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THE RELATIONSHIP BETWEEN WORKING MEMORY AND PROCESSING SPEED: THE INFLUENCE OF DEMOGRAPHIC FACTORS IN THE SOUTH AFRICAN SAMPLE

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Declaration

I declare that this thesis is my own, unaided work. It is being submitted for the Master of Art in Psychology by Coursework and Research Report at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other university.



Thobekile Goodness Cele

Abstract

Working memory (WM) and processing speed (PS) seem to be related cognitive functions, as both play a role in learning and task management; however, demographic factors are often linked to cognitive performance and subject to cultural differences, which can potentially alter the relationship between these variables. This study aimed to explore the relationship between PS and WM, and to investigate whether PS moderates the relationship between demographic variables (age, years of education, language experience, socioeconomic status [SES], and gender) and WM. A total of 97 healthy multilingual adults (mean age = 32.4 and *SD* = 10, and mean years of education = 12.5 and *SD* = 1.8) participated in a battery of cognitive tests, which included the Symbol Digit Modality Test (SDMT), the Digit Span (DS) task, and the Letter Number Sequencing (LNS) test. The study employed a non-experimental, cross-sectional, correlational design. The findings from a correlation analysis indicated a significant association between WM measures and SDMT-Oral. A General Linear Model (GLM) analysis results demonstrated that age, years of education, and English as a first language (EFL) had significant correlations with the majority of cognitive measures, while number of known languages (NL) correlated solely with DS sequencing, and gender exclusively with DS forward. Also, PS, as measured by SDMT-Oral, predicted WM on selected demographic variables. Furthermore, the results confirmed the moderation of PS on the relationship between age and EFL on Long Digit Span Backward (LDSB). Additionally, age interacted with LNS; also, age and Living Standard Measure (LSM) category interacted with LLNS. There was an effect of years of education on SDMT-Oral and LLNS, while no significant interaction between SDMT-Oral, years of education, and WM measures. Overall, this study indicated that PS and demographic variables influence WM performance.

Keywords: cognitive assessment, processing speed, working memory, multilingualism, socioeconomic status, education

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List of Abbreviations

ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
DS	Digit Span
DTI	Diffusion Tensor Imaging
fMRI	Functional Magnetic Resonance Imaging
GLM	General Linear Model
LDSB	Long Digit Span backward
LDSF	Long Digit Span Forward
LDSS	Long Digit Span Sequencing
LLNS	Long Letter Number Sequencing
LNS	Letter Number Sequencing
MANOVA	Multivariate Analysis of Variance
PASAT	Paced Auditory Serial Addition Test
PS	Processing Speed
SDMT	Symbol Digit Modalities Test
WM	Working Memory

Chapter 1 - Introduction

Cognitive abilities, such as working memory (WM) and processing speed (PS), play an important part in a person's daily functioning. Their performance relies on the ability to temporarily store and hold information to carry out mental operations with speed and accuracy (Baddeley, 2012; Cowan, 2013; Horning & Davis, 2012). Both these cognitive constructs are essential to varied cognitive activities, such as language understanding, problem solving, reasoning, and task execution. Despite their concurrent presence in cognitive models, the exact nature of their relationship and how demographic factors influence them remains a key area of research.

Working memory (WM) refers to the ability to manipulate the information being held in the brain for a short period to be able to carry out tasks (Baddeley, 2012; Cowan, 2013). It can be used to control processes, such as focusing attention, updating, and rehearsing information that is in the short-term component of the memory system (Cowan, 2008). Waters and Caplan (2003) highlight that performing cognitive tasks requires a WM system that retains information to make it available during tasks. Based on its vital role, WM is associated with other cognitive functions such as intelligence, short-term memory, attention, and PS (Ackerman et al., 2005; Oberauer, 2019). While PS has been defined as the time it takes to complete or finish a task (Horning & Davis, 2012) and is known to be associated with motor skills, such as the ability to write effectively (Ebaid et al., 2017). A reduced PS may negatively impact the efficiency in completing a task; this deterioration reduces the accuracy of information and increases the response time (Jacobson et al., 2011). Furthermore, PS influences WM performance (Salthouse, 1996), and in older adults, it can be measured with the Symbol Digit Modalities Test (SDMT) (Smith, 1982).

In contrast, short-term memory briefly retains information for a short period, usually for a few moments. It can be regarded as a passive store (Cowan, 2008). It encodes and rehearses information before transferring to long-term memory, where information is kept for a long period (Cowan, 2008). Attention is defined as a limited resource for information processing, and is not unitary. It acts as a control mechanism that selects and filters relevant stimuli, controlling what goes to WM or short-term memory (Oberauer, 2019). According to Cowan (2005), attention can narrow its focus to process a single item or zoom to manage up to four chunks simultaneously. This suggests that WM and attention are limited, which also explains why people can become overloaded when processing too much information simultaneously. While PS controls how quickly and effectively an individual collects, understands, and

responds to information (Deluca, 2008). It sets the speed for cognitive operations (Oberauer, 2019).

Although these WM, short-term memory, attention, and PS are closely interconnected, they are distinct cognitive constructs with boundaries. WM is not different from short-term memory, but encompasses the storage functions of short-term memory with the control functions of attention to allow active manipulation of information. Short-term memory and WM define which information is held and how it is processed, while attention determines which information is prioritised (Cowan, 2008). The hypothesis that WM cannot function without short-term memory and attention originates from the fact that these operations are completed by processing temporarily maintained information (Chun et al., 2011; Oberauer, 2019). PS forms part of this operation as it explains how effectively that information moves through the cognitive system (Deluca, 2008).

Research indicates that WM and PS are closely associated, with a higher PS being frequently associated with improved WM performance (Kim & Park, 2018; Salthouse, 1996). Newbury et al. (2016) demonstrated that when an individual has challenges with PS, they are more likely to have weaker WM capacity. Specifically, Baddeley's model of WM posits that different components of WM can be influenced by PS, which may vary across age groups (Baddeley & Hitch, 1974) as both WM and PS decline naturally as one ages (Bosnes et al., 2022).

Although advanced age is associated with the decline in overall cognitive functioning, including WM and PS, other demographic factors, like level of education and language, have also been demonstrated to influence the performance of cognitive tests (Shuttleworth-Edwards et al., 2004). Moreover, WM and PS follow similar correlation patterns when the level of education and language are concerned, with younger and more educated people performing better than older persons with lower levels of education (Kim & Park, 2018; Kurtz et al., 2013; Monnier et al., 2021; Newbury et al., 2016). In South Africa, the quality of education, not only years of education, strongly correlates with cognitive performance (Shuttleworth-Edwards et al., 2004). This study defines cognitive performance as measurable results of cognitive abilities on a specific task, such as accuracy, response time, and standardised test scores (Lezak et al., 2012; Salthouse, 2010).

Besides age and education, variations in WM have been linked to bi/multilingualism, specifically the number of languages an individual speaks (NL), and the use of English as a

first language (EFL) seems to influence the performance in cognitive tests (Cockcroft et al., 2017). Performance may differ depending on whether tasks are conducted in an individual's first or second language, which can introduce biases in cognitive assessments (Fisher, 2009; Shuttleworth-Edwards et al., 2004). However, little is known about whether bi/multilingual advantages extend to WM capacity and about the influence of speaking more than one or two languages. For example, Cockcroft et al. (2015) compared the cognitive abilities of multilingual South Africans and monolingual British. They found that both groups demonstrated similar performance in WM measures, specifically Digit Span (DS), Letter Number Sequencing (LNS), and Arithmetic subtests, whereas South African multilinguals performed better in PS subtests. This indicated cultural differences between groups, as well as the importance of language used when conducting cognitive assessments. The South African sample struggled in verbal subtests because most of them spoke English as a second language.

Socio-economic status (SES) has also been associated with cognitive outcomes, with individuals from lower SES backgrounds often exhibiting a lower PS and weaker WM, primarily due to limited cognitive stimulation and access to resources (Mooney et al., 2021). In addition, gender differences in WM and PS have been reported, although findings remain inconsistent, often changing by task type and context. Females tend to have a significant advantage in verbal WM (Harness et al., 2008), whereas males excel in visuospatial WM (Robert & Savoie, 2006). Furthermore, research has demonstrated that males tend to react quickly when doing finger-tapping tasks, whereas females are likely to excel in verbal PS tasks (Roivainen, 2010). Verbal WM refers to the capacity to briefly store and manipulate verbal information for use in complex cognitive tasks (Baddeley, 2000; Gathercole & Baddeley, 1993). In this study, verbal WM is operationalised through DS and LNS subtests, which measure the ability to hold and rearrange sequences of verbal stimuli.

1.1. Theoretical Framework

From a cognitive perspective, this study is anchored by theoretical models of WM and PS, which permit an understanding of various cognitive functioning. According to Cowan (2005), four main views on WM are psychometric, multicomponent, storage plus processing, and attentional control. The psychometric approach emphasises short-term storage capacity, like DS, as a key for intellectual tasks. By contrast, Baddeley's (1986) multicomponent model postulates that WM consists of different types of storage systems, like the phonological loop and the visuospatial sketchpad. These are directed by the central executive, accountable for

attentional control and manipulation of information; the above is debated further in Chapter 2. Daneman and Carpenter (1980) storage plus processing extended this view by emphasising the importance of simultaneous and processing demands, particularly in tasks like reading span. Engle et al (1999) contend that central WM relies on the ability to maintain task-relevant information through attention control storage plus processing.

Extending these viewpoints, Salthouse's (1996) theory of PS suggests that age-related cognitive decline and reduced WM performance are mostly ascribed to slower PS. This perspective demonstrated that slower PS may limit the amount of information that can be simultaneously activated and manipulated in WM before deterioration. These theoretical frameworks can be applied to the current study; integrating them allows for a subtle use of how PS may moderate the efficiency of WM components and demographic factors, particularly in bi/multilingual individuals, where language and attentional demands may differ in task performance.

To summarise, conceptual and theoretical considerations indicate that the PS plays an important role in short-term memory, WM, and attention.

1.2. Problem Statement

The influence of demographic factors, such as age, the level of education, language, SES, and gender, on WM and PS has been established in many contexts. However, in South Africa, the impact of variables such as bi/multilingualism on cognitive performance remains under-researched. This creates significant biases in the understanding of cognition and test performance (Ferreira-Correia & Cockcroft, 2023). Additionally, correlations have been established between demographic variables and WM, between the same variables and PS, and between WM and PS (Bosnes et al., 2022; Vonk et al., 2020). However, it remains unclear whether PS moderates the relationship between demographic variables and WM. The demographic diversity of the South African population offers a unique opportunity to investigate the complexities of cognitive functioning and test performance in underrepresented samples.

1.3. Aims

This study aimed to explore the relationship between PS and WM, as well as the potential moderating power that PS has between selected demographic variables and WM performance. Specifically, the study intends to answer the following questions and objectives:

Primary research question

- How does PS impact WM?

Secondary Research Question

- How does PS moderate the relationship between WM and demographic variables?

1.3.1. Study objectives

- To explore the correlation between WM and PS.
- To explore the relationship between WM and demographic variables (age, years of education, language experience, SES, and gender), and between PS and the same demographic variables.
- To determine whether PS and demographic variables predict WM performance.

1.3.2. Research hypotheses

The hypotheses of this study were as follows:

- There would be a significant correlation between WM and PS measures.
- There would be a significant PS moderation on the relationship between demographic factors and WM measures

1.4. Rationale

Understanding the cognitive mechanisms that impact WM was vital, especially in a diverse population like South Africa. However, existing literature has established that WM and PS are closely linked (Cepeda et al., 2013; Kim & Park, 2018). However, there is a gap in how PS functions as a moderator variable, one that can influence the strength and direction of the relationship between other cognitive factors (Field, 2017). In this study, PS was explored as a moderator in the relationship between demographic factors and WM because of its role in cognitive processing and its variability across demographic factors. The theoretical view of Salthouse (1996) emphasises that individuals' differences in WM are influenced by processing efficiency and that PS operates as a limiting mechanism of high-order cognition, limiting the effectiveness of WM across the life span. Caplan and Waters (2005) highlight the role of PS in impacting individual differences in the performance of WM tasks, suggesting that the effect of demographic variables on WM may differ as a function of PS capacity. Some studies have demonstrated the impact of PS on various cognitive performances, as well as influencing demographics (e.g., Caplan & Waters, 2005; Kim & Park, 2018; Salthouse, 1996). Additionally, PS tends to decline with age and might be lower in individuals with fewer years of education or restricted language proficiency (Tran et al., 2018). By

investigating PS as a moderator, this study intended to discover whether the effect of demographic variables on WM was constrained by PS.

The current study was grounded in the acknowledgement that WM performance does not happen in seclusion, but is influenced by the relationship between demographic factors and cognitive processes. Particularly, PS appears as a central cognitive construct that impacts WM and moderates the effect of demographic factors on cognitive performance. This has been somewhat demonstrated by previous studies and theories (see Caplan & Waters, 2005; Kim & Park, 2018; Salthouse, 1996). Examining the role of PS as a moderator of cognitive performance in the South African context could provide an understanding of the reasons for some individuals' delayed response times and others' rapid reaction times. In addition, this study provided insights into how WM and PS performance were affected by demographic factors in heterogeneous healthy adults in South Africa.

1.5. Significance and contribution of the study

Importantly, the study findings have direct implications for the design and interpretation of cognitive assessments, particularly diverse educational, bi/multilingual, and ageing populations. As people with fewer years of education, older adults with diverse languages and cultures may experience challenges while processing information that affects task performance (Ardila, 2005; Pontón & Ardila, 1999; Salthouse, 1996). Recognising how PS interact with demographics to influence WM performance, the study findings sought to identify any disparities in test performance, address the lack of knowledge in cognitive psychology, guide future cognitive test development that are more reasonable, context sensitive cognitive tests that account for all individuals, and create culturally sensitive tests that may accommodate individuals based on their respective languages, educational background, and SES. This could reduce issues of misinterpreting or using the wrong cognitive measures. Besides, standardised cognitive measures frequently developed in Western contexts may not account for distinctions in PS linked to cultural or demographic differences. However, understanding the relationship between these two cognitive constructs has been considered significant for the interpretation of outcomes from cognitive assessments (Nettelbeck & Burns, 2009).

Eventually, the study contributed to the theoretical debate in cognitive psychology by examining competing accounts for WM variability, such as resource theory (Just & Carpenter, 1992; Engle, 2002) versus PS theory (Salthouse, 1996). Putting PS as a moderator

that merges differences in the performance outcome, and allows researchers to explore how cognitive mechanisms interact with demographic factors in WM performance tasks. The current study's findings would not only add to the existing cognitive studies but also inform clinical and neuropsychological practices where interpretation of WM tasks is critical for intervention. It also demonstrates the importance of moving from universal models and incorporating these two constructs into the design and interpretation of test performance.

1.6. Structure of the Research Report

Following this introductory chapter, the second chapter reviews the related literature, conceptualising WM and PS, and also discusses the extent of the literature. Next, Chapter 3 describes the study's methodology, and the findings are presented in Chapter 4. Lastly, Chapter 5 outlines the discussion of the current study's findings.

Chapter 2 - Literature Review

2.1. Introduction

The chapter discusses the literature review, introducing working memory (WM) and processing speed (PS) as major concepts in cognitive psychology. Chapter two presents theoretical models such as Baddeley's multicomponent model, Cowan's attention-based model, and Salthouse's theory of PS, and articulates their implications for understanding individual differences in cognition. It also resolves empirical controversies on the degree to which WM and PS overlap, how they age, and to what extent demographic factors like education, socio-economic status, gender, and language experience influence performance, before addressing the moderating role of PS. In addition, the chapter also cites the controversial beliefs regarding whether WM deficits are caused by either resource constraints primarily, attention control, or processing efficiency, positioning this study in the context thereof and emphasising contextual factors in various groups, such as South Africa.

2.2. Working Memory

2.2.1. Conceptualisation of Working Memory

Miller and his colleagues introduced the term ‘working memory’ in 1960. In their study, Miller et al. (1960) referred to the term as a memory that can be stored for a short period. They did not make a clear differentiation between short-term memory and WM. Modern literature attributes to WM the ability to interact proficiently with and modify data (Engle, 2002) and the capacity to effectively engage with information (Alloway & Copello, 2013).

Additionally, WM influences information processing, retention, and utilisation (Engle, 2018) and involves the simultaneous processing of information (Alloway, 2006; Khalid et al., 2020). Working memory enables us to maintain crucial information in our consciousness while engaging in activities such as problem-solving, decision-making, and multitasking (Cowan, 2013; Hocking et al., 2020). Issues with WM may result in the loss of information before it can be integrated into a cohesive and coherent thinking function. This makes WM essential to everyday functioning (Cowan, 2013). Additionally, Cowan (2013) describes WM as a unified system. However, Miyake and Shah (1999) dispute this notion of unity, contending that WM consists of diverse representational codes or separate subsystems. Although there are several interpretations, there is a general agreement that WM functions as storing and preserving task-relevant information during cognitive tasks (Miyake & Shah, 1999).

Different models of WM have been offered, such as Broadbent (1958), who proposed a general model of the human information-processing system that was primarily designed to account for how we attend to some stimuli while ignoring others. Examples of this system include our selective-attention capabilities and how we retain stimulus information, in various forms, both before and after attending to it. This includes our memory storage capabilities.

Thereafter, by contrast, the Multi Store Model of Memory by Atkinson and Shiffrin (1968) proposed that memory is composed of different sensory-like short-term and long-term stores. They offered a memory model, suggesting that human memory has three storage systems: sensory register, short-term memory, and long-term memory. The short-term memory system was understood to encompass WM functions. They also provided a more precise definition of WM as a cognitive component that maintains information about goals and sub-goals required for problem-solving tasks. According to this model, information is received by the sensory register, where it is temporarily retained before either deteriorating or being moved to short-term memory through the process of attention. Subsequently, information can be additionally encoded and transmitted to the storage of long-term memory through the process of rehearsal. This model suggests that for learning to happen, information storage and maintenance occur in the short-term memory. It has recognised a structure for comprehending the processing and retention of information in the human memory system (Atkinson & Shiffrin, 1968). Although Atkinson and Shiffrin's model was widely held in its time, complications were identified (Baddeley, 2010). For example, the model suggests that short-term memory is essential for the operation of long-term memory. This suggestion has been proven to be inaccurate and entails that long-term memory may not necessarily need short-term memory (Baddeley, 2010).

Subsequently, Baddeley and Hitch (1974) introduced their model, which defined WM as a multi-component system that provides integrated processing and storage. It is functionally significant because it enables various cognitive functions, such as thinking, learning, and comprehension. The idea of the multicomponent model will be briefly discussed separately to provide an additional context as the most widely accepted model of WM (Baddeley & Hitch, 1974).

Another model that was created as an alternative to Baddeley's model is Cowan's embedded process theory (Cowan, 1999). The Cowan's model highlights that WM acts as a short-term storage component that depends on attention and other central executive

processes, highlighting the role of attention in improving WM. This model incorporates some aspects from Baddeley's multicomponent theory, but additionally suggests that the phonological loop and visuospatial sketchpad are responsible for temporary information that is already in long-term WM. The central executive system is responsible for requesting information from long-term memory as a technique of collecting information from incoming stimuli (Cowan, 1999). Although this model has not been as influential as Baddeley's, it has resulted in additional processing theories of WM.

Although different models of WM have been postulated (Atkinson & Shiffrin, 1968; Broadbent, 1958; Cowan, 2008; Miyake & Shah, 1999), the understanding of the association between long-term memory and WM differs among these models. This includes the nature of the executive control process and WM capacity. Nevertheless, the models agree that WM consists of some components that function correspondingly to temporarily store and manipulate information (Cowan, 2008; Miyake & Shah, 1999; Oberauer, 2005). The current study aligns with the definition provided by Baddeley and Hitch (1974), which encompasses the multiple components of short-term storage and manipulation of information, such as language and verbal WM.

2.2.2. The Multicomponent Model of Working Memory

There are different models of WM; however, Baddeley's model was used as one of the frameworks in this study. A model that has been prominent in this field is the multicomponent model by Baddeley and Hitch (1974). This model deviated from that of Atkinson and Shiffrin (1968). Instead, they switched unitary systems with three separate, interacting subsystems, which enhanced the understanding of complex systems. Additionally, this interaction challenged the idea of successive stages, supporting a model capable of similar processing across the subsystems (Baddeley, 2010). This model was introduced as a broad theoretical framework, allowing for a more detailed modelling of the three subsystems—the central executive functions as a control system responsible for attention management and resource distribution. The phonological loop handles the storage of verbal and auditory information. The visuospatial sketchpad deals with visual and spatial data (Baddeley, 2000; Baddeley & Hitch, 1974).

The central executive does not store information directly but controls and manages resources within the WM system (Baddeley & Hitch, 1974). Baddeley (2000) suggests that the central executive is a key component of WM, responsible not only for managing attention

but also for selecting relevant information, switching focus between tasks, and coordinating and making decisions on how the sub-components system should function. The sub-components are divided into the phonological loop and the visuospatial sketchpad. The central executive links information to long-term memory by managing an individual's ability to process verbal and visual information. It also allows manipulation and storage of information in WM by supervising and organising an auxiliary system (Baddeley, 2000). Although the central executive is well established in cognitive theory, its presence is not easy to prove, due to the complicated nature of its functions.

However, Van der Linden et al. (1992) confirmed the existence of the central executive system after assessing patients in the verbal Brown-Peterson task. They reported that the central executive system shows a decline in head-injured patients, which hinders patients from achieving goals and coordinating processes involving maintenance rehearsal. Similarly, Baddeley (1986) examined patients with Alzheimer's and found discrepancies in visuospatial and verbal WM tasks. These findings demonstrate a decline across all slave systems, including the central executive. They emphasise the existence of the central executive, even though it is poorly understood. Baddeley (2017) identified this slave system as a compelling component of WM.

By contrast, despite the main role of the central executive in the model, this idea has drawn criticism for its complexity. For example, Parkin (1998) argued and critiqued the notion of the central executive system, which does not indicate what the WM model defines. Argues that "it is difficult, if not impossible, to accept the idea of a central executive as defined by the WM model," suggesting that the central executive was not unitary. Instead, postulates that executive tasks contain nonoverlapping and specific task control processes. This represents a decentralised model of executive functioning. Additionally, neuroimaging and lesion research have maintained Parkin's (1998) argument, indicating that executive functions, like task switching, inhibition, and updating, utilise separate neural networks in the prefrontal cortex (Miyake et al., 2000; Duncan & Owen, 2000; Stuss &Alexander, 2000). This evidence has demonstrated a need to modify the central executive to reflect a more integrated control system (Alvarez & Emory, 2006; Norman & Shallice, 1986).

The phonological loop is often called verbal WM and is responsible for processing speech and the information it conveys (Baddeley & Hitch, 1974). According to Baddeley (1996), the

phonological loop facilitates learning new vocabulary terms and consists of two subcomponents, namely storage and rehearsal. The phonological storage can hold information based on speech for a few seconds before it disappears and is found in the brain's left hemisphere (Baddeley, 2000). Baddeley (2006) proposes that the phonological loop considers that failing to recall information results from a decline in the store. This is assumed to involve an inner voice that may be utilised to rehearse information, retrieving it before it is articulated, and it is termed the articulatory loop (Baddeley, 2006). The articulatory control process interprets and rehearses the information stored in the phonological store. In other words, it completes the phonological loop. It is further assumed that it filters any distraction in maintaining language information and simultaneously processes visuospatial demands (Baddeley, 2000, 2010).

Evidence to support that the phonological loop plays an important part in learning new words or language, especially unfamiliar language, comes from a succession of research that Papagno and colleagues conducted. Papagno et al. (1991) investigated how articulatory suppression affects learning new words. Participants were native Italian speakers; they were asked to learn familiar and unfamiliar words, using visual and auditory formats. Their findings indicated that suppression significantly reduced the learning of new vocabulary in the Russian language, but had less effect on learning first language or native word pairs. This suggests that learning an unfamiliar language depends on phonological rehearsal, meaning an individual cannot rely on familiar words but must hold and rehearse information in the brain. While learning in a familiar native language, word pairs can be encoded using semantic (meaning of words or phrases) strategies, rather than depending on an auditory basis.

Papago et al. (1991) tested English participants using Russian words. They found it easy to use Russian words, creating a semantic association with words. This brought challenges to the initial purpose of the investigation and interfered with the intended assessment of verbal learning. The researcher tries to make it more difficult by introducing nonsense (unfamiliar) words and later integrating them with Finnish words with less English phonological structure. This activated the phonological loop to reveal its part in non-semantic verbal learning. This had less influence on the English language. The findings were consistent with those of a study using Italian participants. These findings suggest that the phonological loop supports learning unfamiliar words, especially when semantic cues are uninvolved. This aligns with Baddeley (2000), who states that the phonological loop is central to language learning, particularly in early stages.

In terms of bi/multilinguals, these findings emphasise the significant role of the phonological loop throughout the early stages of additional or second language learning. When semantic connections are limited, learning a foreign language or new vocabulary depends more on phonological rehearsal, especially when meaning is not easily accessible (Baddeley, 2000, 2010). It also suggests that those who can manage or speak multiple languages may have stronger and flexible phonological memory. This is supported by the claim that learning new words in a foreign language develops an efficient phonological loop (Baddeley et al., 1998). This may contribute to more effective vocabulary acquisition across languages, which could explain why bi/multilinguals are effective at language learning. In addition, if inner speech is blocked during the articulatory suppression or high cognitive load, this can interrupt new word learning regardless of language background (Baddeley, 1996; Baddeley & Gathercole, 1998).

The visuospatial sketchpad essentially explains how different images and objects are stored. It consists of spatial short-term and object memory, and is assumed to process limited information at a time (Baddeley, 2000). According to Baddeley (2000), this subsystem acts as an inner eye and encodes visual and spatial information presented non-verbally. Evidence supporting the visuospatial sketchpad was found. Baddeley (1992) observed that individuals who struggle with remembering visual objects, like colour and shape, could still remember spatial information, such as a location map and a route. This finding proves that separate WM framework subsystems handle visual and spatial information. Corroborating this, Baddeley (1996) examined participants by asking them to encode and recall a series of spatial sentences using a 4x4 matrix, where participants were asked to put one in a starting square and two in the bottom left square. Participants were able to recall up to eight spatially encoded instructions. This suggests that the visuospatial sketchpad includes two separate functional components. These findings demonstrate the separation of visual and spatial functions in WM and suggest how bi/multilinguals perform differently from monolinguals on specific cognitive tasks.

After the three subsystems, an episodic buffer that temporarily modifies and incorporates different sensory information was introduced. The introduction of the episodic buffer addressed key theoretical gaps by describing the interaction between WM and long-term memory. It serves to integrate other research traditions. For instance, the bottom-up approach focuses on the phonological loop and visuospatial sketchpad, as well as the top-down approach (Baddeley, 2012; Cowan, 2005; Engle, 1999). This buffer is a multidimensional

system that reciprocally connects the phonological loop and visuospatial sketchpad with long-term memory (Baddeley, 2000). It does not just connect these components, but it also connects WM with perception and long-term memory. This is done by holding multidimensional information (combining image, words, and meaning), allowing it to form unified episodes from otherwise separate input types. However, the episodic buffer has limited capacity; it holds a small amount of information at once before it passes (Baddeley, 2000). To engage in sophisticated cognitive processes, such as goal-directed behaviour and problem-solving, all these sub-systems support the mental holding and manipulation of information (Baddeley, 2000; D'Esposito, 2007; Diamond, 2013).

The integrative function of the episodic buffer is particularly pertinent in a bi/multilingual context where individuals manage multiple languages at the same time. For instance, bi/multilinguals often attract verbal and non-verbal prompts, necessitating an episodic buffer to bind them together, as well as phonological, semantic, and contextual information across languages. This is aligned with Baddeley's (2000) view of the episodic buffer as a connector between basic systems, such as the phonological loop and visuospatial sketchpad, higher-order executive function, and attention.

Although the multicomponent model of WM has been explained in terms of the theoretical function, research indicates that PS and demographic variables can differentially affect these components. Baddeley (2007) and Fougnie (2009) indicated that the central executive system allocates processing resources that regulate the efficiency and speed of cognitive and simultaneous cognitive processes. Furthermore, the decline in the central executive system is associated with PS, affecting attention and manipulating information. However, this differs according to the individual. Lengenfelder et al. (2006) suggest that individuals with slow PS experience issues with their articulatory mechanism to rehearse longer words, which then influence the phonological loop. Contrarily, those with faster PS quickly and accurately produce speech sounds, enabling effective verbal processing. Additionally, when the PS is impaired, the WM system, including a multicomponent structure, is disrupted (Lengenfelder et al., 2006). Regarding the visuospatial sketch pad, Salthouse (1996) proposed that people with slow PS struggle with visuospatial tasks due to delays in processing mental images, leading to performance discrepancies (Lengenfelder et al., 2006). This effect was evident in older adults with less visuospatial WM capacity and slower encoding rates (Salthouse, 1994; Cepeda et al., 2001). While the episodic buffer is not connected with PS, it is assumed to limit a storage system capable of integrating information from various sources (Baddeley,

2000). This is demonstrated to emphasise that PS influences the multiple components of WM and demographic factors differently.

