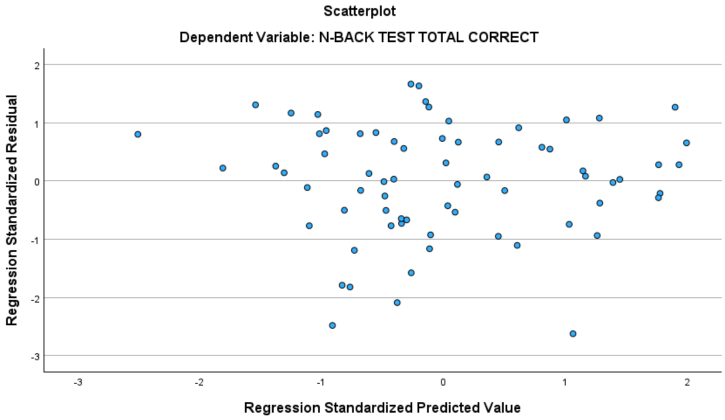
Digit Span



Symbol Span



Symbol Digits Modalities Test



Multiple Regression

Appendix H: Mann Whitney U

Table 1
Mann-Whitney U Test Results for Biological Sex Differences in Cognitive Test Performance (N=70)

	Biological Sex	N	Mean Rank
Digit (F)	Female	47	34.39
	Male	23	37.76
Digit (B)	Female	47	31.87
	Male	23	42.91
Digit (S)	Female	47	33.96
	Male	23	38.65
Digit Span Total	Female	47	32.76
	Male	23	41.11
Symbol Span	Female	47	34.67
	Male	23	37.20
SDMT	Female	47	32.90
	Male	23	40.80
1-Back Test Accuracy	Female	47	37.69
	Male	23	31.02
1-Back Test Total No Response	Female	47	35.27
	Male	23	35.98
1-Back Test Total Average Reaction Time (ms)	Female	47	38.45
	Male	23	29.48
2-Back Test Accuracy	Female	47	32.32
	Male	23	42.00
2-Back Test Total No Response	Female	47	36.06
	Male	23	34.35
2-Back Test Total Average Reaction Time (ms)	Female	47	37.47
	Male	23	31.48
3-Back Test Accuracy	Female	47	30.29
	Male	23	46.15
3-Back Test Total No Response	Female	47	38.77

	Biological Sex	N	Mean Rank
	Male	23	28.83
3-Back Test Total Average Reaction Time (ms)	Female	47	37.34
	Male	23	31.74
n-Back Test Accuracy	Female	47	31.00
	Male	23	44.70
n-Back Test Total No Response	Female	47	37.72
	Male	23	30.96
n-Back Test Total Average Reaction Time (ms)	Female	47	38.06
	Male	23	30.26
SES Score	Female	47	33.23
	Male	23	40.13

Notes. Digit F/B/S: Digit Span Forwards/Backwards/Sequencing. ms: milliseconds. SES: Socioeconomic Status.

Table 2

Mean Ranks for Cognitive Test Performance by Test Administration Order (N=70)

Cognitive Test	Test Order	N	Mean Rank
Digit Span Total	DS, SP, SDMT, *n*-Back	37	31.15
	n-Back, SDMT, DS, SS	33	40.38
Symbol Span	DS, SP, SDMT, *n*-Back	37	34.65
	n-Back, SDMT, DS, SS	33	36.45
SDMT	DS, SP, SDMT, *n*-Back	37	30.97
	n-Back, SDMT, DS, SS	33	40.58
n-Back Test Accuracy	DS, SP, SDMT, *n*-Back	37	34.51
	n-Back, SDMT, DS, SS	33	36.61
n-Back Test Total Average	DS, SP, SDMT, *n*-Back	37	33.86
Reaction Time (Ms)	*n*-Back, SDMT, DS, SS	33	37.33

Notes. DS = Digit Span; SP = Symbol Span; SDMT = Symbol Digits Modalities Test; Ms = Milliseconds