Since different studies have considered WM unitary, measures of WM have become complex. Specific measures have been aligned with specific functions of WM, and other measures tap into multiple functions and attention. This construct is typically assessed by different measures that assess how well an individual keeps information in their mind for a short time. These tasks differ based on their modality, such as verbal, visual, and/or numerical, and the specific cognitive processes they engage. In the current study, the measures used, the Digit Span (DS) subtests of the Wechsler Adult Intelligence Scale-Fourth South African Edition (WAIS-IV-SA), consist of forward, backward, and sequencing formats, and the Letter Number Sequencing (LNS) subtest of the WASI-IV-SA (Wechsler, 2017), which includes both letters and numbers. These tasks required both storage and manipulation.

2.2.3. Neuroanatomical correlates of Working Memory

Studies reporting on the neuroanatomical bases of WM (Chai et al., 2018; Kim et al., 2015b) provide evidence suggesting that the prefrontal cortex is fundamental in completing tasks that require information manipulation (Kim et al., 2015b). For instance, the dorsolateral prefrontal cortex has been found to play a role in updating information and maintaining WM function (Klumpp & Deldin, 2009). Functional imaging studies (e.g., Curtis & D'Esposito, 2003; Smucny et al., 2021) found that a strong activation in the dorsolateral prefrontal cortex occurred during complex WM tasks. This emphasised the dorsolateral prefrontal cortex's involvement in integrating brain region inputs (Curtis & D'Esposito, 2003). Kim et al. (2015b) found that the dorsolateral prefrontal cortex and WM are involved in higher-order cognitive functions, which include executive function, verbal tasks, and integration and manipulation of information. While in verbal processing, the dorsolateral prefrontal cortex engages in goal-directed processing and organising language (Hertrich et al., 2021). The prefrontal cortex and the posterior parietal cortex in the cortical area support the spatial representation and the coordination resources in WM tasks (Klingberg, 2006). In contrast, the cortical area of the frontal lobe operates in tandem with WM and Broca's area, and subvocal rehearsal is linked to Broca's area (Baddeley, 2003). Beyond cortical areas, subcortical structures such as the basal ganglia and thalamus contribute by transferring information within the WM network (Chatham et al., 2014).

2.2.4. Conceptualisation and measurement challenge in working memory

Due to the challenges in defining the exact WM boundaries (Dang et al., 2012), there is controversy regarding the best way to assess this construct. Studies frequently differ on whether WM should be considered a singular or an umbrella term including distinct and/or interactive systems (Donkin et al., 2013; Simmering & Perone, 2013). Measures such as the DS test do not always capture the multifaceted aspect of WM described in theoretical models (Kane et al., 2004) and are often correlated with other abilities such as executive function and fluid intelligence (Kane et al., 2004). Despite this, DS backward is considered a good measure of WM, comprising the central executive and phonological loop (Schaeffner et al., 2020).

Additionally, the LNS task, which measures verbal WM, is challenging. Cowan and Kail (1996) suggest that although LNS is a measure of verbal WM, it requires various types of processing as it simultaneously includes reordering letters and numbers, which causes significant cognitive demands. This increases the chances of individuals making mistakes, as they must retain accuracy while handling dual cognitive operations. Moreover, Mielicki et al. (2018) emphasise that performance in LNS can be affected by other factors, such as the language used by participants and how LNS is administered. These factors may introduce contradictions in performance, posing challenges in isolating the task as a pure measure of WM. By contrast, the validity of the n-back measure of WM has been questioned (Kane et al., 2007), as it also measures other constructs, such as fluid intelligence and matches measures of executive function (Oberauer et al., 2003; Kane et al., 2004). The overlap between WM measures and other cognitive constructs makes it challenging for researchers to advance tasks that separate subsystems.

2.2.5. Justification of measures

The LNS and DS subtests of WAIS-IV-SA are reliable and valid measures of auditory/verbal WM (Wechsler, 2017). Hence, the current study employed the LNS and DS subtests of WAIS-IV-SA. These tasks are widely used in neuropsychological assessments and are appropriate in principle for evaluating WM. The justification for their selection would provide more understanding of why they were chosen, as they have strengths. These subtests have been long-established from the Wechsler scales for years, and are suitable for assessing verbal WM and attention (Wechsler, 2017). Meanwhile, there is supporting and contrasting evidence about using the DS backward test to measure WM. The task is administered in English, which might disadvantage those who do not speak the language. However, most

South Africans speak English as a second language and are still proficient enough to follow instructions. Forward DS primarily taps attention span, while backward and sequencing reflect executive control and manipulation in WM (Wechsler, 2017).

The DS primarily depends on language and requires phonological accuracy, speed of auditory processing, and familiarity with numbers or words in the language used for testing (Baddeley, 2017; Wechsler, 2017). In contrast, LNS measures complex verbal WM by requiring the manipulation of mixed verbal and numerical stimuli. This is more demanding than DS and requires great executive control (Wechsler, 2017). These subtests rely on phonological structure that influences cognitive performance. However, participants who are unfamiliar with the English alphabet may be at a disadvantage. On the other hand, Alloway et al. (2004) and Shuttleworth-Edwards et al. (2013) highlighted that these tasks are not affected by SES nor educational background, and are not language dependent, but examine auditory WM, suggesting that these measures have reduced bias in terms of interpretation.

However, in language-diverse or bi/multilingual populations, these task performances may be biased due to speech articulation, language, and digit familiarity, rather than accurately assessing true WM. These tests may be especially biased against individuals with less exposure to formal schooling in English, as they depend on accurate internal verbal rehearsal and quick recall. This stems from the fact that familiarity with numbers and letters might give an advantage to those using the testing language at school. Consequently, participants may show confusing performance, which can obscure the measured cognitive construct, leading to unclear interpretations of whether these tests truly measure WM or language processing (López et al., 2016; Mielicki et al., 2018). This was demonstrated in Naveh-Benjamin and Ayres' (1986) study, which involved participants speaking various languages (English, Spanish, Hebrew, and Arabic) and used DS, Speeded Digit Reading, and Normal Story Reading.

Their findings demonstrated a strong relationship between memory span and language. This demonstrated that memory span was influenced by specific language or phonological structures, suggesting that dominance or familiarity with the language of testing may affect cognitive assessments. Furthermore, indicated that differences from these tests may stem from the language used or phonological characteristics rather than WM decline. This suggested potential bias in verbal WM, if volunteers were assessed in their dominant language or language used at school, and disadvantages in those with slower reading skills, if

they have a few years of educational background, or a few years of exposure to the language of testing. This also applies to bi/multilinguals assessed in a second or nondominant language.

2.2.6. Working Memory Measures

Researchers have created several measures for WM, such as the n-back test (Kirchner, 1958), Reading span (Daneman & Carpenter, 1980), Operational span (Kane et al., 2004), LNS subtest, and DS subtest of the WAIS-IV-SA (Wechsler, 2017). These measures have been reported to have advantages and disadvantages.

First, the n-back task involves a visuospatial task with four difficulty levels (Kirchner, 1958). Compared to other WM tasks, its exclusive feature is that participants do not need to retrieve information from memory. Instead, they must identify and acknowledge information (Kane et al., 2007). Furthermore, it is often used for assessing WM, requiring participants to determine whether each stimulus in a sequence corresponds to the one that appeared among the previous "n" items (Kirchner, 1958). Nonetheless, the n-back task has not been validated as a reliable test of WM through empirical research, and its psychometric features are now being questioned (Coulacoglou & Saklofske, 2017).

Studies have reported evidence of the n-back task's inaccuracy. For example, Kane et al. (2007) reported that the n-back task demonstrated a weak correlation with Operation Span and is thus difficult to see as a pure WM measure. However, Jaeggi et al. (2010) examined the convergent validity of the n-back task concerning other assessments of WM. They reported a lack of correlation on the Reading Span task, and the reliability of the n-back task was lower than that of the Reading Span. Although DS subtests correlated with n-back, the authors concluded that the n-back task was not useful in assessing WM capacity due to a lack of reliability.

However, tasks like Operational span, where participants are required to solve mathematics and recall the words (Kane et al., 2004), and Reading Span, which utilises a combination of simple words and sentences (Daneman & Carpenter, 1980), are also considered to measure WM. Both these tasks reported reliability and validity in measuring WM. Researchers have reported a good reliability ranging from .69 to .90 on both Operational and Reading Span (Conway et al., 2005; Kane et al., 2004).

Additionally, the LNS and DS subtests of the WAIS-IV-SA have been designed to assess WM capacity, attention, and verbal short-term memory (Wechsler, 2017). The backward and

sequence phases of the DS and LNS tasks are considered to be highly valid measures of WM, according to Wechsler (2017). In the backward phase of the DS subtests, participants are required to retain and reverse a sequence of digits. This demands the holding and manipulation of information at once. There is evidence of these tasks being used; for instance, Egeland (2015) conducted a study examining the WM assessment using the LNS and DS subtests of WAIS-IV. When tasks were examined together, including Spatial Span, LNS, and DS subtests, the findings demonstrated the best fit, indicating that these tasks measure different components of WM. Meanwhile, Engle (2010) raised concerns about the DS subtests; in their study, they indicated that the absence of the complication of simple span may compromise the validity and reliability of the test, and the lack of connection with the real world.

Therefore, it can be argued that WM cannot be measured by one task, but requires various measures that tap into various WM components (Egeland, 2015), such as continuous updating, manipulation, and maintenance of information.

2.3. Influence of Demographic Variables on Working Memory

This section discusses how various demographic characteristics relate to WM. Specifically, it will discuss the relationship between WM and selected demographic factors, such as age, education, language experiences, SES, and gender. The complexities of these demographic variables' impact on WM are also outlined.

2.3.1. Working Memory and Age

It is generally known that cognitive functioning decreases with age (Craik & Salthouse, 2000; Harada et al., 2013; Murman, 2015). As individuals age, information processing and executive function, including WM, deteriorate, thus affecting overall cognition negatively (Craik & Salthouse, 2000). Salthouse (1996) proposed a theory linking this decline to age-related PS reductions. A decrease in PS imposes a fundamental limitation on the efficiency of WM and reduces an individual’s ability to coordinate tasks effectively and retain information without practice (Nettelbeck & Burns, 2009). Consequently, reduced WM harms cognitive choices and ultimately affects cognitive decision-making (Banerjee et al., 2014).

In tasks that require switching, age-related differences are predominantly evident (Kray & Lindenberger, 2000). For instance, Klencklen et al. (2017) investigated WM in 34 young adults aged between 20 and 30, and 35 older adults aged between 65 and 75. They used

various measures, including DS, Vocabulary, Arithmetic, and Similitude subtests, and a Corsi block-tapping test. The results indicated that young adults excelled in all tasks related to WM compared to older adults, highlighting a significant age-related decline (Klencklen et al., 2017). Similarly, Caplan and Waters (2005) reported that older adults exhibited a lower verbal WM capacity than younger adults, as evidenced by their lower performance on verbal WM measures. Additionally, Pliatsikas et al. (2018) further demonstrated a progressive nature of WM decline with age in a larger sample of adults by utilising an oral version of the n-back task. They further revealed that WM continues to deteriorate with advanced age. This decline was present on both visuospatial and verbal WM.

Furthermore, studies by Myerson et al. (2003) and Elliott et al. (2011) offer complementary understandings of how WM changes with age, particularly concerning task complexity. Both studies utilised DS forward and DS backward to assess WM, and they revealed no significant differences between a group of younger adults and a group of older adults in these simpler span tasks. This suggests that the ability to maintain information through basic repetition may remain relatively stable across age groups. However, both studies observed a noticeable deterioration in older adults' performance of more demanding tasks. Specifically, Myerson et al. (2003) found that older adults underperformed in the LNS task, further indicating that age-related decline in executive function may lead to challenges in manipulating and maintaining items in WM. In contrast, Elliott et al. (2011) reported that older adults performed poorly in the Size Judgment Span.

Furthermore, a recent study by Idowu and Szameitat (2023) asserts that older persons experience challenges with complex tasks, which causes delay and inaccuracy in their performance. Therefore, both LNS and the Size Judgment Span might require executive control from an individual to manipulate and integrate information. This is in line with previous research, which showed that the effect of ageing is more observed in tasks demanding flexible cognitive resources than simple recall tasks (Craik & Salthouse, 2000). Further, Bopp and Verhaeghen's (2005) meta-review supports these findings, asserting that WM capacity declines moderately with age and becomes more pronounced as task demands increase.

These studies suggest that simple WM tasks, like DS forward and DS backward, remain quite preserved in older adults. However, tasks that involve more difficult cognitive processes, such as Size Judgment Span or LNS, are more sensitive to age-related changes

(Elliot et al., 2011). This pattern reveals a gradual decrease in cognitive flexibility and attentional control, which are critical components of WM that deteriorate with age (Idowu & Szameitat, 2023). Thus, the outcomes determine the nuanced nature of cognitive decline in older adults and the importance of distinguishing between different types of WM tasks when assessing progressive changes in adults.

Building on the evidence of cognitive decline, researchers have argued that age-related impairments may be partly explained by difficulties in task switching among older adults (Kray & Lindenberger, 2000; Verhaeghen et al., 2019). Specifically, impairment in WM appears to be closely linked to difficulties in the organisation of cognitive processing, which can negatively affect cognitive management (Bopp & Verhaeghen, 2007). However, the degree to which ageing influences task switching remains debated. Kray and Lindenberger (2000) argued that older people can engage and disengage their cognitive systems efficiently, allowing themselves to switch between tasks. This indicates that the challenge does not lie in switching tasks but in managing multiple tasks simultaneously.

Similarly, Mayr (2001) noted that difficulties in recalling and organising multiple tasks may impair an older individual’s performance of complex tasks. Furthermore, a recent study by Wang et al. (2022) provides an additional understanding of the relationship between WM and task switching. Their findings corroborate that WM and task switching activate the same neural, suggesting an overlap in cognitive mechanisms. Furthermore, switching tasks and refreshing cognitive task sets demand effort, including retrieving pertinent information from long-term memory. These findings emphasise the cognitive effort required in task switching and indicate how the decline in WM may affect older adults’ ability to manage cognitive flexibility effectively.

In conclusion, the results of these studies suggest that verbal WM is commonly impaired in older adults compared to young adults. Although no differences were found between the two age groups' DS forward and DS backward, older adults displayed an age-related decline in the Size Judgment Span and LNS. These findings suggested a nuanced pattern of WM decay, with complex spans being more susceptible to age-driven deterioration. Regardless of the absence of the age effect, DS forward and DS backward continue to function as a fundamental measure for simpler WM. By contrast, LNS provides more insight into older adults' WM decline given their higher WM demands, which are more related to increased

age. Moreover, an overlapping mechanism in task switching was identified, demonstrating that older adults encounter multitasking complications, leading to task completion delays.

2.3.2. Working Memory and Education

Educational attainment plays a considerable role in improving WM in adults and enhancing the performance of memory tasks through an individual's lifetime (De Souza-Talarico et al., 2007; Schneider & Niklas, 2017). Studies have demonstrated that higher levels of education are associated with improved cognitive functioning in later stages of life, encouraging cognitive reserve and influencing cognitive abilities such as WM, which is necessary for daily functioning (Galama et al., 2018; Soh et al., 2023). Shuttleworth-Edwards et al. (2004) established how the level of education may influence performance in cognitive tests, specifically in South Africa, where educational disparities that trace back to the apartheid era have led to ongoing challenges. During that period, unequal distribution of educational resources mostly affected government school attendees, leading to lower-quality education and, subsequently, poor cognitive outcomes (Arendse, 2019). Even though research investigating the association between the educational level and WM performance in South African adults remains limited, studies on children suggest that education positively impacts WM. In addition, the studies argue that memory-related activities can be further strengthened through practice (Cockcroft, 2015; Moolla, 2012; Mphahlele et al., 2022).

International research has consistently demonstrated the role of education in WM. De Souza-Talarico et al. (2007) and Kosmidis et al. (2011) assessed the association between WM and education using the DS forward and backward in elderly persons. Both studies reported a significant association between education and WM as measured by the DS backward. De Souza-Talarico et al. (2007) examined 40 participants aged 62 to 90 years with educational levels ranging from 1 to 19 years. By contrast, Kosmidis et al. (2011) investigated 65 participants aged 60 to 80 years across four literacy groups: illiterate, functionally literate, self-educated literate, and school-educated literate. Their samples were exclusive in that volunteers were selected during the Civil War in Greece, a time marked by a lack of resources, poverty, and limited access to formal education.

Despite differences in historical background and sample size, both studies consistently indicated that a high level of education enhances WM, suggesting that educated participants performed better than less educated or illiterate ones, specifically in the DS backward. Kosmidis et al. (2011) further demonstrated that self-educated individuals performed notably

better than illiterate ones, emphasising the role of informal education. In support, Gómez-Pérez and Ostrosky-Solís (2006) found similar findings on a larger sample of 521 volunteers. However, their findings were non-linear due to the heterogeneous sample, specifically those with a 10 to 22 years level of education performed exceptionally well compared to those with fewer years of education.

Similarly, Pliatsikas et al. (2019) used the n-back task to assess the influence of WM on education. They examined a total sample of 754 older adults, aged between 58 and 89, and the level of education ranged from zero to 17 years. A mixed regression analysis indicated that older adults had a decline in their WM, and the effect of age was observed as linear. The results further revealed that education was significantly associated with WM performance. Furthermore, WM was indirectly affected by age and education. This evidence suggests that the relationship between education and WM was moderated by age rather than education itself. This indicated that younger adults with a higher level of education demonstrated improved WM.

The overall evidence above supports the hypothesis that higher levels of education enhance WM and provide cognitive reserve against its age-related decline. Therefore, although older adults generally experience a cognitive decline, those with a higher educational background tend to maintain better WM. Furthermore, the generalisability of these findings is supported by the heterogeneous sample and level of education. However, Kosmidis et al. (2011) included a group division in a small sample size, which limited their ability to perceive more age-related differences. Pliatsikas et al. (2019) involved a larger sample of older adults, allowing for generalising, although participant's age was similar to Kosmidis et al. (2011) study.

This relationship is further demonstrated by neuroanatomical evidence. Goldberg (2022) found that education is likely to influence the brain structure, particularly in areas linked to WM. Additionally, Wang et al. (2017) observed that higher educational attainment was related to enhanced grey matter volume in specific regions of the brain, such as the prefrontal cortex, which plays a crucial role in cognitive processes related to WM and other cognitive processes. These findings demonstrate how education contributes to cognitive systems and neural improvement involved in WM.

The overall evidence points to a significant relationship between education and WM. Moreover, a greater degree of education is likely to enhance cognitive processes by

enhancing WM. Education, therefore, serves a dual role in advancing WM capacity and promoting neural development, particularly in brain regions essential for cognitive elasticity and mental swiftness (Wang et al., 2017). However, most studies on education and WM focus on Western, educated, industrialised, rich, and democratic (WEIRD) populations with limited research on non-WEIRD groups, particularly in a country like South Africa with a historical economic background.

2.3.3. Working Memory and Language Experience

It is widely assumed that speaking more than one language improves WM and other cognitive functions, such as task switching (Marian & Shook, 2012). Theoretical accounts of bilingualism offer valuable insights into understanding the complex language experience and processing. According to Green's (1998) inhibitory control model, bilinguals constrain their dominant language to take control of both languages, allowing more balanced and flexible processing of the second language. This process activates complex neural networks, like cortical and sub-cortical structures, to manage cross-language competition and switching. Bialystok and Feng (2009) proposed a framework on bi/multilingualism that highlights the difficulty of cognitive function and language experience. They argue that people who speak more than one language may demonstrate better executive control. This improvement of executive control results from constant switching and managing two language systems, which helps and benefits the central executive.

Correspondingly, Grundy et al. (2017) further extended this view by demonstrating that the extent of language, such as language dominance, switching, and exposure, builds cognitive processes and neural adaptation. According to Grundy et al. (2017), the brain's structural and functional characteristic is altered by bilinguals; these variations contribute to domain-general cognition. Since bilinguals apply additional frontal resources to handle competition between two languages, these resources gradually increase WM and gray matter structure, enabling connections between the anterior and subcortical or posterior regions. Nonetheless, as bilinguals get used to both languages, their brains change compared to those who speak one language; they use more subcortical or posterior areas than the anterior. This suggests that bilinguals employ brain areas that help them to process stimuli automatically and simultaneously rather than depending on late and top-down processing, a cognitive influence representation of understanding things based on earlier or previous experiences and information (Gilbert & Li, 2013). This helps bilinguals improve even in tasks that do not involve language (Grundy et al., 2017).

For example, bilinguals switch languages effortlessly, even when conversing with others in the middle of sentences. They can speak with people who speak different languages simultaneously and switch between conversations. Bialystok et al. (2012) suggest that bilinguals may possess advantages in inhibition, switching, attention, WM, and retrieval compared to monolinguals in their age groups. This process needs the activation of both languages and cognitive domains. Grundy and Timmer (2017) suggest that these benefits last a lifetime. However, some research argues that there is no bilingual advantage in WM, as bilinguals engage in the ongoing process of suppressing and switching between languages. This may overload the WM, leading to decreased cognitive efficiency in bilinguals, specifically in tasks involving WM (Bialystok, 2015; Poarch & Bialystok, 2015). Marian and Shook (2012) highlight that executive control, which is noticeable during the early stages of development, diminishes throughout the late developmental stages. This is aligned with Green's (1998) framework, demonstrating that bilinguals develop the experience to switch and balance between languages.

Evidence in support of the positive impact of bilingualism on WM has been reported by previous research (Bialystok et al., 2004, 2007; Cockcroft et al., 2017). For example, Bialystok et al. (2004) compared adult monolinguals and bilinguals on WM. Participants were between the ages of 30 and 80 years. A non-verbal Simon task was used to assess participants. The findings demonstrated that bilinguals excelled where high WM demand was required. Another study conducted by Cockcroft et al. (2017) compared monolinguals and multilinguals on a WM function in a sample of 78 South African young adults from a low SES. Participants were divided into two groups: 39 monolinguals who spoke EFL and 39 multilinguals who spoke any African language as a first language and English as a second language. The study focused on verbal storage, visuospatial storage, verbal processing, and visuospatial processing. WM was assessed using the Automated Working Memory Assessment. Digit Recall, Word Recall, and non-Word Recall assessed phonological loop storage. Verbal processing was assessed by Listening Recall, Counting Recall, and Backward Digit Recall. The findings revealed that bi/multilinguals outperformed monolinguals in all WM aspects and demonstrated outstanding visuospatial storage and processing ability. It was further revealed that a multilingual advantage in WM tasks requires less knowledge of English vocabulary. This may be because the bilingual brain can have higher attention and task-switching abilities than the monolingual brain (Grundy & Timmer, 2017).

This aligns with Morales et al. (2015), who suggest that bi/multilingual persons exhibit improved cognitive control and attentional processes, suggesting that these benefits are ascribed to the regular language practice that fortifies cognitive control mechanisms. In addition, Bialystok et al. (2007) found that speaking more than one language was linked to a delayed onset of cognitive weakening and a likelihood of cognitive reserve in later years. Hence, evidence supports the benefit of bi/multilingualism in WM, significantly affecting cognitive performance throughout a person's life. Similarly, Bialystok and Feng (2009) argue that bi/multilinguals engage in executive processes that provision WM; the benefits and disadvantages rely on the task complexity and individuals' proficiency.

However, the evidence concerning the association between bi/multilingual and WM is inconsistent. The connection remains unclear in studies that used similar measures for WM as those in the current investigation, specifically the DS subtests (Ardila, 2003; Kaushanskaya et al., 2011; Ramirez & Harris, 2023). For example, Ardila (2003) examined WM capacity in Spanish monolinguals and Spanish–English bilinguals using DS subtests and reported a bilingual advantage when participants were examined in their first language. The results showed that early bilinguals performed better in DS forward and DS backward compared to late bilinguals. Similarly, Kaushanskaya et al. (2011) examined WM and the retrieval of words in bilinguals who spoke EFL and in English monolinguals. All participants completed the DS subtest to measure verbal short-term memory related to WM. The findings indicated similar performances in both monolinguals and bilinguals. Ramirez and Harris (2023) used DS subtests of WAIS-V to examine 82 young-adult bilinguals who spoke English as a second language. The authors reported that bilinguals did not perform well in DS forward and attention span, such as the Long Digit Span Forward (LDSF).

In contrast, Oltshoorn et al. (2012) highlighted the importance of language in assessments. They reported that those who spoke their first language performed better than others who spoke other languages as their first, specifically when the task was conducted in their dominant language. This demonstrated how important one's first language is for task performance. These findings could be because the individual's performance relies on the language used, highlighting that language differences can impact task performance. This is aligned with the perspective of Grundy et al. (2017) on the advantage of bilingual experience, suggesting that it may be moderated by language dominance and proficiency.

Ardila (2003) and Kaushanskaya et al. (2011) found different results in the performance of the DS tasks. Kaushanskaya et al. (2011) demonstrated that English bilinguals were assessed in their dominant language, rather than their first language, and monolinguals were assessed in their first language, but the findings were similar. This shows that first and second languages are similar in early bilinguals, emphasising that language proficiency can be more influential than language acquisition. By contrast, Ramirez and Harris (2023) added the attention span in their study. They reported that the bilingual performance score failed to predict the performance in the DS backward, DS sequencing, DS total, Long Digit Span Backward (LDSB), and Long Digit Span Sequencing (LDSS). Furthermore, Ardila (2003) highlighted that learning an additional language at an early stage helps one develop a strong phonological loop, which may explain the advantage of early bilinguals compared to late bilinguals in DS performance. In support of this, Verhoeven (2007) emphasised that phonological loops adjust and become more efficient in encoding and retrieving language during the critical stage of neural plasticity to form a strong phonological loop.

These findings suggested that DS subtests may not be influenced by the languages one speaks. Grundy and Timmer (2017) suggested that this may be due to the ambiguity surrounding the classification of tasks as verbal or non-verbal, as DS subtests necessitate almost no language effort and fail to distinguish between verbal and non-verbal tasks.

Moreover, King (2020) investigated the impact of bi/multilingualism on WM in a sample of 280 participants aged 50 to 83 years. Operational span and Symmetric span were used to measure WM. The evidence indicated that bi/multilinguals had challenges while engaging in tasks that require WM, but no significant impact of the NL spoken on Operation span and Symmetric task performances. However, this study did not support the hypothesis that bi/multilingualism would enhance the performance of WM tasks. Moreover, this study distinguishes itself from others, as participants' level of education was high, one volunteer had 40 years of education, and the sample size of monolinguals was much smaller than that of multilinguals. This may be the reason for the lack of differences in task performance.

Despite similar performances on WM tasks demonstrated by bilinguals and monolinguals, Monnier et al. (2021) argue that the performance of WM tasks depends on the language used to administer a test. Their findings demonstrated no differences in the performances of WM tasks by bilinguals and monolinguals when the tasks were conducted in their native language. However, bilinguals indicated an enhancement when they switched to their second language.

This may be attributed to the interference of a dominant language frequently used by bilinguals (Bernardini & Schlyter, 2004), since bilinguals are assumed to have less vocabulary than monolinguals (Kroll & Bialystok, 2013). These findings suggest that the dominant or first language contributes positively to WM performance.

Mielicki et al. (2018) expressed a contradictory view that different approaches to measurement may offer conflicting outcomes. Their study compared young adults (bilinguals and monolinguals) on WM, as measured by the oral version of LNS using the computer screen version. This was done in three separate experiments. Experiment 1 used the oral version of LNS, in which monolinguals outperformed bilinguals. In Experiment 2, a computer version was employed, and no differences were found between the two groups. Additionally, when Experiments 1 and 2 were taken together, the results revealed a monolingual advantage on the oral version of LNS. In Experiment 3, 63 English-speaking university students, between the ages of 18 and 23, were assessed using mixed methods that included oral and visual versions and an updated version of LNS. Findings revealed no difference in the LNS oral version in the two groups, whereas bilingual individuals performed better than monolingual individuals in the visual LNS task. These findings demonstrated a monolingual advantage, as monolinguals performed better in oral LNS, which could be due to their eloquence in language. Additionally, bilingualism demonstrated enhanced visual WM compared to verbal WM. Before the assessment, bilinguals had a chance to practise, which could explain why they matched the pace of the monolinguals in the oral version. Another potential explanation is that the strength of the bilinguals' WM was influenced by their second language, which in turn influenced other cognitive constructs that simultaneously improved their WM (Vejnović et al., 2010).

In summary, the evidence suggests that the relationship between WM and language experience is inconsistent. Other findings suggest that bilinguals may experience shorter response times (Poarch & Krott, 2019). A shorter response time could affect the processing of words in different languages, potentially leading to differences in WM capacity. This can be attributed to the cognitive demands of managing and switching between two languages, which lead to longer processing times and the inability to retrieve familiar words from memory (Yang, 2017).

2.3.4. Working Memory and the Socio-economic Status

In the current investigation, SES was conceptualised as a multidimensional concept that mirrors participants' access to economic and social resources. This includes income or salary, educational background, occupational status, standard of living, and household resources. SES was operationalised by utilising the Living Standard Measure (LSM), which is commonly used in South Africa to measure an individual's lifestyle (South African Audience Research Foundation [SAARF], 2014). Defining SES is very complex, due to various factors contributing to it. These factors include poverty, unemployment, inequality, access to quality education, and health issues (Genesee, 2015). Collectively, these factors negatively impact individuals' progress and development.

To provide a clear understanding of SES, research pointed to indicators. For instance, Magnuson and Duncan (2006) note that SES includes race, education, economic status, and income factors. At the same time, Lareau (2003) assumes that culture and language experience are key indicators. Given the demographic profile of the current study sample, SES was assessed by combining demographic questionnaires and LSM to capture living status, as well as educational and occupational status of parents, income comparison, and ten-step ladder rate. While education was treated as a separate and independent variable to investigate its role, language was accounted for by the influence of language experience, particularly in bi/multilinguals, and is linked to the quality and level of education (Moolla, 2012).

In South Africa, SES can be measured using income, education level, occupation, and living conditions (Taylor & Yu, 2009), which is the most popular indicator of SES used in research (Navarro-Carrillo et al., 2020). However, other countries include healthcare accessibility, the living environment, and social support networks (Shi et al., 2023). It may be suggested that the influence of a low SES on WM differs depending on a given country's specific social and economic circumstances. In South Africa, individuals with a low SES may face systemic imbalances, barriers to resource access, and language barriers, which could make language differences more influential on WM assessments. By contrast, in countries with stronger social and support networks, a low SES may negatively impact WM less. Furthermore, cultural and sociological factors may alter the relationship between SES and WM (Cockcroft et al., 2015).

The SES has been consistently linked to cognitive performance, particularly WM. As mentioned earlier, in South Africa, the complexities of SES disparities are combined with the country's linguistic and cultural diversity (Heugh, 2007). This suggests that individuals from disadvantaged SES backgrounds may display challenges in their cognitive system (Spaull, 2013). Other researchers have examined the influence of SES on WM in children's studies (e.g., Bloch, 2013; Engel et al., 2008; Moolla, 2012). Hackman and Farah (2009) emphasise that SES may generate differences in the cognitive system, including WM. These differences may be evident in neural processing and persist until adulthood. This might continue even if similar performance is observed, suggesting that early SES effects may contribute to cognitive functioning. While this may not immediately reflect in outward performance, they still contribute to long-term cognitive performance among adults.

However, there is still limited research on whether SES in older adults influences measures of WM. Zhang et al. (2020) further noted education as a key factor that mediates the influence of SES on WM. Although Wijeakumar et al. (2019) demonstrate that individuals from disadvantaged-SES groups display weak WM, those from a low SES with high levels of education exhibit improved WM. In their findings, when investigating the influence of SES on WM, the authors found that WM and the brain's prefrontal areas mediate the education level.

Research reveals the negative impact of adversity and a low SES on WM and brain development (Wijeakumar et al., 2019). Oshri et al. (2019) evaluated the brain through WM by incorporating brain images and behaviours in the decision-making of 119 African Americans from low-SES groups, aged 19 to 24 years. WM was assessed using the n-back task and functional magnetic resonance imaging (fMRI). Evidence demonstrates that the decrease in performance of the WM task and low response in a brain region such as the dorsolateral prefrontal cortex is associated with WM function in individuals from low-SES groups. Furthermore, Oshri et al. (2019) showed that living under adversity causes interruption and negatively affects WM.

Similarly, Evans and Schamberg (2009) and Wijeakumar et al. (2019) agree that growing up in a poor environment and with a low SES affects brain development and creates an accumulative cycle of poverty at a later stage. These effects are caused by chronic stress described as allostatic load (Evans & Schamberg, 2009), which refers to repeated difficulties of chronic stress triggered by wear and tearing of the body system (Guidi et al., 2020). Evans

and Schamberg (2009) link allostatic load to changes in the hippocampus and prefrontal cortex, which affect the functioning of the WM system. Furthermore, they emphasise that a stressful environment and low SES negatively impact WM, specifically in youth, and gradually affect individuals as they become older adults. These findings suggest that adversity exposure impacts WM function throughout life, mediated by other features like stress and poverty, with lifetime consequences. Importantly, these studies highlight the need for cultural and contextual sensitivity in WM research, as existing literature focuses on high-income and urban populations.

There is evidence supporting that SES has an influence on WM, specifically in youth. For example, Judd et al. (2020) conducted a longitudinal study on 551 individuals from different SES groups aged 14 to 19. In their study, they examined cognitive function using WM measures. Their findings revealed that participants who were 14 years old and had a weak WM when the research began had developed a strong and improved WM throughout their youth. This was revealed while comparing their WM performance score at the beginning of the investigation with the performance score that they achieved five years later upon completion of the investigation. The results further suggested that individuals from a higher-SES family, with parents with a high education level, demonstrated an enhanced WM performance in their youth. Therefore, it may be inferred that the lifestyle of parents, particularly those who are educated, and the surrounding environment, impact children's cognitive development.

Similarly, Murtha et al. (2022) investigated how family level and SES affect tasks related to executive systems, including WM. They also wanted to determine whether this effect influences the relationship between WM and SES. They examined 1150 youths aged from 8 to 23 years. All participants were assessed using a fractal n-back. The findings revealed high stimulation in the executive function of persons from a high-SES background. This supports the notion that the environment in which a person was born or raised contributes to their cognitive development and shapes their WM. Moreover, these results are consistent with previous studies (e.g., Evans & Schamberg, 2009; Leornard et al., 2015), suggesting that being raised in a disadvantaged-SES group has an adverse effect on WM. Despite utilising different measures of WM and methods in their studies, previous studies consistently reported similar findings, suggesting the significant impact of SES on WM and development.

By contrast, Moolla (2012) examined the influence of SES on WM in a children's sample. The findings indicated no significant differences in WM due to SES. However, SES did impact vocabulary and non-verbal intelligence measures, with participants from a lower SES underperforming compared to those from a higher SES. These findings display a different perspective from previous evidence, suggesting that SES does not consistently affect WM during developmental stages.

In summary, conclusions about the association between WM and SES are inconsistent, indicating the intricacy of this relationship. On the one hand, studies have supported the association between a low SES and WM (Hackman et al., 2015; Mooney et al., 2021). On the other hand, other studies have found that growing up in an advantaged environment with a higher SES contributes positively to cognitive functioning, including WM (Evans & Schamberg, 2009; Leornard et al., 2015; Wijeakumar et al., 2019). Studies on children's samples assert that individuals from a high SES have a stronger WM and higher crystallised intelligence than those from a low SES (Bloch, 2013; Clayden et al., 2023). However, Moolla (2012) had contradictory findings concerning WM measures.

The studies discussed above have shown how SES disparities affect WM by emphasising the potential challenges individuals from lower-SES backgrounds face. Moreover, the differences in these results highlight the importance of considering the various factors that could contribute to the link between SES and WM. The reported connections across various settings and groups can vary depending on cultural and language diversity, age, and the assessment methodologies used to measure SES and WM. Thus, the current study supports the premise that individuals from low-SES backgrounds tend to have worse WM than their counterparts from high-SES backgrounds. However, the level of education may moderate the link between WM and a low SES.

2.3.5. Working Memory and Gender

Gender is an important demographic factor that highlights differences in cognitive abilities. Research suggests that there may be gender differences in how WM functions (Primi et al., 2017; Voyer et al., 2016; Zilles et al., 2016); however, findings have been inconsistent. The general trend indicates that females may surpass males in verbal WM (Harness et al., 2008; Kaufman, 2007), whereas males outperform females in visuospatial WM (Morais et al., 2018; Robert & Savoie, 2006). Exploring these differences can provide an understanding of the underlying mechanisms of cognitive functioning.

Hill et al. (2014) investigated females' and males' neuro-functional variations during WM. They conducted a meta-analysis and utilised activation likelihood estimates from the BrainMap database. Their findings revealed consistent WM networks in both genders. However, during the n-back task and delayed match to sample that measures WM, they also provided evidence for gender-specific networks, where females consistently activated more limbic structures (such as the amygdala, hippocampus, prefrontal areas, and right inferior frontal gyrus). In contrast, males activated a distributed network that includes more parietal regions. Additional findings suggest that males employed more networks associated with spatial processing than females. Conversely, females tended to activate more prefrontal regions and exhibited a greater limbic system involvement in WM processing than males (Hill et al., 2014).

Concerning gender differences in WM, research revealed inconsistencies among different studies. Taborda et al. (2019) proved that males have better attention, information integration, and cognitive functioning than females. They examined the gender differences in WM tasks in 144 adults aged 50 and above. Their findings indicated better performance on males' scores than females in both DS subtests and the Corsi block-tapping test (Taborda et al., 2019). However, females demonstrated enhanced performance in simple span tasks, suggesting a nuanced gender difference. Similarly, Robert and Savoie (2006) examined a sample of 50 males and 50 females. They reported a higher performance by males than females in visuospatial WM tests such as the Corsi block-tapping test. However, they observed no differences in verbal WM, particularly DS forward and DS backward, with females demonstrating superior performance in spatial tasks.

These findings align with Piccardi et al. (2019), who demonstrated that males' spatial WM surpassed that of females. They further found that males outperform females in spatial short-term memory when assessed in the DS forward, DS backward, and Corsi block-tapping test. These gender dissimilarities may be inherent to biological factors noted by Hill et al. (2014), suggesting a complication of cognitive functioning between genders. Taborda et al. (2019) and Robert and Savoie (2006) utilised similar methods and measures, such as the DS and Corsi block-tapping tests. They reached comparable outcomes. However, the participants' age ranges differed, with Taborda et al. (2019) examining older persons and Robert and Savoie (2006) focusing on young adults. Despite the methodological differences, the pattern of male dominance in visuospatial WM stayed consistent.

Contrary to Zilles et al. (2016), who revealed that males surpassed females in spatial and verbal WM, highlighting a contradiction in gender-related findings. Harness et al. (2008) investigated gender differences in WM in a sample of tertiary-level students divided equally by gender. They utilised tasks with and without distraction in verbal and visuospatial WM. Females outperformed males in visuospatial WM and demonstrated better performance in verbal WM with a distraction, and revealed superior recall; no differences were observed when there was no distraction. These inconsistent findings suggest that although specific patterns arise in WM task performance, gender differences may be influenced or moderated by age, specific tasks, and other factors.

In brief, the literature above indicates inconsistent findings. When examining overall outcome, gender-related cognitive performance varies by task, with males having an advantage in visuospatial tasks (Kaufman, 2007; Piccardi et al., 2019; Robert & Savoie, 2006; Taborda et al., 2019), and females seem to have superior verbal WM (Harness et al., 2008; Herlitz & Yonker, 2002). However, the differences in cognitive function where gender is concerned remain unclear, although gender differences in neural network activations are consistently observed (Hill et al., 2014). Overall, these findings emphasise the need for further research to explore factors that shape these patterns.

2.4. Processing Speed

2.4.1. Conceptualisation of Processing Speed

Marshalek et al. (1983) first introduced PS as a performance speed and laid the groundwork for understanding it as a cognitive factor. Afterwards, PS became more complicated, and its characterisation was redefined by Kyllonen et al. (1991), who conceptualised PS as a primary cognitive function that supports reasoning and higher-order cognitive functions. They shifted from a narrow focus to a broader view that included mental efficiency and its role in cognitive processes. The authors further argued that it is not about how fast a task has been performed, but the efficiency of processing information and reasoning (Kyllonen et al., 1991). Finally, Salthouse (1996) defined it as a multidimensional construct that reflects an individual's cognitive performance within a specific time frame. This theory suggests that poor PS has a negative impact on task completion and suggests that when an individual processes information slowly, older information may decay before it can be integrated with new input, thus disrupting cognitive functioning (Salthouse, 1996).

This construct receives less attention in cognitive theories and is poorly defined (Deluca, 2008). Researchers have used reaction time to measure PS (Deluca, 2008; Mather, 2010). However, Jensen (2006) hypothesised reaction time as unnecessary information processing. Further, reaction time is viewed as a system of cognitive or neural restriction of processing a simple stimulus, which reflects the efficiency of accurately and quickly processing information.

Salthouse (2000) demonstrates that the definition of PS is closely linked to how it has been operationalised and measured. This reveals that PS may not be a unitary construct. This construct includes the following measures of speed and accuracy in cognitive tasks:

- *Psychophysical speed*: measures the time it takes to perceive stimuli presented for short durations accurately
- *Reaction time:* refers to the time it takes to respond to a basic stimulus
- *Psychomotor speed measures*: assess the time it takes to complete a task that involves repetitive movements
- *Perceptual speed measures*: assess the time it takes to complete a simple task
- *Decision speed*: measures the time it takes to process and select a response from moderately complex information

Although each component may have variations, they all contribute to the entirety of PS (Salthouse, 2000). Eckert et al. (2010) support the perspective that PS is non-unitary by emphasising that it involves various neural networks. Their findings indicate that motor PS and perceptual PS are predicted by gray matter. Böhr et al. (2007) demonstrate that PS correlates with cerebellar white matter structure differences.

By contrast, PS has been considered by certain scholars as a singular capability, serving as a general explanation for intelligence (Jensen, 2006; Kail, 2007). The unitary model of PS suggests that a single latent variable can be utilised to explain a wide range of timed measurements of PS (Kail, 2007). Kail (2007) states that the model proposes that PS persistently progresses throughout an individual's lifespan. In support of this, Gerst (2017) reported that when latent variables of cognitive function, including PS, were analysed, factor analyses indicated a single latent variable of PS.

Researchers defined PS as the time it takes an individual to complete a mental task (Deluca, 2008; Salthouse, 2000). Salthouse (1996) indicates that the time it takes to complete a task depends on the time it takes for a cognitive system to process the information. Mather

(2010) emphasises that the definition of PS involves the operation and processing of motor movement, i.e., auditory and/or visual stimuli. Holdnack et al. (2015) argue that PS includes these stimuli and how an individual integrates or coordinates information and decision-making.

Conversely, certain studies have argued that PS encompasses task-specific cognitive processes, suggesting that mental processes involved in PS differ depending on the nature of the task (Eckert et al., 2010; McAuley & White, 2011). Eckert et al. (2010) and McAuley and White (2011) further propose that the efficiency of the brain's ability to adapt and execute the cognitive requirements of a given task is reflected in the PS, as some tasks involve decision-making. Other researchers argue that the speed at which information is processed is determined not only by the amount of information that is processed, but also by the effectiveness of the cognitive processes involved (Cepeda et al., 2013; Ploeger et al., 2008). These researchers suggest that persons with higher cognitive efficiency can quickly process information, even when presented with an equivalent amount of information, than individuals with lower cognitive efficiency (Davis et al., 2017; Horning & Davis, 2012).

Moreover, various cognitive tests are typically used to measure PS, each involving different response formats. These comprise paper and pencil tests, such as digit symbol substitution (Wechsler, 2008), symbol search, and coding of WAIS-IV-SA (Wechsler, 2017). Symbol Search is often used to evaluate PS without adjusting for age-related declines (Wechsler, 2017). Another widely used measure is the Symbol Digit Modalities Test (SDMT), which offers oral and verbal versions (Smith, 1982). In addition to these traditional tests, psychophysical assessments, such as Choice Reaction Time (Deary, 2001) and Inspection Time (a computer screen task designed for easy use), are used to evaluate PS (Deary et al., 2007; Deary et al., 2010). Moreover, PS has been identified as a predictor of cognitive performance in other domains (Harvey, 2019).

2.4.2. Justification of Measure

The current study adheres to the definition of task response as the time needed to complete a cognitive or psychomotor task (Mather, 2010; Salthouse, 1996; Salthouse, 2000). Specifically, PS was measured using both oral and verbal versions of SDMT to comprehensively assess participants' mental speed (Smith, 1982). This task has been widely used for clinical and non-clinical purposes and is well-validated as a measure of PS

(Eizaguirre et al., 2020; Munoz et al., 2021). It is sensitive to subtle cognitive dysfunction and is often used in cross-cultural neuropsychology (Eizaguirre et al., 2020).

The written version of SDMT does not rely on language or culture, making it useful in bi/multilingual populations (Cores et al., 2014). However, cultural influence has been shown to affect cognitive task performance, and PS (Cockcroft et al., 2015). The effect of culture has been previously recognised by Eizaguirre et al. (2020), who analysed and compared 129 healthy volunteers from the United States of America (USA), Mexico, and Argentina, and found that there was an intercultural difference in the performance of the oral version of SDMT. Their findings demonstrated a significant intercultural difference. Notably, the performance differences were most evident between Latin American and Anglo-American. However, no differences emerged among Latin Americans when their scores were compared, signifying that variation in cultural attitude, behaviour, and language practice may influence task performance.

Similarly, Cores et al. (2014) examined the performance of the Paced Auditory Serial Addition Test (PASAT) and SDMT-Oral in two groups. The findings demonstrated a cultural effect, with SDMT being the most susceptible to cultural differences. Supporting this, Cockcroft et al. (2015) reported intercultural differences in PS task performance when comparing South African and British students. These studies highlight the influence of cultural factors like beliefs, attitudes, languages, behaviour, and educational background on the performance of PS measures.

2.4.3. Neuroanatomical Correlates of Processing Speed

Processing speed depends on intact white matter connections, which rely on efficient communication between the frontal and parietal lobes (Figueroa-Vargas et al., 2020; Turken et al., 2008). A study by Bartzokis et al. (2003) indicated that the structural integrity of myelin declines with healthy ageing, particularly in late-myelinating regions such as the frontal lobe. Further, it is indicated that white matter naturally changes as an individual's age increases. This deterioration weakens cognitive functions, including PS. In addition, communication between brain regions declines as white matter deteriorates, leading to reduced PS and subsequent impairment of other cognitive functions central to an individual’s cognitive performance (Bartzokis et al., 2003). Studies using Diffusion Tensor Imaging (DTI) have provided supporting evidence that lower white matter integrity is associated with lower PS performance (Deary et al., 2007; Madden et al., 2011).

Empirical evidence supports the association between the neuroanatomical bases of PS. Ekert et al. (2010) found significant associations between PS and other brain regions, such as the bilateral temporal pole, posterior cerebellar hemisphere, anterior, bilateral superior cerebellar and intraparietal sulcus; brainstem; and right superior frontal sulcus. These associations were well defined in tasks that include motor and perceptual speed. Moreover, other network structures, including the brainstem, right superior frontal sulcus, right posterior cingulate sulcus, left inferior temporal gyrus, left inferior frontal gyrus, and left cerebellar hemisphere, also predicted PS. In addition, white matter was related to PS as measured by Connections Simple (Eckert et al., 2010). Kerchner et al. (2012) reported a negative correlation between white matter and PS as measured by fractional anisotropy, and a positive correlation as measured by mean diffusivity. These results demonstrate that a low PS in older adults is associated with the loss of white matter. This suggests a close neuroanatomical relationship between white matter and PS.

2.5. Influence of Demographic Variables on Processing Speed

Cognitive performance is influenced by demographic factors, which cause interactions that potentially impact an individual's PS (Ebaid et al., 2017; Tabibi et al., 2012). This section examines the literature in this area to clarify each of these demographic influences.

2.5.1. Processing Speed and Age

A decline in PS is a noticeable issue that impacts the efficiency and success of several cognitive tasks in age-related cognitive encounters (Eckert, 2010; Salthouse, 2000). The PS ageing theory suggests that older age is associated with decreased PS, leading to cognitive function challenges (Salthouse, 1996). Salthouse (2000) emphasises that PS is a cognitive capacity that weakens with age, as it pertains to the efficacy with which an individual can rapidly comprehend and react to information. Furthermore, Salthouse (2003) identified PS as a highly influential factor in determining older persons' performance in several cognitive activities. Previous research indicates that PS influences older adults' success across several cognitive activities (Salthouse & Ferrer-Caja, 2003). Eckert et al. (2010) suggested that a reduction in PS contributed to delayed completion of tasks, as well as an increased likelihood of early loss of processed information. For example, people with a slow PS may easily forget information, resulting in difficulties with tasks that necessitate multiple cognitive processes, such as stimulus perception, decision-making, motor performance, and task performance (Eckert et al., 2010).

The relationship between age and PS is relevant for most research on ageing that emphasises the impact of cognitive decline on task efficiency and accuracy (Murman, 2015; Span et al., 2004). Ball et al. (2007) propose that the time and manner in which an individual responds to tasks may be influenced by the changes in cognitive functioning that occur with age. Research has consistently demonstrated that PS declines as age increases (Eckert, 2010; Salthouse, 2000). For instance, a normative study by Fellows and Schmitter-Edgecombe (2019) conducted on adults aged 18 to 91 utilised the SDMT, Oral and Written, to assess PS. They observed that older adults performed lower and made more errors than young adults. This was specifically true for the written version, as it had more errors than the oral version. These results align with a previous normative study (Kiely et al., 2014) that also emphasised the impact of ageing on PS through assessment methods of SDMT-Written.

Moreover, Finkel et al. (2007) conducted a longitudinal study over 16 years in 806 participants aged from 50 to 88 years. Their results established that increasing age was inversely associated with progressive declines in processing efficiency, indicating that age is a significant predictor of PS. Hence, lower PS in older adults was also linked with reduced accuracy in task performance. Additionally, Nettelbeck and Burns (2009) emphasised that the decline in PS among older adults has implications beyond simple task completion, as it affects reasoning and decision-making abilities. This supports the view of Salthouse (2000), suggesting that declines in PS significantly contribute to the overall cognitive changes associated with ageing. The persistent relationship between PS and age highlights its critical role in research on cognitive ageing and the importance of identifying methods to moderate PS decline.

Contrary to the notion that PS decline mainly affects older adults, Von Krause et al. (2022) argue that slow decision-making is not pertinent among older adults but can start as early as a person's 20s. Therefore, it is important to note the factors involved in this early decline. Von Krause et al. (2022) studied participants between 10 and 80 years old. They assessed the participants' decision-making processes through a Reaction Time test, Drift Rate (which tests PS), Boundary Separation for decision-making, and non-decision time estimates. The results highlighted that reaction times were shorter from age 10 to 19 and started to slow down thereafter. Specifically, a noticeable decline in PS began around age 30, with more marked reductions expected by age 60 (Von Krause et al., 2022). Kiely et al. (2014) analysed normative data of SDMT-Written; they reported a consistent performance by age until age 35; thereafter, the performance began to decline gradually as individuals age, which was

more visible from the age of 55 years. This is consistent with the findings of Hartshorne and Germine (2015), who found that the decline in cognitive ability began as early as the 20s, contradicting the idea that such declines are entirely observed in older adults. This evidence suggests that although older adults experience challenges due to reduced PS, younger individuals may also face early signs of cognitive PS decline. These findings highlight the necessity for understanding cognitive ageing that incorporates a person's lifespan. Therefore, future interventions should recognise that cognitive efficiency could begin to deteriorate earlier than previously assumed.

Building upon the cognitive evidence of age-related decline, it is important to acknowledge that age also substantially influences motor speed, which declines due to various factors, such as neural degeneration (Eckert et al., 2010). Studies have consistently demonstrated that as individuals grow older, they experience a progressive deterioration in motor speed and coordination, which potentially affects their ability to perform everyday tasks and planning (Cham et al., 2007; Cham et al., 2008; Stöckel et al., 2017). A study by Ebaid et al. (2017) focused on a sample of 67 young first-year university students between 18 and 29 years and 40 older adults aged between 40 and 81 years, with seven to 18 years' educational backgrounds. Participants were assessed in Symbol Search and Coding tasks as part of a paper-and-pencil test. The study's findings confirmed significant differences in motor dexterity across age groups, with young adults performing quicker than older adults (Ebaid et al., 2017). This suggests that, regardless of education as a cognitive reserve, changes in motor speed do occur in older adults. Further supporting these findings, research has revealed evidence linking age to changes in brain anatomy and function and subsequent changes in motor ability (Lee et al., 2022; Seidler et al., 2009). Eckert et al. (2010) emphasised that these motor changes are often accompanied by structural and functional changes in the brain's white and grey matter, further contributing to the observed reduction in PS and response time. Such brain changes suggest a complex interaction among ageing, motor decline, and cognitive processing. This demonstrates that as age increases, natural neural adaptations occur that affect motor performance and, consequently, overall cognitive function.

These findings demonstrate a progressive decrease in cognitive processing and motor speed with advanced age. In addition, changes in a specific neural network affect the overall cognitive functioning as people age. These declines may commence in young adulthood and worsen over time, impeding cognitive functioning and decision-making abilities. Therefore,

the existing research highlights the importance of early interventions to maintain cognitive and motor functions during ageing.

2.5.2. Processing Speed and Education

It is generally recognised that there is a significant correlation between PS and educational attainment (Benner et al., 2007; Rohde & Thompson, 2007). This function is essential in an educational environment because it directly impacts students' capacity to match the pace of instruction, complete tasks, and excel in assessments (Donati et al., 2019). Those with higher PS are inclined to perform better academically because they process information better (Horning & Davis, 2012). This connection persists into old age, safeguarding older adults against cognitive decline (Livingston et al., 2017). However, limited research exists on the relationship between PS and education in healthy South African adults. Given the limited research, one study by Katzef et al. (2019) provided evidence of the connection between education and PS. The study demonstrated the influence of education on PS in a sample of 112 South African Xhosa-speaking healthy young and middle-aged adults between the ages of 20 and 50 years, with seven years or more of education. Additionally, the findings indicated that those with higher education levels performed better on multiple PS measures, such as NeuroScreen PS subtests, Trail Making Test Part A, Symbol Digit Coding, Symbol Search, and Colour Trail Test 1. This suggests that education enhances PS even in non-Western populations (Katzef et al., 2019).

Building on previous evidence, studies by Guerra-Carrillo et al. (2017), Meijer et al. (2009), and Ihle et al. (2017) confirm that higher education levels are associated with higher PS across diverse demographics. Guerra-Carrillo et al. (2017) analysed a large dataset; they found educational advantages across all age groups, whereas Meijer et al. (2009) and Ihle et al. (2017) reported that the influence of education on PS is more evident in older adults. For example, Guerra-Carrillo et al. (2017) found that those with higher educational levels excel on several cognitive measures, including PS, with considerable differences between high school graduates and college-educated participants. Meijer et al. (2009) and Ihle et al. (2017) support the idea that education strengthens cognitive abilities and serves as a cognitive reserve. However, notable differences exist in their study designs and specific outcomes. Meijer et al. (2009) assessed two separate age cohorts of young and middle-aged adults from different educational levels (low and high). They found that middle-aged adults made more mistakes than younger adults, and those with lower educational attainment scored lower in accuracy. Additionally, older adults demonstrated longer reaction times in decision-making

tasks. This indicated a decline in their PS. Still, within each age group, participants with higher education levels consistently outdid those with lower education.

By contrast, Ihle et al. (2017) study focused on an older sample, ranging from 65 to 101 years old, some of whom were employed in cognitively demanding jobs. Their findings support the idea that education enhances cognitive function and provides greater protective benefits for older adults, by strengthening their cognitive functions, likely due to its role in sustaining high cognitive performance over time. This emphasises education's long-term impact on cognitive ability by influencing the speed at which an individual processes information, as evidenced by the maintained cognitive functioning in highly educated older adults.

Although education and PS are generally related, research suggests that the link may be indirect, operating through factors such as intelligence and type of education (Rindermann & Neubauer, 2004; Van Hooren et al., 2007). For instance, Van Hooren et al. (2007) argue that the findings that demonstrate education as a factor that influences cognitive PS in adults may depend on the type of education an individual possesses. This is because high and middle educational levels do not seem to differ when the Letter Digit Substitution test, a modified version of SDMT, measures the PS in adults. Furthermore, the authors indicate that higher education, which is associated with cognitive reserve in adults, does not display any protective factor against cognitive decline. Their study indicated that there was no significant interaction between education and age.

However, Van Hooren et al. (2007) do not explore whether a point of inflexion exists, where the protective effect of education might weaken as age-related decline becomes noticeable. Future research could explore this possibility. Similarly, Rindermann and Neubauer (2004) proposed that PS has no direct relationship with education but mediates the relationship between education, intelligence, and creativity. This suggests that education enhances PS, which then improves intelligence and creativity. This was observed after the analysis of structural equation models, which revealed that when PS was examined with education, a weak or little effect was observed. However, a strong effect on intelligence and creativity was demonstrated. This suggests that PS did not directly influence education, but a higher level of education contributed to faster PS.

The preceding findings demonstrate that although education affects cognitive function, it is more evident in older adults than in young adults. Others suggest that higher PS relies on

the type of education (Meijer et al., 2009; Ihle et al., 2017). However, South Africa's diversity regarding educational backgrounds presents exclusive challenges for standardised cognitive assessments, as measures developed in Western contexts may require careful adaptation and validation. This further demonstrates the importance of studies designed for South African populations to understand better how factors such as adult education level impact PS. Despite the universal evidence linking education and PS, research on this relationship among older South African adults remains limited, requiring further study to understand how educational quality influences cognitive processing.

2.5.3. Processing Speed and Language Experience

In the context of the current study, where participants differ in terms of language background and language proficiency, it is important to consider these theories presented as guidelines for understanding language experience between monolinguals and bi/multilinguals. The adoptive control hypothesis model of Green and Abutalebi (2013) proposed a control mechanism of a third language, involving switching from one language to another. Additionally, PS allows for fast recurrence of competing languages within this model, thereby limiting switching and enhancing task efficiency. Meanwhile, slow PS may increase interference and delay lexical access when switching languages with overlapping phonological and syntactic structures (Green & Abutalebi, 2013). This is congruent with Salthouse's PS theory, which suggests that slower processing of information limits language processing, like sentence understanding (Salthouse, 1996).

In contrast, Ross et al. (2019), in a study of language selection, emphasise that languages are simultaneously activated in a bilingual's brain, which is suggested to be consistent. A previous study by Kroll et al. (2006) indicated that a bi/multilingual person cannot turn off one language in their brain; all languages are always active. In support, construction grammar theory by Holger (2015) suggests that frequent code switching may lead to entrenched bilingual constructions due to language familiarity that reduces processing demand. This illustrates the complexity of language processing in bi/multilingual individuals that PS influences. Grundy et al. (2017) add that bilingual experience can alter cognitive control networks and processing efficiency, but that these effects are moderated by language dominance and proficiency. Therefore, verbal PS tasks may not solely reflect processing efficiency but may also index linguistic fluency or familiarity, particularly in bilingual participants.

Understanding how language experience shapes cognitive abilities is an interesting area of research. Although theories of bi/multilingualism address the complexity of language processing, limited studies focus on language and PS in healthy adults, particularly regarding how individuals manage two or more languages. Language experience, such as bi/multilingualism has been shown to affect PS significantly. Research suggests that individuals who speak more than one language have an enhanced PS (Grant & Dennis, 2017), possibly due to the improved executive function ability required for managing multiple languages (Bialystok et al., 2004; Bialystok et al., 2014; Paap et al., 2015) and attention control (Adesope et al., 2010). For example, Bialystok and Poarch (2014) found that bilinguals exhibited shorter response times in tasks that require cognitive flexibility, suggesting that language experience contributes to improved processing efficiency.

However, the association between PS and language experience is not without controversy. Another study reported significant positive effects. For example, Grant and Dennis (2017) studied young adult English speakers (25 monolinguals and 26 bilinguals) who were university students. All participants completed different memory tests. The study was conducted to determine how and how quickly young adults would perform in memory-related tests. The findings revealed lower PS and accurate responses in bilinguals than in monolinguals. Similarly, Blumenfeld et al. (2016) conducted a study on non-linguistic cognitive control and linguistic competition resolution in younger and older adults, comparing bilinguals and monolinguals. The non-linguistic Stroop task was employed to evaluate participants. Evidence indicated that bilingual young individuals exhibited a higher PS and shorter reaction time than monolinguals. Compared to monolinguals, adult bilinguals had a delayed response time and more response errors.

Other studies have found no differences in PS between monolinguals and bilinguals (Bonifacci et al., 2011; Park et al., 2020; Schmidtke, 2016). Bonifacci et al. (2011) examined a group of bilingual and monolingual children between the ages of 6 and 12 years and youth between the ages of 14 and 22. Participants were examined for their PS by employing a Visual Choice Reaction Time task, which is recognised as a good measure of PS and slightly measures executive function. By contrast, Schmidtke (2016) conducted a study on 53 monolinguals who learned a second language before the age of 10 and on 42 bilinguals who learned a second language from birth. Participants were between the ages of 18 and 35 years and were examined on language experience and cognitive function. The Baseline Reaction Time measured PS, whereas Involuntary Orientation and Conflict Resolution measured

attention. Both Bonifacci et al. (2011) and Schmidtke (2016) revealed no differences and no effect of PS in both monolinguals and bilinguals.

Park et al. (2020) argue that speaking multiple languages does not impact PS, but lower language proficiency leads to a slower PS. This may be because bilinguals lack phonological processing and cannot recall words quickly because of the interference they experience when processing languages that are not their first language (Bernardini & Schlyter, 2004). Supporting this, Kroll et al. (2006) suggest that languages are continuously active in a bilingual's mind, which could cause inference and reduce processing demand. Moreover, Bernardini and Schlyter (2004) suggest that bilinguals apply their first language's grammatical rules and sentence structure to the second language. This may cause language transfer and influence the second language. To converse successfully, bilinguals require a high PS. However, early bilinguals perform differently compared to late bilinguals, who may experience interference in word order, due to the dominant language (Bernardini & Schlyter, 2004).

The possible reasons for these inconsistencies might be attributed to differences in language proficiency, period of language acquisition, the individual’s age, or the tasks used to measure PS. For instance, Reifegerste (2020) argues that age-related decline may mask the advantages of bilingualism in older adults, as the performance of older adults tends to be slower, whereas others suggest that the benefits of language experience are more pronounced in the young population or those with developed proficiency (Bak et al., 2014; Whiteside et al., 2016).

Perspectives on this subject also differ theoretically. Researchers propose that the cognitive control, which is necessary for handling multiple languages, improves overall cognitive abilities, thereby accelerating processing across various tasks (Bialystok et al., 2008; Bialystok et al., 2012). For example, Craik et al. (2010) provided evidence that bilinguals exhibit a delayed onset of dementia compared to monolinguals. This further indicates that bilinguals outperform monolinguals in executive control tasks throughout their lives. Green and Abutalebi (2013) contend that the benefits of language experience are limited to specific tasks, such as linguistic tasks or those that require a high level of executive control.

Nevertheless, with these conflicting results, there is a general agreement that language experience plays a crucial role in cognitive development. However, gaps in understanding

remain regarding the impact of language experience on adults' PS. These gaps underline the need for additional research on the interaction between language experiences and other cognitive variables.

2.5.4. Processing Speed and Socio-economic Status

The inequality in SES remains high in many areas of South Africa (Tunzi & Simo-Kengne, 2019). This affects cognitive functioning in adults, which includes PS. This is due to unequal distribution of resources, such as technology, access to quality healthcare, and educational opportunities (Duncan et al., 2017; Kobayashi et al., 2022). Research has noted that the environment, childhood deprivation, and economic status affect cognitive functioning in young and older adults, resulting in cognitive challenges and slower PS (Duncan et al., 2017; Mutola et al., 2023).

Evidence suggests older adults from a disadvantaged SES tend to display weaker PS when compared with young adults. A study by Zhang et al. (2015) used Digit Symbol Coding to measure PS in a large sample of older adults with a mean age of 71.6 years. They revealed that older adults from low-SES groups had lower PS compared with those from high-SES groups, with education acting as a mediator in the association between SES and PS. Similarly, Schrempft et al. (2022) used the Trail Making Test Part A and the Stroop colour condition to measure PS. They reported that a disadvantaged childhood and a low SES predicted a low PS in older adults. Alternatively, Greenfield and Moorman (2018) showed that although SES was associated with cognitive functioning of older persons, it was not significantly associated with changes in cognition over time. This implies that although childhood SES may impact standard cognitive abilities, it may not substantially shape cognitive changes over an individual's lifespan.

Steptoe and Zaninotto. (2020) conducted a longitudinal study that examined adults' cognition over eight years. They found partial changes of PS in individuals with a high SES and excessive decline in those with a low SES. They also reported that a low SES was associated not only with PS but also with other developmental issues. They further demonstrated that being financially stable contributes to a better environment, leading to an improved cognitive system. Kobayashi et al. (2022) examined a sample of adults aged 40 years and above, providing another perspective on the link among household material resources, cognitive function, and the role of technological services in rural areas of South Africa. The findings revealed a significant association between higher household material

resources, such as technology access, and improved cognitive function over 13 years. These findings suggest that as the levels of household material resources increased, cognitive function, including PS, improved. Moreover, the findings demonstrate that technological services, which are associated with a higher SES and having vehicles at home, play a crucial role in enhancing cognitive function. These results are aligned with the principles of cognitive reserve theory, which emphasises that an improved socioeconomic background may improve an individual's cognition (Stern et al., 2020).

Compared to other studies, these have examined the link between SES and cognitive outcomes, specifically PS. Thus far, their diversity in sample, methodology approaches, and cultural setting permits further examination. Zhang et al. (2015) focused on a larger cross-sectional sample of older adults, using linear regression to examine PS and other cognitive functions. Although it provides a solid foundation, its cross-sectional design restricts causal interpretations. By contrast, Schrempft et al. (2022) applied a larger dataset that included longitudinal SES assessment and cognitive decline. While their approach strengthens the validity of outcomes, the Western context limits generalisability to non-Western backgrounds. Greenfield and Moorman (2018) analysed SES-related cognitive trajectories in the Western community through longitudinal research, employing a culturally embedded measure (WAIS-R). They used factor analysis, which offers a distinct understanding, but the study remains specific to a predominantly Western population. Similarly, Steptoe and Zaninotto (2020) examined a larger sample. Research conducted in low and middle-SES remains infrequent. Kobayashi et al. (2022) demonstrated an important interest by analysing a large rural South African sample. Using a latent variable model to test cognition reflects methodological complexity and increases cultural relevance by capturing cognitive function in non-Western countries with fewer resources. This study emphasises how differences in SES interconnect with adults in under-researched populations and supports the importance of culturally sensitive research.

These studies consistently reported a connection between SES and cognitive performance, including PS. Also, the predominance of the Western population presented a significant limitation. There is still a gap in culturally and contextually diverse research. Aligned with the above view, but focusing on other factors, Heger et al. (2023) and Gkotzamanis et al. (2021) found that an individual's lifestyle was the key driver of cognitive decline, including PS in adults. Their findings emphasised that unhealthy lifestyle choices and related psychosocial stressors worsen cognitive challenges, whereas a better lifestyle, shaped by

higher SES, enhances PS and general cognitive function. Similarly, Gkotzamanis et al. (2021) demonstrated the link between higher SES and other cognitive constructs, supporting the idea that living conditions, combined with a higher SES, improve the flexibility of cognitive function, including PS (Duncan et al., 2017). These studies provided distinctive evidence in the association between SES and PS, as both utilised longitudinal methods by tracking cognitive performance. Gkotzamanis et al. (2021) focused on PS, executive functioning, and verbal fluency by conducting a follow-up at six and 12 years to evaluate the long-term changes and patterns. They also identified SES and lifestyle as major predictors of these challenges. Meanwhile, Heger et al. (2023) concentrated on the pattern of PS, ultimately recognising those at risk for cognitive decline.

Similarly, the findings of Oprandi et al. (2022) show that a low SES worsens psychosocial risk, such as chronic stress that causes distress, which indirectly influences PS. This was demonstrated through an investigation focusing on PS, SES, and psychological distress. This highlights the influence of SES on cognitive function, suggesting that PS may be impacted by psychosocial issues tied to lifestyle choices. Moreover, these studies highlight the impact of SES and lifestyle on cognitive function, including PS, across different people.

The empirical evidence concerning SES and PS in adults is suggestive, but not extensive enough to draw a clear conclusion. Furthermore, studies offer limited clarity on how SES influences PS in older adults, specifically in South Africa. Despite these gaps, the overall results highlight a consistent pattern of the long-lasting impact of SES on cognitive performance, from childhood to adulthood, suggesting cognitive benefits of growing up in a better environment and advantaged SES. The underlying assumption is that persons with higher SES may have greater access to resources, such as educational opportunities, which can lead to an improved PS, which may influence overall cognitive functioning.

2.5.5. Processing Speed and Gender

The influence of gender on PS has been a subject of interest among researchers, with studies indicating notable differences between males and females (Gur et al., 2012; Roivainen, 2011; Siedlecki et al., 2019). There is contradictory evidence in terms of the relationship between gender and PS. Studies agree that females perform better than males in PS tasks (Camarata & Woodcock, 2006; Siedlecki et al., 2019; Strober et al., 2020). For instance, Camarata and Woodcock (2006) found considerable differences in PS between males and females across various age groups, from age 5 to 79 years. The authors used visual

matching, decision speed, and rapid picture naming to measure PS. The findings indicated that males performed poorly in programmed assessments, particularly in reading and writing fluency. Females displayed high performance in all PS measures and reading and writing. Similarly, Roivainen (2011) and Lynn and Mikk (2009) indicated that females have an advantage in tasks involving digit and verbal PS. Both studies employed a larger sample size, which helped reduce bias and strengthen the reliability. Moreover, Roivainen (2011) indicated that the advantage of females in language-related tasks could be attributed to the increased engagement in related activities at school and home, possibly influencing their PS. However, the gender theory by Majeres (2006) argues that female advantage is observed not only on verbal PS but also on speed tasks, because of advantages in phonological coding.

By contrast, males outperform females in tasks requiring psychomotor speed and decision-making. Arango-Lasprilla et al. (2015) integrated data from diverse countries and cultures. They found that males outperformed females in the Trail Making Test in three countries, whereas females only performed better in one country. Dodig et al. (2020) found similar results in a complex psychomotor combination measured by a series of Complex Reactionmeter Drenovac tests. Besides, Roivainen (2011) suggested that males generally have an advantage in tasks that involve response time and hand movement, supporting the idea of task-specific differences between genders. This conclusion is supported by the evidence provided by McPherson and Burns (2008), who examined 70 university students on Digit Symbol, visual matching, decision speed, and computer games. The authors reported that males performed significantly better on computer, psychomotor, and decision-making tasks. Surprisingly, the male advantage persisted regardless of similar education and intellect, signifying inherent differences in psychomotor speed and decision-making. Arnold et al. (2006) and Lynn and Mikk (2009) suggest that males' high performance in finger tapping, fast hand movement, and response time assessments may be linked to other factors, such as physiological factors. Nonetheless, Dodig et al. (2020) highlighted age decline in elderly persons of both genders, indicating a shorter reaction time and decision-making. These findings may be influenced by innate biological and/or environmental factors.

These studies show inconsistent evidence on PS but are strengthened by diverse samples and demanding statistical approaches. Dodig et al. (2020) use General Linear Model (GLM) analysis with multiple predictors. Arango-Lasprilla et al. (2015) provided culturally comparable norms from diverse nations. Roivainen (2011) contributed by analysing cognitive correlates and gender across datasets. Despite these strengths, the cross-sectional design

limits causal interpretation, and reliance on specific measures might delay cross-domain comparison. Cultural differences in task administration across these studies may present unaccounted variability (Arango-Lasprilla et al., 2015; Dodig et al., 2020; Roivainen, 2011).

Building on the previous evidence, further research indicates that gender differences are more pronounced in older than in young adults. Strober et al. (2020) conducted a study on normative data of SDMT-Oral in a sample of 675 healthy individuals. The participants were grouped according to gender and age. They found that females had higher scores than males. The authors further indicate that the performance in SDMT-Oral tends to decline with age, with the most noticeable decline beginning in the third decade of life and continuing into the sixth decade. Similarly, Siedlecki et al. (2019) examined gender differences in neurocognitive functioning in adults aged between 18 and 99. Participants were grouped according to age (18 to 39 years, 40 to 64 years, and 65 to 99 years). The Digit Symbol Substitution, Pattern Comparison, and the Letter Comparison tests were utilised to measure PS. The findings demonstrated that females performed better than males in all PS measures, whereas males had higher proficiency in spatial visualisation evaluations. This pattern was consistent in all three age cohorts.

However, it was demonstrated that age played a moderating role in the gender impact on vocabulary, suggesting that as age increased, the performance on vocabulary became less across genders. In younger ages, vocabulary performance was high. More precisely, in the younger age range, there was a notable gender disparity in vocabulary performance, with females outperforming males. Supporting these findings, Keith et al. (2011) reported congruent findings in a study examining participants between the ages of 5 and 17. Females were found to outperform males in PS measures. This implies that gender disparities are not limited to adults but are present in all age groups.

Other research found no gender differences. Anstey et al. (2021) measured PS by utilising SDMT in a longitudinal study of over 12 years, and Pezzuti et al. (2020) analysed data from WAIS-IV and WAIS-R tests, coding, and DS in adults. Both studies (e.g., Anstey et al., 2021; Pezzuti et al., 2020) assessed various cognitive constructs, including PS.

The effectiveness of PS can be debated in terms of whether gender influences it, as the evidence presented earlier indicates that gender differences in PS are inconsistent. However, despite the inconsistency, females outperform males in cognitive PS. These findings may be influenced by cultural and societal roles (Finkel et al., 2017; Kheloui et al., 2023), suggesting

that environmental factors interact with biological tendencies to form gender differences in PS. Gur et al. (2012) suggest that differences in brain structure and function between genders may contribute to variations in PS, which could be another possible explanation for the complex relationships between gender and PS. The importance of refined methodologies in understanding gender differences in cognitive capacities is highlighted by these findings, which consider a diverse array of factors that impact PS. Overall, these studies revealed that gender differences are task dependent, with males demonstrating dominance in psychomotor tasks, whereas females demonstrate advantages in verbal and language tasks.

In summary, this section explored the influence of gender on PS. The existing literature has indicated differences between males and females, such as verbal PS (Roivainen, 2011) and spatial PS (McPherson & Burns, 2008; Siedlecki et al., 2019). By including gender as a demographic factor that influences PS, the significance of these disparities and their potential impact on an individual's performance in PS can be determined.

2.6. Relationship between Working Memory and Processing Speed

The theoretical perspective of WM and PS is important for comprehension. To debate these two constructs and their relationship, it is important to highlight differences among theories and compare them for a better understanding. Baddeley's (2000) model of WM characterises WM as a multicomponent system involving verbal and non-verbal processes, which are affected differently by task demands and cognitive load. Meanwhile, PS theory (e.g., Salthouse, 1996) has been influential in accounting for age-related differences in PS performance. It also explains the individuals' differences in WM and how these two constructs are linked. According to Salthouse's theory, slow PS reduces the efficiency of mental operations, limiting the amount of information that needs to be maintained in WM. However, other accounts of theories, such as resource theory, argue that WM is not constrained by PS only; there are other cognitive domains, such as attention and mental effort (Engle, 2002; Just & Carpenter, 1992). From this viewpoint, the decline occurred when cognitive demand tasks overshadow or exceed the limited capacity of an individual to coordinate and allocate resources (Engle, 2002; Just & Carpenter, 1992). For instance, Engle's (2002) theory emphasises the role of executive attention as a central component of WM. They reported that those with higher WM capacity are better at resisting distraction and can focus on relevant information.

Unlike PS theory, which shows a linear relationship between PS and WM (Salthouse, 1996), resource theories emphasise the importance of flexible attentional control as key to WM performance (Engle, 2002; Just & Carpenter, 1992). The direct relationship between WM and PS forms the basis of the study's first objective, which is to explore the relationship between WM and PS. Additionally, some theories, such as cognitive reserve and cultural linguistic contexts, suggest that demographic factors such as age, education, language experience, and socioeconomic background influence cognitive outcome through long-term exposure to enriched or constrained environments (Bialystok & Feng, 2009; Grundy et al., 2017; Stern, 2002).

Numerous studies have consistently demonstrated a strong connection between WM and the speed at which information is processed (Barrett et al., 2004; Cepeda et al., 2013; Kim & Park, 2018; Simmering & Perone, 2013). The processing and retention speed of one's WM is important in multiple cognitive tasks, including language comprehension, learning, planning, and spatial relations (Baddeley & Hitch, 1974). For example, Ackerman et al. (2002) revealed a significant link between an individual's PS and WM, indicating that the speed with which a person thinks, learns, and processes information is closely tied to their WM. Similar investigations by Kurtz et al. (2013) extended this connection to task-specific paired association learning among older individuals. The results highlighted the association between WM and PS and their influence on learning outcomes. However, the effect of these cognitive constructs on learning outcomes was not influenced by age. Additionally, individuals with a higher education level perform better in task-specific learning. This suggests that individuals with high WM and PS can learn new tasks effectively, offering practical implications for multitasking and task-switching in both professional and personal settings.

While examining the relationship between WM and PS, research offers contrasting perspectives. Genova et al. (2012) argue that although there is an association between WM and PS, these two cognitive components are distinct, as they contribute individually to cognitive ability. However, slower PS affects the ability to receive or process information from higher-order, including WM, during task performance. Other studies propose varying degrees of connection between these two cognitive constructs (Kim & Park, 2018; Oberauer et al., 2000; Roberts & Stankov, 1999). For instance, Oberauer et al. (2000) posit a connection in tasks of relative simplicity. Kim and Park (2018) highlighted the connection between these two cognitive factors and found that PS can predict intelligence when WM is controlled for. Moreover, additional factors add layers of complexity to this relationship.

These include attention, perceptual speed, and broader influences, which comprise physiological and genetic factors (Chen et al., 2022). Age-related declines and impairments in various cognitive domains also have an influence (Vance et al., 2010). These studies emphasise the multidimensional connection among WM, PS, and the other factors influencing cognitive processing.

In support of the argument presented, Caplan and Waters (2005) highlight the relationship among language, WM, and PS in both young and older individuals. They assessed 50 adults and 48 college students with higher education levels. An Alphabet Span, Reading Span Simple Sentences, Reading Span Complex Sentences, and Subtract 2 Span were utilised to assess WM. Additionally, PS was assessed by the Digit Symbol Substitution task and the Digit Letter task. Caplan and Waters (2005) also tested online sentence processing efficiency. The findings showed that in all WM measures, older adults performed worse than young adults. Increased age was associated with poor performance in both WM and PS. Language processing and PS were significant factors in online measures of sentence processing. The results further indicated that PS mediated the relationship between age and WM. Older people process information more slowly than younger adults, affecting their WM. This implies that the lower performance observed in older adults may be attributed to the mediating effect of PS on WM (Caplan & Waters, 2005).

In their longitudinal study, Nettelbeck and Burns (2009) demonstrated that the interaction process during childhood development increases PS as children grow older, leading to improved WM. Ultimately, this contributes to enhanced reasoning ability. This indicates that although childhood cognitive growth is primarily driven by PS, the decline in reasoning ability as one ages is affected by decreased PS and age-related changes that impact WM, which are separate from PS. This confirms the assertion that PS and WM are closely linked, thus implying that when PS is impacted, WM is also impacted similarly.

In examining the complex connection between WM and PS, it is vital to consider other cognitive frameworks that include overall fluid intelligence. Previous research explored the complex relationships between these cognitive factors, indicating that the connections may be similar. Kim and Park (2018) provide evidence of the relationship among WM, PS, and fluid reasoning. The study was conducted with a sample of 115 participants aged 19 to 60 years. Various tasks, such as DS, LNS, Spatial Addition, and a Symbol Span assessed WM, whereas fluid reasoning was assessed using the Matrix Reasoning and Figure Weight subtests from

the WAIS-IV. Additionally, PS was measured through the Symbol Search and Coding subtests in the WAIS-IV. The results demonstrated WM and PS's significant role and impact on fluid reasoning. The findings revealed that PS predicted fluid reasoning after controlling for visual WM. This further supports the close relationship between WM and PS. Specifically, when visual WM is considered, PS becomes a significant predictor of fluid reasoning. These results support the relationship between the two variables.

In examining the neuroanatomical bases of WM and PS, Zanto et al. (2010) studied how ageing affects the relationship between these variables. They used an electroencephalogram to measure brain activity in a cohort of 22 young adults aged 18 to 29 and 20 older adults aged 60 to 83. They also performed a task that required them to remember colours and motion. The results indicated neural differences in brain activity between the two age groups. Additionally, the study revealed that older adults had more difficulty encoding colour information into WM. The delay in PS observed in older adults may be linked to reduced accuracy of their WM, especially when it comes to colour stimuli.

Older persons with a suppression deficit that refers to an intentional suppression of unwanted or negative thoughts (Stramaccia et al., 2020). They (older adults) demonstrated reduced WM accuracy and longer response times, while older persons without distraction discrepancy performed similarly to younger participants. There were no neural indicators to compare suppression. This suggests a strong association between WM and PS, particularly in cognitive ageing. A crucial cognitive function, like WM, relies on an individual's ability to focus on relevant information while suppressing distractions. Research highlights the significance of neural inhibition, which is the process by which the brain actively filters out irrelevant stimuli (Bays, 2015; Kang et al., 2020). Bays (2015) indicated that when distractive noise impacts neuronal firing, lateral inhibition barely fires, limiting distractions. Lateral inhibition occurs in posterior areas and the prefrontal cortex, which control attention and WM resources (Starc et al., 2016). During WM encoding, top-down modulation enhances applicable neural activity while suppressing responses to noise (Zanto et al., 2010). Optimal performance is not solely about enhancing relevant details but equally hinges on effectively filtering out distractions.

2.7. Moderation Role of Processing Speed

While the relationship between WM and PS has been established (Ackerman et al., 2002; Kurtz et al., 2013), less attention has been given to the idea that PS not only predicts WM but

may also moderate how demographic factors affect WM. In this framework, PS is not just a straight contributor to cognitive performance but a variable that influences the performance of other variables, such as WM and demographic factors. This standpoint develops its role by demonstrating an influential relationship between cognitive constructs and individuals' differences.

The rationale for exploring the moderation role of PS is grounded in various theories. The PS theory by Salthouse (1996) contends that age-related decline in higher-order cognition is caused by decelerated PS, which restricts the amount of information that can be handled in a specified period and later permits information to deteriorate over time. This allows PS to influence how variables like age and education manifest cognitively. Likewise, Stern's (2002) theory of cognitive reserve proposes that individual differences in brain effectiveness and offsetting mechanisms can moderate the effect of ageing or other life factors, suggesting that PS might play a moderating role. In addition, Bialystok et al. (2009) claimed that the cognitive consequences of bilinguals or language experience rely on how an individual manages attention control and switching, of which these processes are strictly tangled in PS. This framework highlights that PS might moderate the influence of demographics on WM; this could constrain the appeal of cognitive resources if compensatory efficiency is not improved.

This is supported by empirical evidence, which indicates that the relationship between age and WM is not uniform but varies based on PS levels, with older adults showing advanced WM performance when their PS remains intact (Park et al., 2002; Kail &Salthouse, 1994). Similarly, Tucker-Drob (2011) reported that the cognitive benefits of more years of education are more noticeable in those with higher PS. By contrast, Hackman and Farah (2009) suggest that the effect of SES on executive function depends on PS efficiency. Hackman and Farah (2009) reported that SES strongly predicts neurocognitive performance and executive function. One with higher PS may use a more efficient neural pathway for executive tasks, such as updating and inhibiting. Given that the executive functions depend on efficient processing, PS may moderate how SES influences WM by supporting or limiting the efficiency of executive control processes across diverse SES. Regarding language, Grundy et al. (2017) observed that faster PS improves bilinguals' ability to engage in cognitive control systems, impacting WM performance in complex tasks. These studies highlight the

interactive nature of PS and demographic factors, signifying that PS acts as a flexibility or susceptibility factor of cognitive constructs.

These theoretical foundations and empirical findings directly inform the aim of the current study: to examine whether PS moderates the relationship between demographics and WM performance. This aim communicates whether PS is important and when and for whom it matters most. Consequently, this results in a discriminated apprehension of cognitive variability in a diverse population.

Chapter 3 - Methods

3.1. Introduction

This chapter provides an overview of the methods employed in the present investigation, which constituted a part of a larger project. The present study investigated the relationship between working memory (WM) and processing speed (PS) and the moderating effect of PS on the relationship between WM and demographic variables. The study objectives were as follows: firstly, to explore the correlation between WM and PS. Secondly**,** to explore the relationship between WM and demographic variables (age, years of education, language experience, SES, and gender). Lastly, to determine whether PS and demographic variables predict WM performance. The research aim that guided this study was to explore the relationship between PS and WM, and to examine the moderating role of PS on selected demographic factors and WM. Furthermore, two hypotheses were developed as a result of the literature review. Firstly, it was hypothesised that PS would significantly impact WM. Secondly, it was hypothesised that PS would be moderated by WM and selected demographic variables.

The study measurements had limitations and strengths. Language limitations were acknowledged; the sample was not stratified by language background, which resulted in an imbalance between monolinguals and bi/multilinguals. Language proficiency was self-reported, with most participants indicating fluency in English and early experience since primary school. However, English was not their first language; social desirability may have influenced some to exaggerate their fluency, given the apparent status of English as the language of formal education. This reliance on self-report limited the study's ability to precisely measure language experience in cognitive performance. The accents of the examiners and participants were not controlled in this study. Future research would benefit from more language background assessment and inclusion of comparison groups to understand better how WM and PS may be differentially influenced by language experience. Notably, one measurement strength was the use of the written version of the Symbol Digit Modalities Test (SDMT), which eliminates language bias. This measure allowed participants to match symbols and numbers rather than language articulation and demands.

This chapter organises detailed information about the sample and sampling methods, the measures used during data collection, the procedure that followed data collection, and the ethical considerations.

3.2. Research Design

The positivist paradigm was suited for this study since it relies on measurement and reason; the information was revealed from unbiased and quantifiable observation of various actions, and the number of variables cannot always be controlled (Du Plooy-Cilliers et al., 2014). A quantitative study method was utilised to examine the statistical link between variables. Specifically, this study utilised a cross-sectional design, as it was conducted at one point in time (Fouché et al., 2021). The study can be classified as correlational as it sought to examine the associations between multiple variables without the researcher being able to manipulate or control any of them (Fouché et al., 2021). Furthermore, it is non-experimental research as it relied on interpretations or observations rather than implementing control, manipulation, or alteration of the individuals involved (Fouché et al., 2021).

3.3. Sample and Sampling

The total sample included 97 South Africans from various SES backgrounds with diverse languages. This study used a combination of non-probability sampling approaches (Fouché et al., 2021). Convenience sampling was used to request volunteers by advertising posters on social media such as Facebook and WhatsApp. A purposeful sampling was employed and was suitable to meet (Fouché et al., 2021). The sample consisted of healthy adults recruited in various locations, such as KwaZulu-Natal, Durban, Limpopo, and Gauteng, where it was convenient for the researcher and co-researchers. Moreover, participants were recruited via snowball sampling, where participants refer others who meet requirements, and other volunteers were recruited by word of mouth (Fouché et al., 2021). Participants were given contact details, which were written on a poster, to reach the researcher if they were interested in participating. Those referred by other participants were given the researcher's contact details.

3.3.1. Inclusion criteria

Only volunteers who could converse in English were included, since all tasks were administered in English. Volunteers had to be between 18 and 60 years old, with a level of education between seven and 16 years.

3.3.2. Exclusion criteria

Participants were excluded if they reported a history of neurological, psychiatric, immunological, or metabolic illnesses, or a history of substance abuse and usage of medication that could impair cognitive skills, or sensory impairment that could affect test

performance. Although formal medical screening was not conducted, self-reporting and demographic screening questions were used to minimise potential confounding variables.

Given the multilingual setting of South Africa, the language aspect was cautiously considered. All tasks were administered in English, warranting consistency among volunteers. Only those who demonstrated conversational fluency in English were recruited to reduce potential linguistic mismatches. This decision was made to control for variations in test comprehension that may arise when participants are assessed in a language other than their dominant one. However, it is acknowledged that the absence of objective language proficiency measures (e.g., standardised tests) and reliance on self-reported language ability represent a limitation. Moreover, the verbal nature of specific cognitive tasks (e.g., Digit Span (DS), Letter Number Sequencing (LNS), SDMT-Oral) may have interacted with individual differences in English proficiency. This limitation is explicitly recognised in the discussion chapter.

While non-probability sampling was appropriate due to resource limitations and the study's exploratory nature, the absence of randomisation limits the generalisability of the findings. Additionally, the lack of formal screening of neurological and psychiatric conditions and the absence of language proficiency assessments might introduce uncontrolled variability in findings. These are considered methodological limitations and should be considered when interpreting the results. A summary of the demographic characteristics of the sample is presented in Table 1.

Table 1

Demographic Characteristics of the Sample

Characteristic	Category	N (%)	Min	Max	Mean (SD)	IR	Missing data
Age	18-60	97	18	60	32.4 (10)	24(40)	1(1%)
Years of education	7-16	96	7	16	12.5 (1.8)	12(13)	
Gender	Female	64 (66)					
	Male	33 (34)					
NL	1	5 (5)					
	2	32 (33)					
	3	60 (62)					
English as first language (EFL)	Yes	20 (21)					
	No	76 (79)					1(1%)
Living Standard Measure (LSM) levels	5	1 (1)					
	6	11 (11)					
	7	12 (12)					
	8	11 (11)					
	9	28 (29)					
	10	34 (35)					
LSM group	5-7	24 (25)					
	8-10	73 (75)					

Note: N=97. NL=Number of languages. LSM=Living Standard Measure. Min=Minimum. Max=Maximum. SD=Standard Deviation. IR=Interquartile Range. Missing data resulted from incomplete responses on some questionnaires.

3.4. Instruments

The current study was part of a larger project investigating the relationship between PS and several cognitive functions. Although this specific project focused on PS and WM, the data collection included a wide selection of tests, specifically: Letter Number Sequencing (LNS) subtest of WAIS-IV-SA (Wechsler, 2017), the Digit Span (DS) subtest of WAIS-IV-SA (Wechsler, 2017), the Symbol Digit Modalities test (SDMT) (Smith, 1982), Stroop effect (Stroop, 1935), Comprehensive Trail Making Test (Reynolds, 2002), Controlled Oral Word Association Test (COWAT) (Benton et al., 1983). However, only the instruments used are described below for this study. We administered these measures and questionnaires with two other students working on the same project in English. Although trained professionals typically utilise these tests, the researcher and two students were explicitly trained for the current larger project purpose. After training sessions, they were approved by the supervisor to conduct measures used in the current study. Instructions were followed exactly as per the

administration procedure outlined in the manual. The training process will be outlined in detail later in this chapter.

Demographic Questionnaire was used to collect information regarding the participants' sociodemographic characteristics (Ferreira & Cockcroft, 2023), such as age, gender, years of education, occupational status, and level of education of their parents. It took approximately five minutes to complete (Appendix A).

Living Standard Measure (LSM) (South African Audience Research Foundation [SAARF], 2014) was used to determine living conditions based on geographic indicators and access to services and materials (SAARF, 2014). The LSM was utilised and incorporated with demographic questionnaires to measure socioeconomic status (SES) and collect essential demographic information (Appendix B). It estimates participants' SES based on household amenities, living conditions, and occupations. It also records parents' education levels. Participants rated their income comparison on a five-point Likert scale, classifying their financial condition as above average or below average. They rank their household compared to others in the community and visualise a ten-step ladder to determine their subjective standing. Participants were requested to respond with either 'true' or 'false' to 29 items. These items included questions regarding material possessions, like car and household ownership. The LSM score was scored according to the latest release of SAARF (SAARF, 2014). Higher ratings correspond to a higher living standard, and the scores ranged from one to 10, with a higher score indicating a higher living standard (Appendix B).

Cockcroft (2022) reported using the LSM in a South African sample and investigating the advantage of WM in bilingual young adults. However, the LSM is not a psychometric scale; therefore, SAARF did not report any internal reliability or Cronbach's Alpha.

Shortened Version of Language Experience and Proficiency Questionnaire (LEAP-Q). The LEAP-Q is a self-report of language proficiency tool administered to all participants, assessing their language proficiency using a paper-and-pencil format (Marian et al., 2007). The tool requests that participants self-assess their ability to read, speak, and understand the languages they report as knowing on a scale from 0 (indicating no proficiency) to 10 (representing flawless ability). The participants were requested to furnish details regarding the age at which they acquired language, and it took approximately 10 minutes to finish (Appendix C). Participants were not screened for familiarity with the English alphabet. They were not allowed to respond in any language other than English.

Marian et al. (2007) established LEAP-Q's internal validity and reliability, although they did not report a single overall Cronbach's Alpha. However, they reported first language competency, Cronbach's α = .85, and second language proficiency, α = .92. This measure has been used by Cockcroft et al. (2017) in South African young adults.

The Letter Number Sequencing Subtest of WAIS-IV-SA (LNS) (Wechsler, 2017). The LNS is a cognitive task utilised to assess auditory attention, mental manipulation, WM, and cognitive flexibility. The tests require that the individual mentally organises a randomised series of letters and numbers upon auditory presentation, afterward reciting them in ascending numerical and alphabetical order (Wechsler, 2017). All participants followed the exact administration procedure the examiner provided, as outlined in the manual. There were no time limits for the assessment. The assessment comprised seven tasks with three trials, estimated at around 10 minutes.

The LNS has good psychometric properties and is highly effective in testing the executive aspect of WM (Shelton et al., 2009). Waters and Caplan (2003) reported internal consistency of verbal WM tasks to have ranged between .52 and .81, although their study did not mention direct internal consistency of LNS; these estimates provide a general estimation of LNS given its dependence on similar cognitive and language processes. The WAIS IV-SA adaptation offers standards for the South African population (Wechsler, 2017), although the norms have been criticised for not representing the country's cultural diversity (Shuttleworth-Edwards, 2016).

The Digit Span (DS) subtest of Wechsler-IV-SA (Wechsler, 2017). This subtest measures verbal short-term memory capacity, attention, and WM. It focuses on the ability to maintain information temporarily in short-term memory. This task can be used in three formats: forward, backward, and sequencing. Instructions were explained to the participants, and the researcher followed the exact administration procedures outlined in the manual. Participants completed the tasks in the order they were presented in the original test, following instructions given by the examiner. The subtests consist of forward, backward, and sequencing. There were no time limits for all tests (Wechsler, 2017). The DS subtest of Wechsler-IV-SA indicates good psychometric properties, supporting its validity and reliability measure of WM (Schaeffner et al., 2020). The WAIS-IV technical manual reveals that DS subtest scores have an internal consistency reliability of .93, demonstrating high internal consistency in each condition (Wechsler, 2008). However, Gignac et al. (2017)

estimate a stratified coefficient of DS to .81, and suggest that the internal consistency of DS is .73, based on their omega hierarchical. Additionally, Waters and Caplan (2003) estimated the Cronbach's Alpha of DS to be .75. It has been used in South Africa by Fisher (2009), who assessed 109 South African young and older adults. The DS subtests were used to measure WM, and they showed consistency and reliability in the DS subtests.

Symbol-Digit Modalities Test (SDMT) (Smith, 1982), the SDMT was developed by Smith (1982) to assess psychomotor speed. The test consisted of two parts, which were written and oral. The participant has to pair numbers with symbols for 90 seconds each (Smith, 1982). It is generally regarded as a culture-free test that may be given to individuals regardless of their cultural background (Ryan et al., 2020). Participants followed the exact administration procedure provided by the examiner as outlined in the manual. It has been reported by Strober et al. (2021) to have high psychometric properties, with a high reliability of .83 to .86. Benedict et al. (2012) reported a test-retest reliability consistency of above .80, and Van Oirschot et al. (2020) estimated Cronbach's Alpha from .875 to .978.

Cassimjee and Motswai (2016) administered the SDMT to 83 South African adults, assessing the changes in neurological functioning among young and older adults. SDTM demonstrated validity when PS was assessed.

3.5. Procedure

3.5.1. Training

As mentioned earlier, the researcher underwent several training sessions before collecting data to learn how to administer and score the instruments in the research assessment protocol. These sessions were led by the research supervisor, Associate Professor Aline Ferreira-Correia (Clinical Psychologist/Neuropsychologist, HPCSA PS0122742), and Saleha Mahomed-Kola (independent psychometrist and research intern, HPCSA PMT0090646). The training was completed when the researcher could administer all tests independently and without errors. The researcher was then permitted to proceed with data collection.

3.5.2. Data collection

The present study formed part of a larger project entitled "*Exploring the relationship between demographic factors, processing speed, and the performance in selected cognitive tests*". The research was conducted after obtaining ethical clearance from the Human Research Ethics Committee Non-Medical (HREC-NM) at the University of Witwatersrand, under clearance number MAPSYC/23/02 (Appendix D). Additionally, permission to perform

the research on selected locations was received from a community church in Durban (Appendix E) and the University of Witwatersrand (Appendix F). Subsequently, participants' recruitment was conducted through advertising posters on social media platforms, such as WhatsApp and Facebook (Appendix G). The data were collected in KwaZulu-Natal, Limpopo, and Gauteng; however, the researcher of the present study collected part of the data in KwaZulu-Natal and Gauteng. Other co-researchers collected other parts since this study was part of the larger project. We (the researcher and co-researchers) conducted all questionnaires and tests from the above locations. English was used during the data collection, as all participants reported speaking English fluently.

Interested volunteers contacted the researcher, and a suitable date and time were arranged for data collection. A session with them was booked in a church office with a quiet atmosphere, featuring a table and chairs at a convenient time for the researcher and participant. Sessions were conducted individually. The examiner (the researcher of this study) was seated opposite each participant when all tasks were administered. Participants were provided complete study information (see Participant Information Sheet (PIS), Appendix H). In addition, the researcher verbally explained the purpose and aims of the study, the activities, the duration of the sessions, how the results would be used, and how they could access the findings should they wish. After this, and if the person agreed, the participants were required to sign a consent form (Appendix I). The research assessment protocol took one hour to complete. The tasks included were completed in the following order, as instructed by the examiner: Demographic Questionnaire, LSM, LEAP-Q, DS subtests (forward, backward, and sequencing), LNS, and SDMT. All tasks were administered in English; participants were excluded from participation if they reported proficiency in other languages except English. All tasks and scoring were done manually, and standardised conditions and criteria were followed. Participants were reimbursed with R90 to cover their transportation costs when the data collection was completed.

3.6. Ethical considerations

The research study received ethical approval from the Human Research Ethics Committee (Non-Medical) at the University of Witwatersrand, clearance number MAPSYC/23/02 (Appendix D). The present investigation posed minimal risk to the individuals involved. The researcher ensured that participants understood their voluntary involvement in the study and explicitly communicated to them that they were under no obligation to participate in the study. Participants were informed about the nature and procedures of the study in detail and

in writing using the PIS (Appendix H) and given the chance to ask unclear questions, thereby facilitating a comprehensive understanding of the study's content and scope. Before the commencement of the study, the participants were requested to provide their informed consent by signing the document (Appendix I).

Because of the in-person format of the testing procedure, complete anonymity could not be ensured, although confidentiality was maintained. Participants were duly informed of their right to withdraw from the study at any given point voluntarily or to exercise their discretion in abstaining from responding to any questioning, without incurring any negative repercussions.

The researcher safeguarded and respected confidentiality by assigning unique participant numbers to all volunteers, although complete anonymity was not guaranteed. The participants' responses were only accessible to the researchers. All data collected was securely stored in a password-protected computer, and only the researcher and supervisor had access to the data.

There were no rewards for participating in this study; however, volunteers were reimbursed with R90 for transportation costs.

3.7. Data Analysis

The statistical analyses of all data were performed using Statistical Analysis System (SAS) version 9.4 for Windows (SAS Institute Inc. 2002). A 5% significance level was used. The first step in the data analysis was to describe all the variables in terms of frequencies, mean, standard deviation, minimum, and maximum (Field, 2017). By theoretical models of cognitive ageing (e.g., Salthouse, 1996) and language-related cognitive processing (Bialystok & Craik, 2010), moderation analysis was suited for this study. Specifically, this analysis investigates whether PS moderated the relationship between demographic variables (age, education, language experience, SES, and gender) and WM performance. Given a recognised role of PS as a fundamental underlying individual difference in WM, and its possibility to either worsen or buffer the effect of age, education, or language experience. These models were theoretically driven rather than post hoc.

The General Linear Model (GLM) analysis was selected for this study over multiple regression analysis and multivariate analysis of variance (MANOVA) because it accommodated categorical and continuous predictors, allowing modelling of confounding relationships, including interaction effects. The GLM analysis focused on a broader

framework, encompassing other models, such as Analysis of variance (ANOVA) and MANOVA (Hair et al., 2013). This analysis goes beyond multivariate regression by allowing linear transformation and linear multiple dependent variables, further necessitating the connection between dependent and independent variables and error distribution (DeShon & Morris, 2004). Whereas multiple regressions assume that all predictors were continuous (Nayebi, 2020), and MANOVA is intended to analyse multiple dependent variables simultaneously (Hair et al., 2013), which could not yield strong and effective findings specifically for the current study.

Secondly, all assumptions for each statistical test were verified, and the data were examined to determine if they met the underlying assumption of GLM analysis, which were set to be met for tests to reveal accurate findings. If these assumptions were violated, the interpretation of findings may be incorrect (Nimon, 2012). The primary assumptions associated with GLM were linearity, normality (outliers), homoscedasticity, and multicollinearity. Linearity was assessed, and the plot points were randomly scattered around zero, indicating normality. It was assessed by model fit indices (R^2) for independent and dependent variables; this confirms the relationships between independent and dependent variables. Next, normality requires data to be generally distributed among residuals (Nimon, 2012). This assumption was assessed using the Shapiro-Wilk test, with no deviation from normal distribution, a p-value of .05, and normality of data was assumed. Cramer's V for pairings of categorical variables was used to understand categorical variables, which included gender, and EFL (V >= .5), suggesting a moderate association between categorical variables. Cohen's d was used to compare pairs of categorical-continuous variables (d >= .8). This indicates a large effect size, that the difference between the groups was substantial (Warne, 2017). Homoscedasticity was assessed using a scatterplot; it was indicated that the residuals were randomly distributed around zero, with no evidence of a systematic pattern, and the residuals' variance was constant across predicted value levels. However, one outlier was identified. After removal, a more uniform spread was observed. High correlations between independent variables (r >= .7) suggest potential multicollinearity, while significant correlations between independent variables and the dependent variable provide evidence of linear associations. The multicollinearity assumption was evaluated by assessing the link between independent variables. Variance inflation factor (VIF) and condition indices were used to detect multicollinearity. Highly correlated independent variables were identified, and a moderate to strong association was observed between the LSM category and EFL

(Cramers' V = 0.56). Years of education and EFL (Cohen's d = 1.9) suggest a possible overlap in the variance explained by these variables. LSM categories and LSM groups were confounded. Notwithstanding, all variables were retained due to theoretical relevance. Lastly, outliers were identified and addressed; specifically, one outlier was identified and removed from the WM test scores. This outlier was identified during the preliminary data analysis and could disproportionately influence the results.

After the statistical assumptions of GLM were analysed, a Pearson's correlation coefficient was used to assess the association between dependent variables. This was done to assess the strength and direction of dependent variables. Thereafter, the moderating effect of PS on the relationship between WM and demographic variables was investigated using nested GLM analysis. The GLM is a conventional linear regression model for continuous and categorical predictors; it explains the relationship between independent variables and dependent variables, while testing the influence of the moderator on this relationship (Hair et al., 2013). Moderation involves determining whether the effect of an independent variable on a dependent variable changes depending on the level of a third variable, known as the moderator (Baron & Kenny, 1986). This allowed checking, first, whether there was a significant correlation between the independent and dependent variables (Model 1) and second, to assess the association between the moderator (PS) and the independent and dependent variables, assuming any significant association. Some form of moderation occurred (Model 2). However, if there was no significant association, then no moderation occurred. If there were significant associations in Models 1 and 2, then a moderation occurred. Thereafter, Model 3 added an interaction between independent, dependent, and moderating variables (SDMT-Oral). This allowed us to test whether the effect of the independent variable on the dependent variable changed depending on the level of the moderator. It also explored whether there was a significant interaction between moderating and independent variables and whether a moderation effect was present. Lastly, Model 4 confirmed the moderation effect by comparing all three models. In order to get the most parsimonious model for interpretation, non-significant variables were excluded from this model.

3.8. Conclusion

In conclusion, this chapter has drawn the methods employed to answer the research questions and hypotheses of the study. It provided the research design and explained the recruitment of participants, instruments, and procedures employed. This chapter further

describes the statistical analyses selected to assess correlations, predictive association, and moderation effects. It provided the rationale for their use in answering the study objectives and assessing whether the data supported the basic assumptions of GLM. It also described the models employed. Finally, ethical considerations were addressed to ensure the study followed research standards. Collectively, these method selections offer a basis for presenting results in the subsequent section.

Chapter 4 – Results

4.1. Introduction

This chapter presents the findings of the current study. It starts with descriptive statistics to characterise the study sample. The findings are then described according to the study objectives. Notably, the results detail the relationship between working memory (WM) and processing speed (PS), how these constructs relate to demographic variables, how PS predicts the relationship between WM and demographic variables, and how PS moderates the relationship between WM and demographic variables. The findings are presented systematically, with tables and figures included. Their interpretation and implications are kept for Chapter 5.

The main aim of this research was to explore the moderation effect of PS as measured by Symbol Digit Modalities Test (SDMT) Oral trial on the relationship between demographic variables (age, years of education, language experience, Socioeconomic Status [SES] and gender) and WM as measured by Digit Span (DS) forward, DS backward, DS sequencing and Letter Number Sequencing (LNS).

The first part of the results comprises the descriptive statistics used to describe the data, the descriptive statistics of WM and PS, and the correlation between WM and PS. The second part presents results from General Linear Model (GLM) analysis, which consists of one to four models. Models were created by investigating one variable at a time, first gender, then age, years of education, followed by SES measures, namely Living Standard Measure (LSM) category, then Number of Languages (NL), and English as First Language (EFL). Also, the association between independent, dependent, and moderator variables was examined. The study will further present the results of the interaction effect of PS, followed by a confirmation of the moderation effect across all independent variables.

4.2. Description of demographic characteristics of differences in performance

The total sample size was 97 South Africans from various SES backgrounds, diverse linguistic background and the majority of them were females (66%), age ranged from 18 to 60 years with level of education between seven and 16 years, and males (34%), with age between 18 and 49 years and their level of education were between 10 and 16 years. Also presented monolinguals (n = 5), bilinguals (n = 33), and multilinguals (n = 62). The majority of the sample spoke English as a secondary language (n = 76), and a minority spoke English as a first language (EFL) (n = 20). Their standard of living was categorised into two groups,

one group including participants with the lowest means (levels five to seven; $n = 24$) and participants with the highest means (levels eight to ten, $n = 73$). The mean age of participants was 32.4 ($SD = 10$), and the mean years of schooling was 12.5 ($SD = 1.8$). The descriptive summary is displayed below in Table 2.

Table 2

Summary of Descriptive Characteristics of Sample

Characteristic	Category	N (%)	Total N	Min	Max	Mean (SD)	Median	IR	Missing data
Age	Female	64 (66)	97	18	60	32.4 (10)	30	24(40)	1(1%)
	Male	33 (34)		18	60				
Years of education	Female	64 (66)	96	7	16	12.5 (1.8)	12	12(13)	
	Male	33 (34)		10	16				
Gender	Female	64 (66)							
	Male	33 (34)							
NL	1	5 (5)							
	2	32 (33)							
	3	60 (62)							
English as first language (EFL)	Yes	20 (21)							
	No	76 (79)							1(1%)
Living Standard Measure (LSM) levels	5	1 (1)							
	6	11 (11)							
	7	12 (12)							
	8	11 (11)							
	9	28 (29)							
	10	34 (35)							
LSM group	5-7	24 (25)							
	8-10	73 (75)							

Note: N = 97. NL = Number of languages. LSM = Living Standard Measure. Min = Minimum. Max = Maximum. SD = Standard Deviation. IR = Interquartile Range. Missing data resulted from incomplete responses on some questionnaires.

4.3. Description of the sample's performance on all the cognitive tasks.

Descriptive statistics for all measures were calculated to summarise information about the dependent variables, which can be found in Table 3. The sample size was slightly smaller in some variables because a few participants did not complete the tasks. The mean and standard deviation (SD) for DS backwards (M = 7, SD = 2.3) and sequencing (M = 7.2, SD = 2) were very similar, and lower than the DS forwards *(*M = 9.4, SD = 2.5), which was expected given that DS forwards was easier, so a better raw performance was expected. The means for the measures of span in the DS task seem to be organised by level of difficulty, with one word difference per trial, specifically in the following order: LDSF (M = 6.2, SD = 1.4), LDSS (M = 5.1, SD = 1.1), and LDSB *(*M = 4.0, SD = 1.3). Similarly, the span of LNS (M = 4.5, SD = 1.0) fell between the means of the span in the sequencing and backwards tasks. The mean and SD for SDMT-Oral (M = 50.8, SD = 13.8) were higher than SDMT-Written (M = 41.9, SD = 11.7). The dataset was assessed for outliers; one outlier was identified and removed from the LNS score.

Additionally, Skewness and Kurtosis were examined for normality. Skewness and Kurtosis indicate the distribution's spread, which measures asymmetry and peakedness (Kim, 2013). For a distribution to be classified as normal, the Skewness and Kurtosis values need to range from -1 to 1, with 0 indicating a perfectly normal distribution, and -2 to +2 is generally accepted (Hair et al., 2022). For DS subtests, all Skewness indicated a slightly positive skew, and Kurtosis ranged close to normal, with slightly platykurtic. The Skewness and Kurtosis of SDMT-Written and SDMT-Oral indicated that both distributions are approximately symmetrical and close to normal with no significant deviation in Skewness or peakedness; meanwhile, the Skewness values fall under -1 to 1, and the Kurtosis values range from -1 to 3. However, LNS demonstrated a more moderate skew, shifting the distribution near the higher value. Kurtosis showed a leptokurtic distribution, meaning the data had a more peaked shape with a heavier tail than a normal distribution since the skewness was beyond the normal range. Kurtosis exceeded 3.0; outliers were checked and removed. The descriptive results for WM and PS tasks are displayed below in Table 3.

Table 3

Summary of Descriptive Statistic Results of Cognitive Variables

Variable	n	Mean	SD	Med	Min	Max	Skewness	Kurtosis
DS forwards	95	9.4	2.5	9	3	15	0.53	0.20
DS backwards	97	7.0	2.3	7	2	14	0.44	0.11
DS sequencing	95	7.2	2.0	7	3	12	0.26	-0.39
DS total score	97	24	5.4	23	12	38	0.42	-0.07
LDSF	95	6.2	1.4	6	4	9	0.56	-0.33
LDSB	96	4.0	1.4	4	2	8	0.59	0.00
LDSS	94	5.1	1.1	5	3	8	0.29	-0.38
LLNS	94	4.5	1.0	4	2	7	0.03	-0.55
LNS	94	17	3.7	17	1	25	-1.16	3.40
SDMT-Written	96	49	11.7	42	8	74	-0.06	0.37
SDMT-Oral	96	50.8	13.8	52	12	79	-0.29	0.09

Note. All scores are raw scores. n = number of participants. SD = Standard Deviation. Min = Minimum Score. Max = Maximum score. DS = Digit Span. LDSF = Long Digit Span Forward. LDSB = Long Digit Span Backward. LDSS = Long Digit Span Sequencing. LLNS = Long Letter Number Sequencing. LNS = Letter Number Sequencing. SDMT = Symbol Digit Modalities Test.

4.4. The correlation between working memory and processing speed.

The first objective was to explore the relationship between WM and PS. The study found significant and positive correlations between WM measures. As hypothesised, the DS subtest scores correlated with the total scores, and the span measures correlated with the DS total score. Notably, less powerful correlations, like DS sequencing and DS backward (r = .560, p = <.0001), seem to respond to these tasks' differences in difficulty levels.

Pearson correlations between all the measures were conducted and are presented in Table 4. First, the correlations between all the WM measures were explored and, as hypothesised, they were all statistically significant. Second, the correlations between PS measures were correlated with each other. Then the correlation between WM and PS is presented. Additionally, a significant moderate positive correlation between DS backward (r =.472, p = <.0001) and DS sequencing (r =520, p = <.0001). DS total (r = .549, p = <.0001), LNS (r = .560, p < .0001), DS backward (r = .458, p = <.0001), and DS sequencing (r = .458, p = <.0001) showed a moderate to strong correlation with SDMT - Oral. SDMT- Written had a significant moderate positive association with LDSF (r = .333, p = .001). All cognitive measures were highly correlated among themselves, demonstrating that attention span, WM,

and PS are closely related, which challenges the notion that these assessments are specific to single cognitive constructs.

Table 4

Correlation Coefficients for Cognitive Variables

	DS forward	DS backward	DS sequencing	DS total	LDSF	LDSB	LDSS	LLNS	LNS	SDMT-Written	SDMT-Oral
	.416* <.0001										
DS backward											
	.256	.560	1								
	.013	<,0001									
DS sequencing											
	.716**	.770**	.733**	1							
	<.0001	<.0001	<.0001								
DS total											
	.915**	.497**	.338**	.728**	1						
	<.0001	<.0001	.0009	<.0001							
LDSF											
	.385**	.950**	.586**	.748**	.483**	1					
	.0001	<.0001	<.0001	<.0001	<.0001						
LDSB											
	.228*	.537**	.924**	.680**	.328*	.562	1				
	.029	<.0001	<.0001	<.0001	.0014	<.0001					
LDSS											
	.327*	.541**	.636**	.623**	.403**	.533**	.588**	1			
	.0015	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001				
LLNS											
	.441**	.562**	.555**	.634**	.463**	.535**	.539**	.827**	1		
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001			
LNS											
	.283*	.472*	.520**	.549**	.333**	.475**	.505**	.517**	.560**	1	
	.0057	<.0001	<.0001	<.0001	.001	<.0001	<.0001	<.0001	<.0001		
SDMT-Written											
	.366*	.458**	.458*	.529**	.413**	.436**	.413**	.432**	.496**	.819**	1
	.0003	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	
SDMT-Oral											

Note: **. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

4.4. Exploration into the moderation effects of processing speed.

This section presents the results of the four models created to investigate the moderation effect of PS on the relationships between demographic variables and WM. The study objectives guided these models to explore the correlation between WM and PS. Secondly, explored the relationship between WM and demographic variables (age, years of education, language experience, SES, and gender), and between PS and the same demographic variables. Lastly, determined whether PS and demographic variables predict WM performance. The study results were provided in line with the abovementioned research objectives. Regarding the relationship between WM measures and demographic variables, the findings indicated a significant association between all demographic variables and WM measures. PS was significantly associated with age, years of education, and LSM category. Regarding how PS and demographic variables predict WM, the findings demonstrated that PS predicted WM performance on selected demographic variables. However, the moderation effect of PS was observed on selected demographic variables.

4.4.1. Model 1: The relationship between working memory and demographic variables

This model presents the study's second objective, which was to explore the relationship between WM and demographic variables (age, years of education, language experience, gender, SES, and gender). Model 1 investigated one variable at a time: gender, age, years of education, SES (LSM category and LSM group), NL, and EFL. This part of model 1 focused specifically on DS forward, DS backward, DS sequencing, and LNS. The researcher first analysed the association between WM measures and demographic variables using GLM analysis in this model. Only statistically significant results have been included; the non-significant ones can be found in the appendices. These results are illustrated in Table 5.

The findings demonstrated a significant association between gender and DS forward (F = 5.34; $Pr > F$ = .0230; p = < .0001), with males exhibiting a lower mean for DS forward score. However, the model's explanatory power was weak (R^2 = .054) (see Table 5). In contrast, the findings suggested that age (F = 1.36; $Pr > F$ = .2469), years of education (F = 2.84; $Pr > F$ = .0951), LSM category (F = .5762; $Pr > F$ = .5762), LSM group (F = 0.02; $Pr > F$ = .8775), NL (F = 1.06; $Pr > F$ = .3516) and EFL (F = 0.32; $Pr > F$ = .5701) were not significantly associated with DS forward. These variables contribute to the predictive model, suggesting

that although they have a weak relationship with DS forward, they add explanatory power. Differences in education and age may contribute to varying performance in DS forward found between males and females; this could be partially explained by differences in age and education between genders (see Table 2). However, these results were not included in the moderation analysis since they were insignificant (Appendix A). These results suggested that female participants scored better than males on DS forward.

Furthermore, the findings demonstrated a significant negative association between DS backward and age (F =12.65; $Pr>F$ =.0006; R^2 = 0.12), meaning that as age increased, the performance score of DS backward decreased. Years of education displayed a significant positive association with DS backward (F = 30.21, $Pr> F$ = <.0001, R^2 = .24); the model fit increased on DS backward. This suggested that more years of education contributed significantly to the model that predicted the variance in DS backward. Furthermore, EFL and DS backward were significantly associated (F = 10.68, $Pr>F$ = .0015, R^2 = .10), suggesting that speaking EFL significantly contributed to the model explaining the DS backward performance difference. These findings demonstrated that young adults with a higher level of education who spoke EFL outperformed their peers who were older with a low level of education and who spoke other languages as their first language except English. (see Table 5)

The DS sequencing score and independent variables, including age, years of education, LSM category, NL, and EFL, were assessed for their correlation. DS sequencing and age had a strong negative association (F = 10.59; $Pr > F$ = .0016; p = .0006). DS sequencing decreased as age increased (R^2 = .10), suggesting that age significantly contributed to the model that explains the variance of DS sequencing. A significant positive correlation was observed between years of education and DS sequencing (F = 27.23; $Pr > F$ = < .0001; p = .059), with increased years of education, DS sequencing performance increased (R^2 = .23), suggesting that years of education contributed to the model that explains the variance in DS sequencing. Additionally, LSM category and DS sequencing (F = 2.56; $Pr > F$ = .0436; p = .0002) were found to be significantly associated, implying that with higher LSM, performance score increased (R^2 =.10). This finding indicated that a higher level of LSM significantly contributed to the model that explains the variance in DS sequencing. This was true between NL and DS sequencing (F = 3.90; $Pr > F$ = .0238; p = < .0001), this suggested that speaking more than one language contributed to a better performance model that explains the variance on the DS sequencing, EFL and DS sequencing was significantly and positive

correlated (F = 15.96; $Pr > F$ = .0001; p = .0015). The model fit improved (R^2 = .15), suggesting that EFL significantly contributed to the model explaining the DS sequencing variance. This suggested that young adults with a higher level of education, speaking EFL, and having a higher LSM category performed better in DS sequencing (see Table 5).

The relationship between the DS total score and independent variables, which were age, years of education, EFL, gender, NL, LSM category, and LSM groups, was examined by using GLM analysis. The findings indicated a significant negative association between age and DS total score (F = 7.90; $Pr > F$ = .0060, p = < .0001), and it was concluded that the DS total decreased as age increased (R^2 = .07). Also, a strong positive association between DS total and years of education (F = 26.09; $Pr > F$ = <. 0001); p = .0016) were observed. This demonstrated that the DS total score increased as years of education increased. This suggested that the independent variable - years of education contributed to the model that explains the variance of DS total. Also, EFL and DS total (F = 13.99; p = < .0001), (R^2 = .13) were found to be significant associated. This means that speaking EFL improved the performance score of DS total, suggesting that individuals who spoke EFL significantly contributed to the explanation of the variance in DS total. In contrast, the findings further indicated an insignificant association between DS total score and gender (F = 0.73; $Pr > F$ = .3965), LSM category (F = 2.09; $Pr > F$ = .0878), LSM-groups (F = .87; $Pr > F$ = .3522), and NL (F = 1.87; $Pr > F$ = .1599). This implies that being monolingual or bi/multilingual, of any gender or level of SES, did not contribute to the total performance of DS.

These findings suggest that younger participants with more years of education who speak EFL outperformed older participants with fewer years of education who do not. Furthermore, significant variables were further analysed in the next model. However, variables that did not correlate significantly with DS Total (gender, LSM category, LSM-groups, and NL) were excluded from the moderation analysis but can be found in Appendix B.

Concerning the relationship between LNS and demographic variables (age, gender, years of education, LSM category and EFL), the results revealed that age was significantly negative associated with LNS (F = 12.13; $Pr > F$ = .0008; p = .0020), evidenced by the decreasing LNS score with increasing age (R^2 = .12), this suggested that age significantly contributed to the model that explains the variance in LNS performance. Gender (F = 5.48; $Pr > F$ = .0215; p = < .0001) also displayed a significant association with the performance of the LNS score, in which the mean was lower for males and the model's explanatory power was poor (R^2 =

.057), meaning that gender had a significant contribution towards explaining the variance in LNS performance. Years of education and LNS score ($F = 14.10$; $Pr > F = .0003$; $p = .0019$) were significantly positively correlated, suggesting that the LNS score increased as years of education increased, as indicated by ($R^2 = .13$). This means that years of education significantly contributed to the model that explains the difference in LNS performance. Furthermore, the LSM category was significantly associated with LNS ($F = 2.79$; $Pr > F = .0312$; $p = .0001$), which was seen in simultaneous increases of LSM and LNS performance ($R^2 = .11$), meaning that the LSM category contributed to explaining the differences in LNS performance. There was a strong association between EFL and LNS ($F = 18.89$; $Pr > F = <.0001$; $p = .0015$) as evidenced by a higher LNS performance score among those with EFL ($R^2 = .17$), suggesting that EFL contributed to explaining the differences in the performance score of LNS (see Table 5). According to these findings, female young adults with a higher level of education, speaking EFL with a higher LSM category, demonstrated better performance scores on LNS.

The SDMT-Written score was also analysed as a dependent variable with independent variables, like age, gender, years of education, LSM category, LSM group, EFL, and NL. The results indicated that age and SDMT-Written score ($F = 56.02$; $Pr > F = < .0001$; $p = .0001$, $R^2 = .37$) were negatively associated, indicating that SDMT-Written score decreased as age increased. This means that the significant association between age and SDMT-Written was meaningful to the model and explains the variance in the performance of SDMT-Written. Years of education ($F = 47.07$; $Pr > F = < .0001$) revealed a significant association with SDMT-Written, demonstrating that individuals with more years of education had a higher score on SDMT-Written, $p = .0001$ ($R^2 = .34$), and years of education contributed to the model that explains the variance in SDMT-Written. Also, LSM category was significant associated with SDMT-Written ($F = 4.31$; $Pr > F = .0031$; $p = .0001$), indicated that increased LSM category enhanced the performance of SDMT-Written score and therefore demonstrated significant correlations ($R^2 = .16$). This was also true for gender ($F = 1.11$; $Pr > F = < .2941$) and demonstrated that gender explains the differences in SDMT-Written performance. A significant positive association was observed between SDMT-Written and LSM groups ($F = 2.90$; $Pr > F = .0918$; $p = 1.000$; $R^2 = .030$), indicating that SDMT-Written scores were high in the high LSM group. Furthermore, NL and SDMT-Written ($F = 2.65$; $Pr > F = 0.0760$, $R^2 = .054$) were significantly associated, indicating that bi/multilingual participants scored high on SDMT-Written. However, EFL ($F = 49.52$; $Pr > F = < .0001$; $p = .0001$; $R^2 = .34$) had no

significant correlation. These results suggest that being a young female with a higher level of education, speaking multiple languages, and having a high LSM category were linked to a higher score of SDMT-Written. In contrast to speaking EFL, this did not improve the performance of SDMT-Written. The findings from this model were illustrated in Table 5.

Table 5

Summary of the GLM correlation analysis between Demographic Variables, Working Memory and SDMT-Written.

Dependent variable	Independent Variable	F value	Pr >F	p value	R^2
DS forward	Gender - female	5.34	.0230	< .0001	.054
DS backward	Age	12.95	.0006	.0008	.12
	Years of education	30.21	<.0001	.055	.24
	EFL	10.68	.0015	.0003	.10
DS sequencing	Age	10.59	.0016	.0006	.10
	Years of education	27.23	<.0001	.059	.23
	LSM category	.28	.0436	.0002	.10
	NL	3.9	.0238	<.0001	.10
	EFL	15.96	.0001	.0015	.15
DS total	Age	7.90	.0060	< .0001	.08
	Years of education	26.09	<.0001	.0016	.22
	EFL	13.99	.0003	< .0001	.13
LNS	Age	12.13	.0008	.0020	.12
	Gender	5.48	.0215	< .0001	.056
	Years of education	14.10	.0003	.0019	.13
	LSM category	2.79	.0312	.0001	.11
	EFL	18.51	< .0001	.0015	.17
SDMT-Written	Age	56.02	<.0001	.0001	.37
	Years of education	47.07	<.0001	.0001	.34
	LSM category	4.31	.0031	.0001	.16

Note. LNS = Letter Number Sequencing. SDMT = Symbol Digit Modalities Test. EFL = English as a first language. LSM = Living standard measure. NL = Number of languages. This table demonstrates the connection between demographic factors, SDMT-Written score, and WM as measured by DS forward, DS backward, DS sequencing, DS total scores, and LNS score. It incorporated the significant independent variables. All significant variables were expanded on the subsequent model, which is a moderation analysis. *Significance level $p < 0.05$.

A similar correlation identified from a previous section applies to this section, which evaluates the association between attention span (LDSF, LDSB, LDSS, and LLNS) and independent variables (age, years of education, gender, LSM category, and LSM group). This section also investigates one variable at a time: gender, age, years of education, SES (LSM

category and LSM group), NL, and EFL. The results demonstrated that age was significantly negatively associated with LDSF ($F = 5.79$; $Pr > F = .0181$), indicating that as age increased, the performance score of LDSB decreased. A significant negative correlation was observed between age and LDSB (F = 13.62; Pr > F = .004; p = <.0001). Again, age was significant negative associated with LDSS ($F = 9.50$; $Pr >$ F = .0027; $p = .0051$), and LLNS ($F = 8.48$; $Pr >$ F = .0045). These findings suggest that LDSF, LDSB, LDSS, and LLNS performance scores decrease as age increases. These findings suggested that age significantly contributed to the models that explain the variance in LDSF, LDSB, LDSS, and LNS performance. Years of education was found to be positively correlated with LDSF ($F = 4.69$; $Pr >$ F = .0330), LDSB ($F = 27.58$; $Pr >$ F = <. 0001; $p = < .0001$), LDSS ($F = 24.98$; $Pr >$ F = < .0001; $p = .0051$), and LLNS ($F = 20.03$; $Pr >$ F = < .0001), ($R2 = .09$). This demonstrated that individuals with more years of education had a higher performance score on LDSF, LDSB, LDSS and LLNS. These results concluded that more years of education improved LDSF, LDSB, LDSS, and LLNS performance. This was also true between gender and LDSF ($F = 4.61$; $Pr >$ F = .0345), where females performed better than males on LDSF. Furthermore, a significant association was found between EFL and LDSB ($F = 11.25$; $Pr >$ F = .0012; $p = .12$), EFL and LDSS ($F = 10.80$; $Pr >$ F = .0014), and EFL and LLNS ($F = 18.51$; $Pr >$F = < .0001), demonstrating that speaking EFL contributed positively to the LDSB, LDSS, and LLNS performance scores. Moreover, the LLNS had a significant association with LSM category ($F = 4.35$; $Pr >$ F = .0029) and LSM groups ($F = 4.32$; $Pr >$ F = .0405), demonstrating that having a high LSM level or group increased the performance on LLNS.

In contrast, the results indicated that the association between LDSF and LSM category ($F = 0.43$; $Pr > F = .7895$) and LSM group ($F = 0.00$; $Pr > F = .9598$) was not significantly correlated, suggesting that LSM level and group did not contribute to the performance score of LDSF. The association between LDSB and LSM category ($F = 2.32$, $Pr >$ F = .0628) and LSM group ($F = 3.56$, $Pr > F = .0624$) revealed no significant association. Also, between LDSS and LSM category ($F = 1.56$; $Pr > F = .1909$); LSM - groups ($F = 1.53$; $Pr > F = .2199$) no significant association observed. This suggested that SES, as measured by LSM, did not significantly affect the performance of LDSB and LDSS. Also, NL ($F = 1.37$; $Pr >$ F = .26.4) revealed no significant association with LDSF, and EFL ($F = 1.01$; $Pr >$ F = .3174) did not have a significant correlation with LDSF. An insignificant association was also observed between NL ($F = 0.92$, $Pr>$ F = .4003) and LDSB, meaning that the NL spoken by an individual did not contribute to the LDSB performance score. The association between

LLNS and NL (F = 1.58; Pr > F = .2106) was insignificant, meaning that being monolingual and bi/multilingual failed to contribute to the LLNS performance. Additionally, the association between LDSB and gender (F = 0.74; Pr > F = .3934) and between gender and LDSS (F = .00; Pr > F = .9606) was not significant, suggesting that being neither female nor male did not contribute to the performance of LDSB and LDSS.

These findings suggest that being a young female speaking EFL, having a higher level of education, and having a high LSM enhance attention span performance. These individuals exhibit strong attention compared to older adults with few years of education and speaking other languages other than English as their first language. The results are summarised below in Table 6.

Table 6

Summary of GLM correlation analysis between Demographic Variables and Attention Spans.

Dependent variable	Independent variable	F value	Pr> F	R^2
LDSF	Age	5.79	.0181	.06
	Gender	4.61	.0345	.05
	Years of education	4.69	.033	.05
LDSB	Age	9.50	.0027	.09
	Years of education	24.98	<.0001	.22
	EFL	11.25	.0012	.11
LDSS	Age	9.50	.0027	.09
	Years of education	24.98	< .0001	.22
	EFL	1.99	.1618	.11
LLNS	Age	8.48	.0045	.09
	Years of education	20.03	<.0001	.18
	LSM category	4.35	.0029	.16
	LSM group	4.32	.045	.04
	EFL	18.51	<.0001	.17

Note. This table presents significant variables only. LDSF = Long Digit Span Forward. LDSB = Long Digit Span Backwards. LDSS = Long Digit Span Sequencing. LLNS = Long Letter Number Sequencing. EFL = English as a first language. LSM = Living standard measure. Following these findings, all significant variables were expanded in the next model, which presents a moderation analysis. *Significance level p <0.05.

4.4.2. Model 2: Prediction of processing speed and demographic variables on working memory performance

Model 2. This model presents the third objective of this study, which was to determine whether PS, as measured by SDMT-Oral and demographic variables, predicts the performance of WM as measured by DS forward, DS backward, DS sequencing, DS total,

and LNS. The analysis of the previous section guided the selection of the variables that would be included in this model. Before exploring the moderating effect, it was determined that all the WM measures were correlated with the PS measures. Model 1 investigated the association between measures of WM and demographic variables; however, the GLM would help understand if PS predicts WM in this model (Model 2), and whether it was moderated by demographic variables (age, gender, years of education, EFL, NL, LSM category, and LSM-group). The summary of these findings is presented in Table 7.

The results revealed that gender (F = 4.54; $Pr > F$ = .0357) and SDMT-Oral (F = 11.87; $Pr >$F = .0009) had a significant association with DS forward. The model fit improved (R^2 = .17), and the F-test results demonstrated that Model 2 was a significantly better fit to the data (p = .0006) than Model 1 of DS forward. These findings suggested that gender and SDMT-Oral significantly contributed to the performance of DS forward, but no moderation occurred.

In addition, the DS backward demonstrated no significant association with age (F= 0.62; $Pr >F$ = .4339), and EFL (F = 1.20; $Pr >F$ = 0.2765). However, there was a positive and significant association between SDMT-Oral and DS backward (F = 12.75; $Pr >F$ = 0.0006), with an improved model fit (R^2 = .22; p = .0003). This positive association suggested that a higher SDMT-Oral score was associated with higher DS backward performance, and the non-significant association between age and DS backward indicated that age did not impact DS backward performance. This implies that SDMT-Oral was a better predictor of DS backward than age. Years of education (F= 8.08; $Pr >F$ = .0055) and SDMT-Oral (F= 4.58; $Pr >F$ = 0.0350) had a positive association with DS backward, but the model fit had not improved significantly (p = .055)**.** SDMT-Oral and DS backward performance improved as years of education increased, suggesting that more years of education significantly contributed to the model that explains the variance in DS backward. Additionally, the effect of years of education on SDMT-Oral predicted the performance score of DS backwards. Specifically, there was a relationship between SDMT-Oral and DS backward, with the performance of SDMT-Oral predicting the performance of DS backward; thus, no moderation occurred (see Table 7).

When analysing DS sequencing, years of education (F = 6.61; $Pr > F$ = .0118) and SDMT-Oral (F = 4.67; $Pr > F$ = .0333) were significantly and positively connected with the DS sequencing, but there was no significant improvement in model fit (R^2 = .059), suggesting that individuals with more years of education and high SDMT-Oral score performed better on

DS sequencing. The significant positive association between SDMT-Oral and DS sequencing suggests that SDMT-Oral contributed to the performance of DS sequencing. Although these variables demonstrated a significant association, including these variables in the model did not improve how the model explained the variance of the DS sequencing score. This demonstrated that SDMT-Oral did not moderate this association. Furthermore, NL ($F = 4.11$; $Pr > F = .0197$; $R^2 = .27$; $p < .0001$) and SDMT-Oral ($F = 24.12$; $Pr > F = <.0001$) were significantly associated with DS sequencing and the model fit improved ($R^2 = .27$). These findings indicated that speaking more than one language and having high SDMT-Oral score contributed to the high-performance score of DS sequencing. The improved model fit suggests that although NL and SDMT-Oral demonstrated significant association with DS total, their inclusion did not add explanatory power to the model. It was concluded that EFL ($F =3.47$; $Pr > F = .0658$; $R^2 = .24$; $p = .0015$) and SDMT-Oral ($F = 11.35$; $Pr > F = .0011$) were significantly and positively associated with the DS sequencing, meaning that speaking EFL improved the DS sequencing performance score. An improved model fit was observed. These findings indicated that both EFL and SDMT-Oral were significantly associated with DS sequencing, and they significantly contributed to the prediction of DS sequencing. It was concluded that these significant relationships were not moderated by PS (see Table 7).

While age ($F =.18$) was insignificantly associated with DS sequencing and indirectly predicted the performance of DS sequencing, the model showed a good fit ($R^2 = .21$; $p = .0006$); however, SDMT-Oral predicted the performance of DS sequencing. Additionally, the LSM category ($F = 0.54$; $Pr > F = .7079$) had no significant association with DS sequencing. The positive association was observed between DS sequencing and SDMT-Oral ($F = 21$; $Pr > F = .0003$), signifying that the LSM category did not contribute to both SDMT-Oral and DS sequencing performance scores, but SDMT-Oral predicted the performance of DS sequencing.

These findings indicated that participants with more years of education, who spoke more than one language, and who had EFL performed better on both SDMT-Oral and DS sequencing performance scores. This suggests that SDMT-Oral predicted the performance of DS sequencing. However, SDMT-Oral did not moderate DS sequencing.

Regarding the DS total score, the findings indicated no significant association with age ($F = 0.63$; $Pr > F = .4284$, the model fit improved ($R^2 = .28$; $p < .0001$). The insignificant association between age and DS total suggests that age alone does not predict the

performance of DS total. A significant positive association between SDMT-Oral and DS total suggested that a high SDMT-Oral score contributed to the high DS total score. The improved model fit demonstrated that including age and SDMT-Oral meaningfully improved the model that explains DS total. Years of education and DS total ($F = 3.53$; $Pr > F$ .0636; $R^2 = .30$; $p = .016$) were not significantly associated, but SDMT-Oral was positively associated with DS total, suggesting that high SDMT-Oral performance improved DS total performance. This means that SDMT-Oral was able to predict the performance of DS total. The enhanced model fit was observed, suggesting that including years of education and SDMT-Oral contributed to the meaningful explanation of the model. An insignificant association between EFL and DS total ($F = 1.46$, $Pr > F = .2294$) was observed. The model fit had improved significantly ($R^2 = .28$; $p < .0001$), suggesting that including SDMT-Oral in the model improved how well the model explained the variability of DS total score. A positive and significant association between SDMT-Oral and the DS total was observed, suggesting that a high SDMT-Oral score influenced the high performance on DS total.

These results suggested that SDMT-Oral influenced the insignificant association between DS total and age, years of education, and EFL. This suggests that SDMT-Oral predicted the performance of the DS total score but was not moderated by SDMT-Oral. Furthermore, being young, having only a few years of education, and speaking EFL did not affect the model (see Table 7).

After analysing the DS subtest scores, SDMT-Oral, and demographics, the LNS, SDMT-Oral, and demographics were analysed. The demographic variables (independent variables), SDMT-Oral, and LNS score were explored during this step. The independent variables were then added one at a time. Findings showed that age ($F = 0.23$; $Pr > F = .6303$) was not significantly associated with LNS, while SDMT-Oral ($F = 13.14$; $Pr > F = .0005$) was positively and significantly associated with LNS ($F= 11.90$; $R^2 = .21$). This suggests that age does not directly predict the performance of LNS, but SDMT-Oral does. The model fit was significantly improved ($R^2 = .21$; $p = .0020$), meaning that including age and SDMT-Oral contributed to the explanation of how well the model explained the variance of LNS performance. This suggested that age alone did not contribute to the performance of SDMT-Oral. However, the high performance of SDMT-Oral contributed to the higher performance score of LNS, and SDMT-Oral predicted the performance of LNS and enhanced the explanatory power of the model. Moreover, years of education ($F = 0.92$; $Pr > F = .3392$)

were no longer significantly associated with the LNS. However, SDMT-Oral (F = 10.07; $Pr > F$ = .0021) was positively and significantly associated with the LNS, and model fit significantly improved (R^2 = .22; p = .0019). These findings suggested that although SDMT-Oral predicted the performance of LNS, years of education did not contribute to SDMT-Oral performance. When both SDMT-Oral and LNS were considered, the improvement in the model explained the variance in LNS. The LSM category (F = 17.02; R^2 = .26; p = .0001) was not significantly associated with LNS, but SDMT-Oral was positively and significantly associated with LNS, suggesting that the high SDMT-Oral score predicted the high LNS performance score. On the other hand, gender (F = 5.58; $Pr > F$ = .0203) and SDMT-Oral (F = 19.47; $Pr > F$ = <.0001) were significantly associated with LNS. Model fit had improved (R^2 = .26; p < .0001), indicating that including gender and SDMT-Oral significantly improved the model fit. This means that gender and SDMT-Oral contributed to explaining the variance of LNS. Also, EFL (F = 5.85; Pr > F = .0177) and SDMT-Oral (F = 9.85; $Pr > F$ = .0023) were significantly associated with LNS, indicating that speaking EFL and a high SDMT-Oral score were linked with a high LNS performance score. Model fit had improved (R^2 = .26; p = .0015), suggesting that adding both EFL and SDMT-Oral improved the model's explanatory power in LNS. It was concluded that EFL and SDMT-Oral explained the variance in LNS performance. The findings in this model did not indicate any moderation (see Table 7).

These results suggested that as the SDMT-Oral score increases, the LNS score increases, implying that PS predicts the performance of WM. Neither being young nor old was associated with LNS. Having more years of education, the LSM category showed no significant association with LNS. However, being female and speaking EFL contributed to the higher score on LNS and the effect of SDMT-Oral. Therefore, SDMT-Oral, as a moderating variable, could predict the relationship between demographic variables (gender and EFL) and LNS. The results of the prediction effect of SDMT-Oral on the relationship between WM performance and demographic variables are summarised below in Table 7.

Table 7

Summary of the Prediction Effect of SDMT-Oral on the Relationship Between Demographic Variables and Working Memory performance (DS forward, DS backward, DS sequencing and LNS).

Dependent Variable	Independent Variable	F value	Pr >F	p value	R^2
DS forward	Gender	4.54	.0357		
	SDMT-Oral	11.87	.0009	.0006	.17
DS backward	Years of education	8.08	.0055	.055	.22
	SDMT-Oral	4.58	.035	-	-
DS sequencing	Years of education	6.61	.0118	.0006	.21
	SDMT-Oral	4.67	.0333	-	-
	NL	4.11	.0197	<.0001	.27
	SDMT-Oral	24.12	<.0001	-	-
	EFL	3.47	.0658	.0015	.24
	SDMT-Oral	11.35	.0011	-	-
DS total	Age	0.63	.4284	-	-
	SDMT-Oral	28.57	<.0001	<.0001	.28
	Years of education	3.53	.0636	-	-
	SDMT-Oral	11.4	.0011	.016	.29
	EFL	1.46	.2294	-	-
	SDMT-Oral	21.56	<.0001	<.0001	.29
LNS	Gender	5.58	.0203	.0001	.26
	SDMT-Oral	19.47	<.0001	-	-
	EFL	5.85	.0177	.0015	.26
	SDMT-Oral	9.85	.0023	-	-

Note. DS = Digit Span. SDMT = Symbol Digit Modalities Test. LNS = Letter number sequencing. NL = Number of languages. EFL = English as a first language. *Significance level p <0.05.

The following section examines attention spans, as it was previously noted that WM was significantly linked to them. This section adheres to a similar analysis and process as the previous section, commencing with LDSF, followed by LDSB, LDSS, and LLNS. The analysis was conducted to elucidate SDMT-Oral's prediction of the association between significant independent variables and the performance of dependent variables. A summary of these results is presented in Table 8. The interaction will be explained by the model that follows the current model.

The dependent variable LDSF, SDMT-Oral as a moderating variable, was examined, with independent variables (age, gender, and years of education) added one at a time. The results indicated that age ($Pr > F$ =.8783; R^2 = .17), gender ($Pr > F$ =.0920; R^2 = .20), and years of

education ($Pr > F = .5813$; $R^2 = .20$; $p = .0008$) were no longer significantly associated with the LDSF. Nevertheless, the model fit was significantly improved ($p < .0001$), suggesting that including age, gender, and years of education and SDMT-Oral meaningfully improved the model that explains LDSF. The SDMT-Oral was positively and significantly associated with the LDSF, meaning a higher SDMT-Oral performance score predicted a higher LDSF performance score. It was concluded that SDMT-Oral predicted the performance of LDSF. These findings suggested that age, years of education, and being female or male did not influence the performance score of SDMT-Oral. However, the performance of SDMT-Oral contributed to a better performance of LDSF, and SDMT-Oral did not moderate this relationship.

The significant independent variables (age, years of education, and EFL), dependent variable (LDSB), and moderator variable (SDMT-Oral) were analysed. Age and LDSB (F=1.22; $R^2 = .20$; $p = .0056$) were insignificant, and model fit significantly improved. This suggests that age did not directly predict the performance of LDSB and SDMT-Oral. However, SDMT-Oral ($F = 9.93$; $Pr > F = .2732$) was positively and significantly associated with the LDSB, meaning that an increased SDMT-Oral score predicted a high-performance score of LDSB. Additionally, EFL ($F = 1.99$, $Pr > F = .1618$) was no longer significantly associated with the LDSB, suggesting that EFL did not predict the performance of LDSB; however, SDMT-Oral was positively and significantly associated with the LDSB ($F = 11.71$). This indicated that SDMT-Oral performance predicted the performance of LDSB. Furthermore, the model fit had improved considerably ($R^2 = .21$; p = .0010), suggesting that including age, EFL, and SDMT-Oral enhanced the model explaining the variance in LDSB. Years of education and LDSB ($F = 8.26$; $Pr > F = .0050$) were significantly associated, indicating that as years of education increased, so did the performance score of LDSB; however, SDMT-Oral ($F = 3.56$, $Pr > F = .0625$) was no longer significantly related to the LDSB. This indicated that years of education were directly associated with LDSB, but SDMT-Oral did not predict the performance of LDSB. The model fit did not improve ($R^2 = .25$; $p = .12$), suggesting that including years of education and SDMT-Oral did not contribute to the model's explanatory power.

These findings demonstrated that participants with more years of education achieved a higher score on the LDSB than those with fewer years of education. However, SDMT-Oral did not affect LDSB. There was no association between increased age and LDSB, suggesting

that age did not contribute to its performance. Furthermore, participants who spoke EFL did not perform well on LDSB, suggesting that speaking EFL does not affect its performance, but their higher score on SDMT-Oral improved LDSB.

The dependent variable LDSS, independent variables, including age, years of education, and EFL, were examined individually with SDMT-Oral. The results indicated age and LDSS (F = 0.28; $Pr > F$ = .5962, p = .30) were not significantly associated; the model fit had improved (R^2 = .17; p = .0051), while SDMT-Oral was positive and significantly associated with LDSS. These findings suggested that age did not directly predict LDSS performance, but SDMT-Oral did. The significantly improved model fit suggested that both age and SDMT-Oral contributed to the explanatory power of the model. While no significant association between EFL and LDSS (F = 1.98; $Pr > F$ = .1626), the model fit improved (R^2 = .19; p = .0039). However, SDMT-Oral ($Pr > F$ = .0023) was positively associated with LDSS, suggesting that a high SDMT-Oral score predicted a high LDSS performance score, and the model fit improved. This indicated that EFL had no direct influence on LDSS performance, but adding EFL and SDMT-Oral contributed to the explanatory power of the model. Years of education (F = 7.19; $Pr > F$ = .0087; p = .13) were significantly associated with LDSS, and model fit did not improve. The SDMT-Oral was not significantly associated with LDSS. These findings suggested that years of education directly contributed to the performance of LDSS, while adding both variables (years of education and SDMT-Oral) did not contribute to a meaningful explanation of the model. It was concluded that SDMT-Oral did not predict LDSS performance in terms of years of education.

These findings suggested that individuals with more years of education had a higher score on the LDSS than those with fewer years of education. However, SDMT-Oral did not have a significant effect on education. Being young and speaking EFL made no difference, hence, did not predict the relationship between LDSS and SDMT-Oral.

Demographic variables (age, years of education, LSM category, LSM group, and EFL) were analysed individually with LLNS and SDMT-Oral. Age (F = 0.02; $Pr > F$ = .8859) had no significant association with LLNS, while SDMT-Oral (F = 12.52; $Pr > F$ = .0006) was positively and significantly correlated with LLNS, meaning that a high SDMT-Oral performance score contributed to the high LLNS performance score. There was a significant improvement in model fit *(*R^2 = .19; p = .0009). This suggested that age does not directly predict LLNS; however, high SDMT-Oral was significantly associated with and predicted

LLNS. Both age and SDMT-Oral contributed to the meaningfully improved model that explains LLNS. The LSM category (F = 2.20; *Pr* > *F* =.0756) was no longer significantly associated with LLNS; however, a positive significant association between SDMT-Oral (F = 11.78; *Pr* > *F* =.0009) and LLNS was demonstrated. This suggested that the LSM category does not directly predict LLNS; however, high SDMT-Oral significantly predicted LLNS. The LSM category and SDMT-Oral contributed to the meaningfully improved model that explains LLNS. The model fit (R^2 = .26; *p* = .0009) had also improved. To conclude, the LSM group (*F* = 1.37; *Pr* > *F* = 2446) was no longer statistically linked with LLNS, although SDMT-Oral was positively and significantly associated with it, and the model fit improved significantly (R^2 = .20; *p* = .0001). This suggested that the LSM group does not directly predict LLNS; however, high SDMT-Oral significantly predicted LLNS. The LSM group and SDMT-Oral contributed to the meaningfully improved model that explains LLNS. Despite the insignificant association between age, LSM category, and LLNS, these findings demonstrate that SDMT-Oral, independently of demographic variables, predicted the performance of LLNS.

In contrast, findings of years of education (*F* = 4.02; *Pr* > *F* = .0480) and SDMT-Oral (*F* = 5.56; *Pr* > *F* = .0205) showed that both were significantly associated with LLNS (*F* = 12.80; *p* = .29), the model fit had significantly improved (R^2 = .22; *p* = .034). This suggested that years of education directly contributed to the performance of LLNS, with high SDMT-Oral significantly contributing to the high performance of LLNS. Both years of education and SDMT-Oral contributed meaningfully to the improved explanatory power of the LLNS. Furthermore, EFL and SDMT-Oral (*F* = 14.09; *Pr* > *F* = < .0001) were strongly connected to LLNS. The model fit (R^2 = .24; *p* = .0052) had also improved significantly. It was concluded that EFL directly contributed to the enhanced LLNS performance, improving SDMT-Oral performance. Adding EFL and SDMT-Oral improved the explanatory power of LLNS. The performance of SDMT-Oral was able to predict the performance of LLNS.

These results indicated that participants with more years of education who spoke EFL with high SDMT-Oral simultaneously contributed to the increased LLNS performance compared to those with few years of education who spoke languages other than English as their first language. The GLM analysis results of the effect of SDMT-Oral on LDSB, LDSS, LLNS, and demographic variables were summarised in Table 8.

Table 8

Summary of the Effect of SDMT-Oral on LDSB, LDSS, LLNS, and Demographic Variables.

Dependent Variable	Independent Variable	F value	Pr> F	p value	R^2
LDSB	Age	9.93	.2732	.0056	.20
	SDMT-Oral	9.93	.0022	-	-
	Years of education	8.26	0.005	.12	.25
	SDMT-Oral	3.56	.0625	-	-
	EFL	1.99	.1618	.0010	.21
	SDMT-Oral	11.71	.0009	-	-
LDSS	Years of education	7.19	.0087	.13	.24
	SDMT-Oral	3.26	.0742	-	-
LLNS	Years of education	4.02	.0480	.034	.22
	SDMT-Oral	5.56	.0205	-	
	EFL	6.10	.0154	.0052	.24
	SDMT-Oral	8.63	.0042	-	

Note. SDMT = Symbol Digit Modalities Test. EFL = English as a first language. The best model was LDSS years of education. Nevertheless, years of education and SDMT-Oral were independently associated with LDSS. *Significance level p <0.05.

Overall, the best model to predict DS backward, DS sequencing, DS total, LNS, LDSS, and LLNS involved SDMT-Oral and years of education and age in Model 2 because of its great explanatory power. Gender in Model 2 was the best predictor of the relationship between LNS and SDMT-Oral.

4.4.3. Model 3. The interaction effect of processing speed

The previous model investigated the prediction between PS and WM measures. A GLM analysis was performed; this model (Model 3) was set to explore the interaction effect between independent variables, dependent variables, and SDMT-Oral as a moderating effect on the significant variables. Thereafter, Model 4 will compare all models and confirm the moderation.

To begin with, gender as an independent variable, DS forward as a dependent variable, and SDMT-Oral as a moderator were examined. This model assessed the simultaneous change between variables. The interaction between SDMT-Oral and gender ($Pr > F = 0.0929$) was no longer significant with DS forward; however, the main effect of SDMT-Oral was significant ($Pr > F = 0.0002$), suggesting that SDMT-Oral independently predicted the performance of DS forward. No improvement in the model fit was noted ($p = .069$).

Furthermore, the findings indicated that Model 2 was the most powerful model among the other models on DS forward. These results showed that gender and SDMT-Oral were independently associated with the DS forward; however, SDMT-Oral did not moderate the relationship between gender and the DS forward.

The DS backward, age, years of education, EFL, and SDMT-Oral were analysed. This was conducted individually to determine the interaction among these variables. The results demonstrated that the interaction between age and SDMT-Oral (F = 1.36; $Pr > F$ = .2464), model fit (p =.26), was not significant. The main effect of SDMT-Oral was significant, and the model fit was not improved (p=.26). These findings suggested that age and SDMT-Oral were independently associated with DS backward; SDMT-Oral did not moderate the relationship between age and DS backward. Years of education, SDMT-Oral, and their interaction (F = .20; Pr >F = .6577) were not significantly associated with DS backward; the model fit (p =.26) did not improve. Adding these variables to the model did not improve the model fit. This suggested that SDMT-Oral did not moderate the association between years of education and DS backward. The interaction between EFL and SDMT-Oral (F = 1.73; $Pr > F$ = .1923) was insignificant, suggesting that the effect of EFL independently contributes to the variance of the model. The model fit (p =.28) did not improve. This indicated that including EFL and SDMT-Oral did not improve the explanatory power of DS backward. However, the main effect of SDMT-Oral on EFL was significant, suggesting that SDMT-Oral contributed independently to DS backward. It was concluded that EFL did not moderate the relationship between SDMT and DS backward. Speaking EFL did not moderate the relationship between SDMT-Oral and DS backward, which means that PS, as measured by SDMT-Oral alone, seems to predict WM performance as measured by DS backward (Appendix B).

These findings indicated a significant effect between SDMT-Oral and DS backward on age and EFL, demonstrating that being young and speaking EFL contributed to an improved performance score. Additionally, there was a significant effect between SDMT-Oral and DS backward, with the performance of SDMT-Oral predicting the performance of DS backward.

In addition, the DS sequencing (dependent variable) and independent variables, including age, years of education, LSM category, NL, EFL, and moderator (SDMT-Oral), were analysed. The findings revealed no significant interaction between DS sequencing, SDMT-Oral, and independent variables like age (F = 0.85; $Pr > F$ = .3599; p = .29), years of education (F = 1.80; $Pr > F$ = 18.31; p = .12), LSM category (F = 1.77; $Pr > F$ = .1431; p =

.19), NL (F = 0.03; Pr > F = .9707; p = .27), EFL (F = 0.41; $Pr > F$ = .5223; p > .99). These findings suggested that age, years of education, LSM category, NL and EFL were independently associated with DS sequencing. The main effect of SDMT-Oral was significant, but the model fit did not improve. It was concluded that SDMT-Oral did not moderate the relationship between age, years of education, LSM category, NL, EFL, and DS sequencing.

These results showed that SDMT-Oral did not have any interaction effects with age, years of education, LSM, NL, or EFL. Also, including these variables in the model did not contribute to the improvement that explains the variance in DS sequencing. This means that PS, as measured by SDMT-Oral alone, seems to predict WM performance as measured by DS sequencing (Appendix B).

Moreover, DS totals, age, years of education, EFL, and SDMT-Oral were analysed. The results revealed that only the main effect of SDMT-Oral was significant, suggesting that SDMT-Oral independently predicted the performance of DS total. While the interaction did not indicate any significant association between DS total, SDMT-Oral and age (F = 0.98; $Pr > F$ = .3254; R^2 = .29), years of education (F = 2. 01; $Pr > F$ = .1595; $R^{2=}$.31), and EFL (F = 1.93; $Pr > F$ = .1685; $R^{2=}$.31). The model fit had not gotten any better, suggesting that these variables did not contribute to the variance that explains DS total, and SDMT-Oral did not moderate the relationship between age, years of education and EFL and DS total. These findings were summarised in Appendix B.

These findings suggested that being young, having more years of education, and speaking EFL did not affect or improve the performance of the DS total score. However, the increased performance on SDMT-Oral led to an improvement in the overall DS total score. This means that demographic variables, such as age, years of education, and EFL, did not mediate the relationship between SDMT-Oral and DS total, which means that PS alone seems to predict WM performance as measured by DS total.

The interaction between LNS, SDMT-Oral, and independent variables (age, gender, years of education, LSM category, and EFL) was examined. The results demonstrated no significant association between age and SDMT-Oral (F = 2.68; $Pr > F$ = .1055), suggesting that age was independently associated with LNS, implying that as age increased, the negative effect of age on LNS decreased. Gender and SDMT-Oral (F = .26; $Pr > F$ = .6145) were found to be insignificantly associated with LNS, years of education, and SDMT-Oral (F =

.45; *Pr* > *F* = .5027) were not significantly associated with LNS, LSM category, and SDMT-Oral (*F*= 1.37; *Pr* > *F* = .2520) were not significantly associated with LNS and EFL, and SDMT-Oral (*F* .31= *Pr* > *F* =.5821) were not significantly associated with LNS. The model fit on these variables had not improved. The main effect of SDMT-Oral was observed. Moreover, these findings suggested that being a young female or male, with more education, speaking EFL, and having high LSM did not contribute to the interaction between LNS and SDMT-Oral; only the main effect of SDMT-Oral was significant. Although age was not significantly associated with SDMT-Oral performance, it remained significant with LNS, suggesting that PS did not entirely affect age-related differences. This implied that age-sensitivity mechanisms like attention control contributed to this decline. This aligns with Salthouse's (1996) theory, indicating that age-related decline originates from an individual's inability to process information rapidly. It was concluded that age, gender, year of education, LSM, EFL, and SDMT-Oral were independently associated with LNS; therefore, they did not mediate the relationship between SDMT-Oral and LNS. This suggested that PS, as measured by SDMT-Oral, solely contributed to the prediction of WM performance as measured by LNS.

After the analysis of WM measures, the attention span was analysed systematically: LDSF, LDSB, LDSS, and LLNS. This analysis assessed the interaction between the independent variables of age, gender, and years of education, SDMT-Oral, and their interaction with LDSF. The results indicated that the main effect of SDMT-Oral (p = <.05) was significant in age, gender, and years of education. This means that SDMT-Oral alone significantly predicts LDSF performance regardless of age, gender, and years of education. Additionally, the results revealed that an interaction between SDMT-Oral and age (F = 0.87, *Pr* > *F* = .3531, p => .05), gender (F = 0.22, *Pr* > *F* = .6379, p => .05), and years of education (F = .05, Pr>F = .8225) was not significant with LDSF. The model fit was not improved with a p-value ranging from .30 to>.99. These results suggested that when these variables were combined with SDMT-Oral and their interaction, there were no identifiable associations with LDSF. Based on these results, SDMT-Oral score and demographic variables did not have a moderating effect on the performance of the LDSF score.

The next step of the analysis involved exploring the interaction between the demographic factors, such as age, years of education, and EFL, SDMT-Oral, and LDSB performance. The findings illustrated a significant interaction between age and SDMT-Oral (F = 4.65, *Pr* > *F* = .0337), and the model fit was significantly improved (R^2 = .24; p = .031). Additionally, the

interaction between EFL and SDMT-Oral was significant ($F = 4.88$, $Pr > F = .0298$), and demonstrated an improved model fit ($R^2 = .25$; $p = .031$). The results did not show any association with LDSB when looking at the interaction between years of education and SDMT-Oral and how that affected LDSB ($F = 2.35$, $Pr > F = .1292$), suggesting that years of education and SDMT-Oral did not impact LDSB. Therefore, the model fit did not improve ($p = .12$). These outcomes demonstrated the moderation effect of SDMT-Oral on the relationship with age and LDSB, suggesting that those with higher PS scores demonstrated less age-related decline in LDSB performance. This implies that the negative effect of age can be shielded by faster PS on LDSB. This directionality support was consistent with PS theory (Salthouse, 1996) and cognitive reserve theory (Stern, 2002). Similarly, SDMT-Oral moderated the association between EFL and LDSB. This suggests that participants whose English was not their first language and with higher PS performed similarly to those who spoke EFL on LDSB. Further suggests that faster PS may lessen the additional cognitive load associated with WM tasks in non-dominant language. However, no moderation occurred between years of education and LDSB (Table 9).

Table 9

Summary of the Interaction between SDMT-Oral, LDSB, and Demographic Variables.

Dependent Variable	Independent Variable	Mean Square	F value	Pr > F
LDSB	Age	3.28223135	2.4	.125
	SDMT-Oral	13.89864835	10.15	.002
	Age*SDMT-Oral	6.36477651	4.65	.00337
	EFL	5.11580014	3.74	.0563
	SDMT-Oral	20.88406094	15.26	.0002
	EFL*SDMT-Oral	6.67371687	4.88	.0298

Note. SDMT = Symbol Digit Modalities Test. EFL = English as a first language.
*Significance level p <0.05.

The impact of demographic variables, SDMT-Oral, and their interactions with significant independent variables on LDSS performance was examined. This was done to indicate a significant interaction between independent variables and SDMT-Oral, which acts as a moderator. The GLM analysis was performed, and the results indicated no association between age, SDMT-Oral ($F = 0.61$; $Pr > F = .4369$), and their interaction with LDSS, nor did model fit improve ($p = .30$), suggesting that age did not predict SDMT-Oral and did not influence LDSS. Including age and its interaction in the model did not improve the model in

explaining the variance in SDMT-Oral. Years of education, SDMT-Oral (F = 1.09; $Pr > F$ = .3000), and their interaction were not associated with LDSS, and the model fit had not improved (p = .28), meaning that there was no meaningful association between years of education and SDMT-Oral. The effect of years of education on SDMT-Oral did not influence LDSS. Adding years of education and their interaction did not explain the variance in SDMT-Oral. Apart from the main impact of SDMT-Oral, which was statistically significant, there was no evidence of any significant interaction between EFL and SDMT-Oral (F = 0.91; $Pr > F$ = .3431). There was no improvement in the model fit (p = .30). This suggested that high SDMT-Oral predicted LDSS performance. The lack of significant interaction demonstrated that the impact of SDMT-Oral on EFL did not change nor add explanatory value to LDSS. This suggested that SDMT-Oral did not moderate the relationship between these demographic variables and LDSS.

Finally, the independent variables, SDMT-Oral as a moderator, and their interactions with LLNS were analysed to rule out a significant interaction effect on the association between independent variables and SDMT-Oral. The interaction between SDMT-Oral and age (F = 3.55; p = .067), suggesting that age did not predict SDMT-Oral and did not influence LLNS, years of education, and SDMT-Oral (F = 1.07; p = .29), was not significantly associated with LLNS. No significant interaction was observed between LSM category and SDMT-Oral (F = 1.44; p = .22) and LLNS; LSM group and SDMT-Oral (F = 1.15; p = .29) were not significantly associated, EFL and SDMT-Oral (F = 0.57; p = .28) were not significantly associated with LLNS. While the main effect of SDMT-Oral on age, LSM category, LSM group, and EFL was significant, the model fit did not improve.

Based on the above results, no moderation occurred between LLNS, SDMT-Oral, and age, years of education, LSM category, and LSM group. The main effect of SDMT-Oral suggested a meaningful association between SDMT-Oral and demographic variables, indicating that SDMT-Oral predicted the performance of LLNS.

4.4.4. Overview of Model 4 and Variable Selection across Analyses

This section presents a detailed analysis confirming the moderating effect of SDMT-Oral on the relationship between demographic variables and WM. This model was the last step of GLM analysis that was applied to dependent variables (DS backward, DS sequencing, LDSF, LDSS, LLNS, and LNS) with a consistent structure, including independent variables, SDMT-Oral, and the interactions for all significant variables. It also presented a detailed analysis of

models, compared all models of this study, and presented the modified model (Model 4P) to confirm whether moderation occurred. However, adjustments were necessary to avoid multicollinearity due to strong associations between certain independent variables (e.g., years of education and EFL, or LSM category and LSM group). Moreover, specific exclusions and selections were necessary to maintain the model's validity and interpretability. All insignificant variables were excluded from the interpretation of the strongest model.

4.4.5. Examining the moderation effect of SDMT-Oral in Model 4

The independent variables, the moderating variable (SDMT-Oral), and the interaction with DS backward were assessed. The demographic variables years of education and EFL were excluded in this model because their strong association had already been established (see Table 7). Years of education in Model 2 had a stronger explanatory power (higher R^2 = .30) than EFL (R^2 = .22) in Model 2. No significant interaction was observed between age and SDMT-Oral (F = 2.40; $Pr > F$ .1248), or years of education, and SDMT-Oral (F = 0.30; $Pr > F$ = .5822). In addition, the main effect of SDMT-Oral was not significant, nor was the main effect of age and years of education on DS backward. This was done to prove if the effect of PS moderated the relationship between demographic variables and WM measures.

Model 1 showed that age, years of education, and EFL were significantly associated with DS backward. The most powerful model was Model 2 because years of education correlated with SDMT-Oral, which predicted the performance of DS backward. Additionally, the model fit was significantly better than that of an independent variable age (p = .28) in Model 3, but not an independent variable year of education (p = .26) in Model 3. Therefore, it was determined that years of education and SDMT-Oral as a moderator have a separate association with the DS backward. At the same time, SDMT-Oral did not moderate the relationship between years of education and the DS backward.

The next step examined SDMT-Oral and a significant interaction with DS sequencing. Years of education, EFL, and LSM were excluded from the same model due to their strong correlation. This was done to demonstrate SDMT-Oral's moderating role. The interaction between age, years of education, and NL was insignificant with DS sequencing, as were the main effects of SDMT-Oral, and these three demographic variables. The model fit was not better than Model 3, which comprised independent variables age, years of education, and NL. Furthermore, Model 2 and Model 3 were created to determine if SDMT-Oral moderated the relationship between demographic variables and DS sequencing. Model 2, years of education

had greater explanatory power (higher R^2) than EFL and LSM in Model 2. Also, years of education and SDMT-Oral, NL, and SDMT-Oral have shown a positive correlation with DS sequencing. While in Model 3, no significant interactions were observed; however, the age and LSM categories showed a positive association between the main effects of SDMT-Oral, age, and LSM, without any improvement in the model fit. Moreover, it was determined that the most powerful model was Model 4P, with significant effects for years of education (F = 4.84; $Pr > F$ = .0305), NL (F = 6.59; $Pr > F$ = .0120), and SDMT-Oral (F = 6.37; $Pr > F$ = .0134). However, SDMT-Oral did not moderate the relationship between years of education and DS sequencing or the relationship between NL and DS sequencing. These findings were summarised in Table 10.

The interaction between independent variables and SDMT-Oral with DS total was investigated. As previously shown, the model excluded years of education and EFL because of their strong association. Years of education ($R^{2\ =}$ .30) were chosen as Model 2 because they displayed greater explanatory power (higher R^2) than EFL in Model 2. The interactions between the years of education, age, and SDMT-Oral were insignificant. In addition, the main effects of SDMT-Oral, years of education, and EFL were not significant. The model fit was not significantly better than age (R^2 = .29) or years of education (R^2 = .31) in Model 3. It was determined that years of education and SDMT-Oral were independently associated with the DS total. However, SDMT-Oral did not moderate the relationship between years of education and the DS total.

In addition, the attention span was also analysed in this model to determine the moderation effect between three significant independent variables (i.e., age, years of education, and gender), SDMT-Oral, and their interactions with LDSF. The interactions between significant variables like age (F = 0.79, $Pr > F$ = .3779), gender (F = 0.09, $Pr > F$ = .7688), years of education (F = 0.03, $Pr > F$ = .8698), and SDMT-Oral were not found to be significant. Similarly, the main effect of SDMT-Oral was insignificant, and neither were the main effects of age, years of education, nor gender. The model fit was not significantly better than age, gender, or years of education in Model 3. The only significant effect was Model 4P-SDMT-Oral (F = 18.94, Pr > F = <. 0001, R^2 = .17). Additionally, Model 2 introduced SDMT-Oral as a moderator. However, only the positive correlation between SDMT-Oral and LDSF showed any significant association. In Model 3, the interaction of independent variables and LDSF was not significant; however, the main effect of SDMT-Oral was significant, and the model fit did not improve. Thereafter, it was established that SDMT-Oral was independently

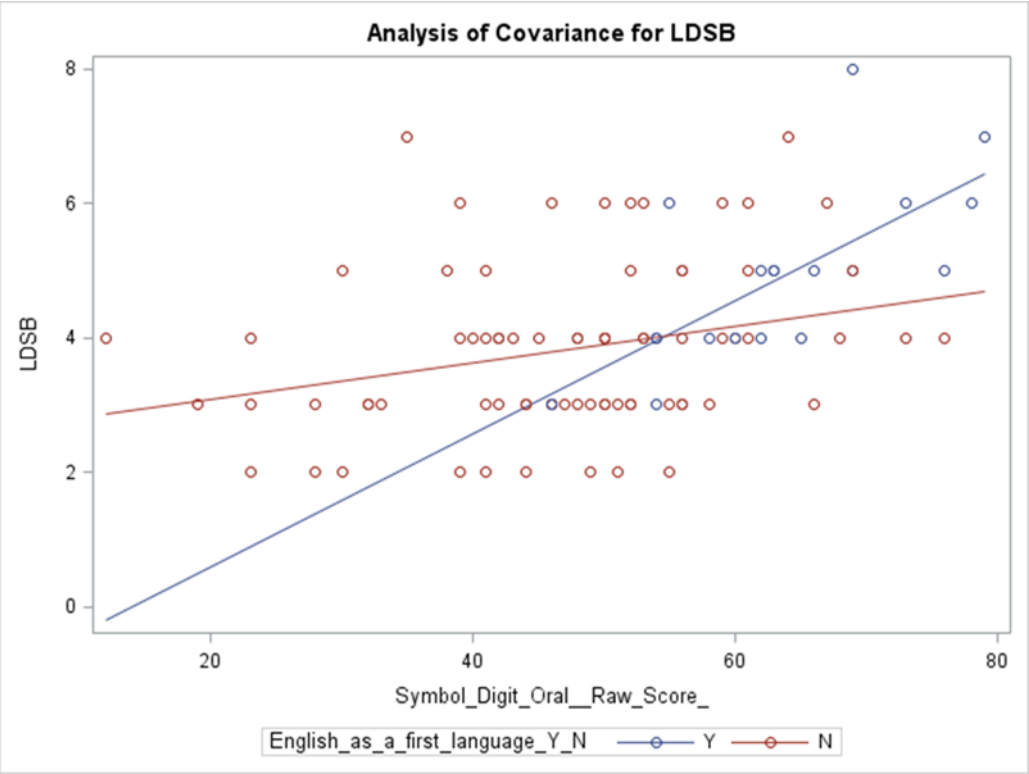
associated with the LDSF and did not exhibit any moderating effects on the demographic variables.

After that, three independent variables were incorporated: age, EFL, years of education, and a potential moderator, SDMT-Oral. The interactions between the independent variables and SDMT-Oral were examined, as was their influence on LDSB performance. Previous demonstrations confirmed a strong association between years of education and EFL, leading to their exclusion from this model. The decision to include EFL in Model 3 was influenced by its significant moderating effect on SDMT-Oral, while Model 3, which had years of education, did not display this effect. Furthermore, the interaction between EFL and SDMT-Oral was significant, whereas the interaction between age and SDMT-Oral did not reach significance. Moreover, at this stage, age's main effect was insignificant. The model fit of Model 4 was not significantly better than that of age in Model 2, gender in Model 2, or years of education in Model 2. The most parsimonious model was EFL in Model 3, which only revealed significant effects for SDMT-Oral. The Model 3 results indicated a significant effect of SDMT-Oral score on participants who speak EFL ($F = 4.88$; $Pr > F = .0298$; $R^2 = 0.25$, $p = .031$), showing that higher SDMT-Oral performance was associated with speaking EFL. However, in Model 4, these effects were moderated by the significant interaction between SDMT-Oral score and EFL ($F = 5.10$; $Pr > F = .0265$).

In brief, these results indicated that for the WM tests, PS did not show any moderation, for the case of attention span, PS moderated the relationship between EFL and LDSB and between age and LDSB, as well as age, LSM category, and LLNS analysis. These findings indicate that SDMT-Oral has a moderating effect on the relationship between EFL and LDSB. Specifically, the findings showed that for individuals whose first language is not English, SDMT-Oral did not have much influence on their LDSB performance. For those whose first language was English, increased SDMT-Oral was associated with improved LDSB performance. The plot below visualises the results of the moderation effect of SDMT-Oral on EFL, in particular, the graph below represents an Analysis of Covariance (ANCOVA), which is an extension of the analysis of variance (ANOVA) and the linear regression (Philippas, 2014). The ANCOVA evaluated the association between SDMT-Oral raw score (on the x-axis) and LDSB (on the y-axis), and assessed whether they were moderated by EFL (Figure 1).

Figure 1

The moderating effect of SDMT-Oral on the relationship between EFL and LDSB.



Note. EFL = English as a first language. SDMT = Symbol Digit Modalities Test. LDSB = Long Digit Span Backward. At the bottom of the plot, EFL is represented by separate lines for Y (Yes) and N (No). The two lines on the graph represent the relationship between SDMT-Oral score and LDSB for individuals who speak EFL (Y-blue line) versus those who do not (N-red line). The cross lines suggested that there was an interaction effect. This indicated that the high performance in SDMT-Oral influenced the high LDSB performance in those who spoke EFL, but those who did not speak EFL demonstrated a weaker association. The crossing lines indicated that participants who spoke EFL excelled on SDMT-Oral performance. In contrast, those who did not speak EFL demonstrated weaker performance in LDSB as the SDMT-Oral score increased. The outcomes were presented in this figure to visualise the moderating effect between SDMT-Oral and EFL on LDSB and to illustrate the outline of the results.

Furthermore, Model 4 for LDSS was designed to include three independent variables: years of education, EFL, and age, PS (SDMT-Oral), and the interaction terms for PS with each of the three independent variables on LDSS. However, it was not practicable to include both years of education and EFL in the same model because of their strong association, which could lead to multicollinearity and undermine the model's reliability. This was done to establish the moderating effect of SDMT-Oral on the relationship between the independent and dependent variables.

To overcome this, years of education were selected above EFL because previous analyses (e.g., years of education in Model 2 and EFL in Model 2) displayed that those with more years of education had a stronger explanatory power (higher R^2). This decision ensured that the model captured the most variance in the dependent variable while maintaining statistical reliability and avoiding redundancy among predictor variables.

The interactions and main effect of years of education, EFL, and SDMT-Oral were insignificant, suggesting that the association between SDMT-Oral and LDSS did not depend on the levels of years of education and EFL. In Model 3, age as a moderating variable between SDMT-Oral and LDSS had a significantly better model fit than years of education in Model 3. After considering the results of the analyses, age, and SDMT-Oral, years of education, and SDMT-Oral, it became evident that the most parsimonious model was Model 2 (years of education). It was determined that years of education and SDMT-Oral were independently associated with the LDSS. SDMT-Oral did not moderate the relationship between years of education and the LDSS.

The oral version of SDMT was added, as well as three of the independent variables' interactions: age, years of education, LSM category, and the dependent variable, LLNS. Years of education and EFL, LSM category and EFL, LSM category and group were excluded from the model because their association had already been established. It was decided that the LSM category would be used rather than the LSM group because Model 2 had a higher R-squared ($R^2 = .26$), and that years of education would be selected rather than EFL because it had a higher R-squared ($R^2 = .24$) than years of education. The results indicated that the interactions between age, LSM category, and SDMT-Oral were significant, while the correlation between years of education and SDMT-Oral was insignificant. This aligned with the hypothesis that PS would moderate the relationship between demographic variables and WM measures. However, the main effect of years of education was significant, but the model fit was not better than that of age, LSM, and years of education in Model 3. It was concluded that SDMT-Oral did not moderate the relationship between years of education and LLNS.

An adjusted version of Model 4, Model 4P, was developed to address multicollinearity and improve model fit. It was demonstrated as the most parsimonious model, incorporating age, SDMT-Oral, their interaction ($F = 4.35$; $Pr > F = .0400$), and the main effect of years of education ($F = 4.90$; $Pr > F = .0295$). A summary of these findings is presented in Table 10.

Table 10

Summary of Significant Effects of Demographic Variables and SDMT-Oral on DS Sequencing, and the Significant Interaction of Age and SDMT-Oral on LLNS.

Dependent Variable	Independent Variable	F Value	Pr>F	R^2
DS sequencing	Years of education	4.84	.0305	.31
	NL	6.59	.012	-
	SDMT-Oral	6.37	.0134	-
LDSF	SDMT-Oral	18.94	<.0001	.17
LLNS	Age	4.03	.0477	.26
	Years of education	4.90	.0295	-
	SDMT-Oral	8.09	.0055	-
	Age*SDMT-Oral	4.35	.0400	-

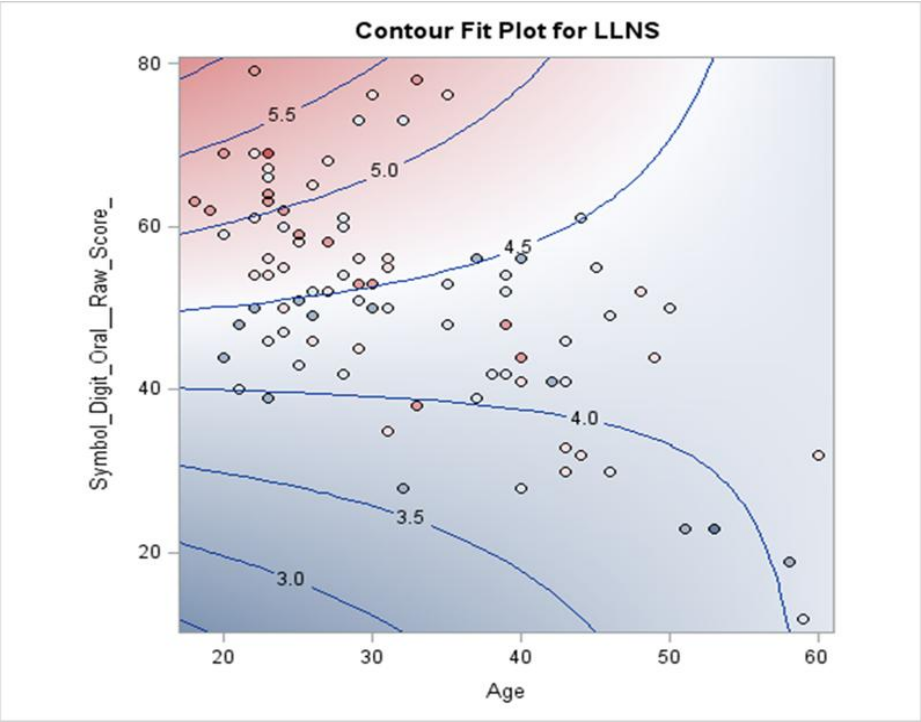
Note. DS = Digit Span. LDSF = Long DS sequencing. LLNS = Long Letter Number Sequencing. SDMT = Symbol Digit Modalities Test. NL = Number of languages. *Significance level p <0.05.

This analysis used the contour value in the contour fit plot below (Figure 2) to illustrate the interaction between age, SDMT-Oral, and LLNS. For example, a contour plot fit with clearly labelled x and y axes, with x showing how age and SDMT-Oral (y axis) affect the LLNS. The line chart was used to indicate trends across age groups, and SDMT-Oral, making it easier to observe the moderating effect of the demographic variable (age).

A moderation of SDMT-Oral on the relationship between age ($F = 10.25$; $Pr > F = .0020$), LSM category ($F = 2.99$; $Pr > F = .0236$), and LLNS was confirmed. The results indicated that having a high LSM category, at a younger age, increased SDMT-Oral was associated with an abrupt increase in the LLNS score. As individuals age, the effect of increasing SDMT-Oral on the LLNS score was minimal. At an older age, it was observed that increased SDMT-Oral performance did not drastically influence the LLNS score. Moreover, the findings further show that more years of education were associated with higher LLNS scores. This suggested that participants with more years of education achieved higher scores on the LLNS. This further showed an independent association between SDMT-Oral and years of education with the LLNS score. SDMT-Oral did not moderate the relationship between years of education and the LLNS score. The contour below summarises the effect of age on LLNS (Figure 2).

Figure 2

The impact of age and SDMT-Oral on LLNS.



Note. The lines in this contour point at the participant's age and the SDMT-Oral performance score. Participants established a lower performance score as they aged. The lower score began slightly after age 40 and continues as they age.

In summary, the findings showed that the effect of years of education on PS measures by SDMT-Oral predicted the performance of DS backward and LDSB. Participants with a high level of education, who were bi/multilingual and spoke EFL, performed better on SDMT-Oral, predicting the DS sequencing performance. Age, years of education, EFL, and DS total were influenced by SDMT-Oral, suggesting that SDMT-Oral predicted the performance of the DS total score. At an older age, it was observed that increased SDMT-Oral performance did not drastically influence the LLNS score. Further results suggested that as the SDMT-Oral score increases, the LNS score increases by gender and EFL. The results indicated that participants with more years of education and who spoke EFL performed better on SDMT-Oral and LLNS, and SDMT-Oral predicted the performance of LLNS.

Gender and SDMT-Oral were found to be independently associated with the DS forward. At the same time, significant moderation occurred due to an interaction between age and SDMT-Oral. The main effect of SDMT-Oral on age, years of education, LSM category, LSM group, and EFL was significant. The interaction between EFL and SDMT-Oral was significant. The findings concluded that SDMT-Oral moderated the relationship between EFL

and LDSB and between EFL and LLNS. Additionally, the moderation effect of SDMT-Oral was observed in the relationship between age, LSM category, and LLNS, and the main effect of SDMT-Oral on LDSF was observed. These results support the research aim of exploring how PS and demographic variables predict WM performance.

Chapter 5 – Discussion

5.1. Introduction

This chapter contextualises and discusses the findings reported in the previous chapter concerning the research questions, theoretical frameworks, and broader literature. It begins by recalling the main aims of the research and the key findings. The focus then shifts to the interaction between processing speed (PS) and working memory (WM), as well as the moderating effect of PS on demographic factors such as age, education, socio-economic status (SES), gender, and language experience. Some major debates are examined, including whether WM deficiencies are primarily due to storage capacity, attentional control, or processing efficiency, and how much demographic diversity contributes to cognitive variation. Additionally, the chapter explores the significance of the findings for theory, research, and practice in socio-culturally diverse and multilingual societies like South Africa. The study's limitations are acknowledged, and recommendations for future research are provided to promote a balanced and critical discussion.

5.2. Recap of the study aim

This study aimed to determine whether processing PS affects the relationship between WM and demographic variables in South African adults, and three specific research objectives were addressed. First, it explored the relationship between WM and PS. Second, the relationship between WM and demographic variables was examined, and third, the relationship between PS and demographic variables was investigated, and lastly, explored how PS and demographic variables predict WM as measured by Digit Span (DS) forward, DS backwards, DS sequence, and Letter Number Sequencing (LNS) tests. In the previous chapter, the results aligned with the abovementioned research objectives. The results of the current study demonstrated a significant positive association between WM and PS, whereby faster PS contributed to the high WM performance, which was aligned with Salthouse's (1996) PS theory. All demographic variables correlated significantly with WM measures. A significant association was observed between SDMT-Written score and selected demographic variables. Moreover, PS predicted WM performance in selected demographic variables.

Furthermore, the findings confirmed the moderating effect of PS on the relationship between WM and selected demographic variables. Specifically, PS moderated the relationship between age and Long Digit Span Backward (LDSB). Second, the moderation effect of PS was observed on the relationship between English as a first language (EFL) and

LDSB. Third, the effect of PS was found to moderate the association between age, Living Standard Measure (LSM) category, and Long Letter Number Sequencing (LLNS). Lastly, PS moderated the relationship between age and LNS. These findings support previous research demonstrating that PS supports WM efficiency (Fournier, 2014). This chapter discusses these results concerning this study's research objectives and within the context of the existing literature.

5.3. The association between working memory and processing speed

The first objective of this study was to explore the correlation between WM and PS. This was determined through Pearson's correlation analysis. Additionally, this study hypothesised that there would be a significant correlation between WM and PS measures. This was demonstrated by the study findings, indicating that all cognitive measures were highly and significantly correlated with each other, indicating that attention span, WM, and PS were closely related. This challenges the notion that these assessments assess specific and different constructs. This is aligned with Baddeley (2003) and Fournier (2014), who support this perspective of a close link by indicating the association among these three constructs. Cowan's (1999) theory supports the current results by assuming that WM and attention are inseparable, suggesting that attention supports WM by filtering information and determining what goes to WM. In turn, PS influences both WM and attention. This suggests that the association of these constructs may mean that they are more associated than unitary. Such findings imply that a more integrative approach is needed for cognitive assessment.

These findings are inconsistent with the literature that contradicts Fougnie's (2008) and Unsworth and Engle's (2007) argument that WM, PS, and attention are naturally related, as they assumed that these variables interact closely through manipulation and encoding.

5.4. The relationship between working memory and demographic variables

The second objective of this study was to explore the relationship between WM and demographic variables, as well as the relationships between PS and the same demographic variables. The General Linear Model (GLM) analysis established a positive association between all demographic variables and WM tasks. Particularly, all tasks correlated significantly with age, years of education, and EFL, except DS forward. The DS sequencing, LNS, and LLNS were significantly associated with the LSM category, whereas the LSM group had a positive association with LLNS. Furthermore, the number of languages (NL) had a significant association with the performance in DS sequencing. However, gender only had a

significant positive correlation with DS forward, Long Digit Span Forward (LDSF), and LNS scores, whereby females demonstrated better performance than males on DS forward, LDSF, and LNS.

Expectedly, a significant correlation was observed between WM tasks, age, and years of education, whereby better performance was associated with young adults who had more years of education in the majority of WM tasks. This aligns with Salthouse's (1996) PS theory, which links age-related decline in WM to a reduced processing efficiency. Also, Stern's (2002) cognitive reserve theory explains the protective effect of higher education on cognitive performance. Furthermore, these findings indicated the common trend in cognitive research and were consistent with the literature. Previous research highlights that WM declines with age (Caplan & Waters, 2005; Klencklen et al., 2017). Idowu and Szameitat (2023) emphasise that older adults experience difficulties with complex tasks, such as LNS, that require more cognitive demand and switching and may challenge an individual's ability to incorporate and manipulate information. Moreover, Klencklen et al. (2017) provided evidence in support of these findings by indicating that young adults outperform older adults in all DS subtests. This indicates that the significant correlation between WM tasks and age was linear. By contrast, Myerson et al. (2003) and Elliott et al. (2011) demonstrated no differences in DS forward and backward in all age groups.

The findings concerning years of education support the hypothesis that higher levels of education enhance WM in adults and promote cognitive reserve (De Souza-Talarico et al., 2007; Kosmidis et al., 2011). Particularly, the results of LNS and LLNS suggest that participants could manipulate information and effectively organise strategies for managing WM tasks. In support of these findings, Goldberg (2022) and Wang et al. (2017) suggest that the neuronal design and prefrontal cortex of the brain that are associated with WM are influenced by education. Similar results were found in studies that used different and similar WM tests on samples that differed from this study (Brockmole & Logie, 2013; Marnoufi et al., 2020; Pliatsikas et al., 2018). This suggests that the following may be a consistent finding that can be generalised across countries: A high educational level enhances WM performance.

As mentioned earlier, EFL correlated positively with most WM measures, excluding DS forward, whereas NL indicated a significant association with DS sequencing only, aligning with bilingual advantage accounts (Bialystok & Feng, 2009; Grundy et al., 2017). Suggesting

better proficiency in a first or dominant language enables executive control and complex tasks, although performance in specific WM components may differ depending on language dominance and task demands. This is also consistent with the literature, which indicates a higher performance score for individuals who are EFL speakers. In support of these findings, Mielicki et al. (2018) used the LNS task on monolinguals who spoke EFL and bilinguals. The participants were examined in different experiments. The findings revealed that monolinguals who spoke EFL performed better on the LNS test. The reason would be that the LNS involves phonological WM, which enables one to hold and manipulate information. This task involves switching between letters and numbers, which is demanding for those who speak other languages as their first language. In addition, speed and accuracy are necessary for an individual to perform well. By contrast, as mentioned earlier, NL had a significant association with DS sequencing only. Previous research produced similar results (Bialystok et al., 2012; Calvo et al., 2016; Cockcroft et al., 2017). However, these studies employed different measures and methodologies from the current research. The benefits may be ascribed to the regular practice of language switching, which enhances and strengthens the brain's cognitive control mechanisms (Morales et al., 2015). Contrary to previous studies that used different measures (the Peabody Picture Vocabulary Test, Corsi Block task, and Spatial WM test), monolinguals performed better than bilinguals (Bialystok et al., 2008; Engel de Abreu et al., 2011; Feng, 2008).

The findings of the significant impact of EFL on DS backward compared to DS forward can be explained by a psycholinguistic context and different cognitive demands. The DS forward reflects short-term storage and rehearsal, which allows participants to rely on chunking strategies and low processing demands that can extend their performance, and this aligns with Miller (1956). This does not give EFL participants an advantage over non-EFL participants, as both depend on their basic WM capacity than on language proficiency. While the DS backward involves manipulation and reordering, it demands a higher cognitive load and executive control processes. EFL participants used their native language, simultaneously and effectively processing, reordering, retrieving, and manipulating information, outperforming those who spoke other languages as their first. This is aligned with the inhibitory control model by Green (1998), emphasising that language dominance weakens interference. Supporting this, Bialystok and Feng (2009) and Grundy et al. (2017) highlight how language dominance turns influential when task demands are high. These perspectives suggest that language proficiency is interconnected with cognitive load, meaning that the

higher the processing required, the more language dominance or fluency is needed for WM performance. This explains why EFL participants indicated more substantial advantages in DS backward than DS forward.

The findings of this study contradict Kaushanskaya et al. (2011), who reported no difference between monolinguals' and bilinguals' performance in DS subtests. One possible explanation is that the tests were administered in participants' native language (those who spoke EFL), which was the dominant language, giving them an advantage over those who did not speak EFL. Perhaps the outcomes of the present study might vary if the assessments were carried out in the participants' first language. Specifically, South Africa is a highly diverse nation with various cultures and languages. Most participants spoke African languages as their first language, while English was their second language.

Furthermore, the findings related to language experience could be explained by the limitations in language as a variable and how these factors might have affected the results. This involves a sample not stratified according to language background, resulting in inequality among monolinguals and bi/multilinguals. Language proficiency was self-reported, with most participants indicating fluency in English and early experience, although English was not their first language. There is a possibility that these factors might have negatively influenced the findings, since participants might have exaggerated their fluency, given the apparent status of English as the language of formal education. So, these challenges may have affected how non-native English speakers performed in all cognitive tasks, as they were conducted in English.

Gender did not correlate with the performance of most tasks, except DS forward, LDSF, and LNS, which partially support the mixed findings in the literature. However, in these tasks, females significantly outperformed males, although this trend was not consistent across tasks; it does align with the literature, which claims that females exhibit higher verbal WM than males (Herlitz & Yonker, 2002). The literature on gender differences in WM is inconsistent. For instance, it indicates that females perform better than males in verbal WM assessment, and that males perform better in visuospatial WM (Herlitz & Yonker, 2002; Hill et al., 2014; Robert & Savoie, 2006; Taborda et al., 2019); however, the current study did not investigate visual WM, hence this pattern was not investigated.

Therefore, based on the aforementioned studies, it was predicted that females would outperform males in verbal WM tasks (Morais et al., 2018). A possible explanation for these

results could be that the sample consisted of more females than males in this study. The data of this study revealed that males were younger (aged 18–49 years) than females (aged 18–60 years). The age distribution in each gender group may have created a bias that could potentially impact the findings.

Furthermore, the findings of this study showed a significant positive correlation between WM tasks and LSM, which measures SES. Improved performance in DS sequencing, LNS, and LLNS was related to those from high LSM categories. The LSM group showed a positive association with LLNS only, demonstrating that better performance in LLNS was associated with those who belonged to a higher LSM group. These results align with the literature that emphasises the impact of SES on WM performance (Judd et al., 2020). Higher SES was associated with access to education and a conducive environment, which may improve WM function (Murtha et al., 2023; Zhang et al., 2020). This was expected considering DS sequencing comprises simple WM tasks, such as those measuring the short-term phonological portion of WM (Moolla, 2012).

However, LNS was the most challenging test, as it necessitates high mental flexibility and the manipulation of information. Therefore, individuals from higher SES were assumed to exhibit better recall and ability to switch between letters and numbers compared to those from low SES. These findings were consistent with the literature that supports these findings by emphasising that individuals from low SES perform poorly in WM tasks (Bloch, 2013; Cockcroft et al., 2015; Moolla, 2012). Furthermore, this association supports the theory that emphasises that growing up in a poor environment and low SES affects brain development and causes a cycle of poverty at a later stage. This, in turn, negatively affects WM functioning (Evans & Schamberg, 2009; Wijeakumar et al., 2019), hence the lower performance of those in the lower LSM category.

5.5. The relationship between processing speed and demographic variables

The objective of this study was to explore the relationship between PS and demographic variables. This study's results indicated that the SDMT-Written score was significantly associated with age, years of education, and LSM category. Age had a linear effect on the SDMT-Written score, as the score decreased with an increase in age. By contrast, being young and having a higher level of education and a higher LSM category were linked to a higher score on the SDMT-Written. This reflected greater access to education in younger participants in higher LSM categories. An explanation for these findings could be that young

adults with higher education had an improved PS. In contrast, high SES provided them with access to education, which promotes cognitive function, including PS. Also, SDMT-Written requires motor movement, which may favour young adults, and it is possible that people with higher education were exposed to more training on activities that required writing, which could represent an advantage in the SDMT-Written task. Although motor movement is required to complete the SDMT-Written task, the completion may be determined more by mental processing in the brain than motor movement (Kiely et al., 2014).

The findings mentioned above are aligned with the literature, specifically Kiely et al. (2014), who analysed normative data of SDMT-Written; they included participants of different ages with 10 years of tertiary education. Additionally, they reported a consistent performance by age until age 35; thereafter, as age increases, the performance gradually declines and becomes noticeable from age 55 upwards. This aligns with the current findings, which demonstrated a better performance on young adults than older adults. Likewise, a recent study by Schrempft et al. (2022) reported poor performance by individuals from low-SES groups in PS tests with people between the ages of 35 and 75. The present study also demonstrated that individuals from low SES with a low level of education scored lower on the SDMT-Written task. This mainly suggests that age, level of education, and SES affect how people process information.

By contrast, Sheridan et al. (2006) did not observe any significant relationship between age and SDMT in adults aged 20 to 49 with 12 or more years of education. This can be explained by the methodology used for sample recruitment. In Sheridan et al. (2006), the age range was limited, SES was high, and the level of education was slightly higher than that in the current study. It is possible that the variability of years of education in the current study could have facilitated the identification of the effect of age on the SDMT. The consistency of the evidence across WM measures supports the suggestion of the literature, despite varied measurements and methods in the sample recruitment process. This consistency may enable the generalisation of this study's findings.

5.6. Prediction of processing speed on working memory and demographic variables

One of the study objectives was to determine whether PS and demographic variables predict WM performance. The hypothesis was that PS would moderate the relationship between demographic variables and WM tasks. The findings of Model 2 indicated that PS, as measured by SDMT-Oral, does predict WM on selected demographic variables. A higher

SDMT-Oral score was linked with better WM measures and attention span performance scores. The data offered evidence for the hypothesis that PS is involved in sustaining WM efficiency (Fournier, 2014). Notably, the findings of Model 2 first demonstrated that the relationship between years of education and the SDMT-Oral score was significantly associated with DS backward, DS sequencing, LDSB, Long Digit Span Sequencing (LDSS), LNS, and LLNS. Further, it was demonstrated that years of education and SDMT-Oral score independently predicted the performance score of DS backward, DS sequencing, DS total, LNS, and LLNS.

However, SDMT-Oral was not significantly associated with LDSB and LDSS, where years of education were a concern, suggesting that SDMT-Oral did not predict the performance of LDSB and LDSS. Neither years of education nor SDMT-Oral contributed to the model that explains the variance observed in LDSB and LDSS; hence, PS did not moderate the relationship between years of education and WM measures, as well as attention spans. Moreover, the relationship between EFL and SDMT-Oral was significant with DS sequencing, LNS, and LLNS. This indicated that EFL and high SDMT-Oral performance score contributed to the high DS sequencing, LNS, and LLNS performance score, suggesting that EFL directly contributed to the model that explains the variance observed in LNS and LLNS performance.

Adding EFL and SDMT-Oral in the model improved the explanatory power of LLNS. While no significant relationship was found between EFL and DS backward, DS total, LDSF, LDSB, and LDSS, suggesting that EFL did not directly predict the performance of DS backward, DS total, LDSF, LDSB, and LDSS, but SDMT-Oral did predict the performance of these tasks. Thereafter, the significant association between NL and SDMT-Oral with DS sequencing was observed, indicating that NL and high SDMT-Oral score contributed to the increased DS sequencing performance. This further indicated that NL directly contributed to the model that explains the variance of DS sequencing, suggesting that SDMT-Oral score predicted the performance score of DS sequencing. While SDMT-Oral positively and significantly predicted age on LNS, DS total, LDSF, LDSB, LDSS, and LLNS, suggesting that a high SDMT-Oral score was linked to high LNS, DS total, LDSF, LDSB, LDSS, and LLNS performance scores. The LSM category, LSM group, and SDMT-Oral were found not to be significantly associated with DS sequencing, LNS, and LLNS, but PS was significantly, positively associated with DS sequencing, LNS, and LLNS; these variables indirectly affect WM measures, suggesting that a high SDMT-Oral score contributed to the high DS

sequencing, LNS, and LLNS. Lastly, gender had a significant relationship with SDMT-Oral and two WM measures, which were DS forward and LNS.

Most demographics, except for gender, correlated significantly with all WM measures. When SDMT-Oral was introduced as a moderator variable on the GLM, those relationships changed; some stayed significantly correlated, and others did not. The best model to predict the performance of DS backward, DS sequencing, DS total, LDSS, LLNS, and LNS involved PS, age, and LSM. This relationship was mediated by the effect of SDMT-Oral on WM measures.

To begin with, the findings on education and EFL were consistent with the literature review, where previous research suggested that years of education and speaking EFL improve WM and PS in adults (Cockcroft et al., 2017; De Souza-Talarico et al., 2007; Guerra-Carrillo et al., 2017; Meijer et al., 2009). The results of years of education were comparable to those of Nebes et al. (2006), who demonstrated that individuals with a higher level of education exhibit higher PS in their WM. In support of this, Fan et al. (2015) found similar evidence through DS and other tests in a sample with low and middle levels of education. The findings indicated an association among more years of education, high performance in WM measures, and higher PS.

The current findings further indicated that years of education and SDMT-Oral independently predicted the performance of DS backward, DS sequencing, LDSB, LDSS, LNS, and LLNS. Therefore, PS did not moderate the relationship. While the literature review consistently supports the idea that a high level of education is generally associated with enhanced WM and faster PS (De Souza-Talarico et al., 2007; Guerra-Carrillo et al., 2017; Kosmidis et al.,2011), some evidence suggests that these benefits may gradually diminish with age (Guerra-Carrillo et al., 2017; Meijer et al.,2009). In support of this, Rindermann and Neubauer (2004) proposed that PS has no direct relationship with education. They demonstrated that although education influences cognitive function, it is more evident in older adults than in young adults. However, given that PS is a key predictor of WM performance, it remains an important factor when investigating WM using DS subtests, such as the LNS subtest of WAIS-SA-IV. Furthermore, the findings of a significant association between EFL and selected WM tasks aligned with those of Cockcroft et al. (2017), who examined English monolinguals and bilinguals in terms of WM and revealed that EFL monolinguals outperformed multilinguals in one of the WM measures. This finding was

different from that of other researchers, who reported a negative correlation between EFL and WM performance (De Sousa, 2016; Marton et al., 2016).

Interestingly, the null finding indicating that SDMT-Oral was not significantly associated with LDSB and LDSS, where education was a concern, may reflect the nature of LDSB and LDSS tasks that necessitate manipulation and reordering rather than a straight recall. This cognitive process requires more demands than PS per se. Consistent with previous studies suggesting that complex span draws from a broader cognitive resource, such as executive control and cognitive flexibility (e.g., Baddeley, 2000; Kane & Engle, 2002). Another possibility could be that the oral version of SDMT was unable to sense PS differences pertinent to more demanding WM tasks, where education is a concern. This lack of moderation may further suggest that the cognitive benefits of educational level may be demonstrated differently across WM performance, and that individuals may demonstrate differences in processing efficiency. This is aligned with the notion of cognitive reserve, on which individuals with a higher education level perform better than others with fewer years of education and similar age (Stern, 2002). Supporting this, Zahodne et al. (2011) reported that educational level does not moderate the decline in PS and WM. Otherwise, PS and education independently contributed to cognitive functioning. Another possibility was that other factors, such as language, SES, and task-specific strategies, may impact the performance of LDSB and LDSS. This could be linked to the case of language, for example, Cockcroft et al. (2017) and Newbury et al. (2016) emphasised how language experience interacts with PS and WM performance. Further, suggested that language proficiency can mediate performance in WM tasks, perhaps influencing outcomes even when language was not the primary focus. In this case, the insignificance may indicate latent language-related issues that were not accounted for. Specifically, in bi/multilinguals, it could be that WM performance was influenced by language dominance and proficiency than by PS or education.

The discrepancy effect of EFL on WM measures aligns with psycholinguistics theory that points out the interaction between language experience and executive control, and tasks like DS sequencing, LNS, and LLNS necessitate active rearrangement of verbal information. As highlighted in the literature, Green's (1998) inhibitory control model emphasised that individuals who are fluent or dominant in testing language tend to suppress irrelevant information and involve controlled retrieval. However, this cognitive demand is more

noticeable in complex tasks, in this case, like LNS and LLNS, which require an individual to switch between numbers and letters. This process needs both attentional control and switching, which require constantly handling cross-language activation that necessitates better executive control. Similarly, Bialystok and Feng (2009) argue that the cognitive benefits of language proficiency outward under high cognitive load, particularly when verbal mediation is vital. This explains why EFL significantly contributed to the performance of selected complex span tasks over simple span tasks.

Although NL and SDMT-Oral were significantly correlated with DS sequencing only, this demonstrated that both NL and SDMT-Oral play a role in the performance of DS sequencing; this pattern is consistent with psycholinguistic and PS theory (Bialystok & Feng, 2009; Salthouse, 1996). These results suggested that the influence of NL on DS sequencing might be influenced by PS. While the significant association between NL and DS sequencing was consistent with the literature, which revealed an advantage for bilinguals in verbal WM capacity (Monnier et al., 2021). Additionally, the significant positive correlation between SDMT-Oral and DS sequencing means that as the SDMT-Oral score increased, the DS sequencing performance score also increased. This demonstrated that PS influences WM performance. Since SDMT-Oral only assessed PS in the current study, the observed correlation suggested that individuals with fast PS were able to manipulate information and recall sequences of the DS task efficiently. These findings corroborate Salthouse's view (1996), which indicates that PS is essential for WM performance. However, it was surprising that NL positively correlated with only DS sequencing, as it was hypothesised that bi/multilinguals have enhanced WM and process information quickly. Notably, the literature on DS tasks is inconsistent; for instance, Ardila (2003) reported bilinguals' advantage on DS task performance when participants were assessed in their first language. On the other hand, Kaushanskaya et al. (2011) reported no significant differences between monolinguals and bilinguals. This highlights that DS subtests may not be influenced by the language and/or the NL that an individual speaks. In addition, the findings suggest inconsistency when bilinguals are assessed with DS subtests.

Interestingly, the current study demonstrated that age was not significantly associated with any of the WM measures included in the model, but PS predicted WM performance. Similarly, SES (measured by LSM category and LSM group) was not significantly associated with WM measures. However, in both age and SES, SDMT-Oral significantly predicted WM

performance. Although these findings did not show any significant association between age, SES, and WM performance, this should not be understood as indicating that SES is unimportant in cognitive function. While the current study focuses on the adult sample, early life SES circumstances are recognised to form the foundation of the cognitive system, including WM. This finding aligns with the literature review by Hackman and Farah (2009), highlighting how SES impacts early cognitive development and familiarity with environments. Unfamiliarity with the environment may negatively impact those from low SES, negatively affect their confidence, and overall task engagement. This places additional demands on their executive resources, especially in WM task performance, which demands attention and fast processing. This suggests that low SES students are unaccustomed to planned cognitive tasks, which affects engagement or approach use, such as verbal rehearsal.

Additionally, verbal mediation strategies, like self-talk to support task performance, are more likely to develop in an environment with solid language experience. However, those from higher SES might benefit from exposure to verbal mediation strategies (Hackman & Farah, 2009; Noble et al., 2005). Likewise, studies by Aikens and Barbarin (2008) and Noble et al. (2005) support the continuing effect of socioeconomic factors on cognitive development, indicating that cognitive differences may persist throughout adulthood. This is suggested to be linked to the variation of SES. Hence, despite that the association has been insignificant in these findings, the cognitive implications of SES warrant further exploration, as these implications are assumed to persist throughout adulthood. Fascinatingly, the current findings further demonstrated that not only SES, but age was also found to be insignificantly correlated with WM measures when SDMT-Oral was introduced. This suggests that PS may mediate or nullify the effects of age and SES on WM, highlighting its importance in adults' cognitive functioning. Further suggested that SDMT-Oral was the stronger predictor of WM measures rather than demographic variables, like age and SES.

The findings further demonstrated that SDMT-Oral positively and significantly predicted WM performance in various tasks, such as LNS, DS total, LDSF, LDSB, LDSS, and LLNS, even when age was included in the model. This indicates that PS, as measured by SDMT-Oral, is associated with improved performance on complex and simple spans. This aligns with PS theory, which hypothesises that the age-related decline in cognitive performance is mostly influenced by slower PS. The literature review indicated that slow PS reduces the efficiency of mental operations that limit the amount of information that needs to be maintained in WM (Salthouse, 1996). In support, Fry and Hale (2000) highlight that faster PS

allows efficient encoding, rehearsal, and manipulation of information with a limited time for WM tasks. Moreover, the prediction of SDMT-Oral across these tasks supports the idea that PS is not only effective for storage and processing but for executive components of WM as well (Baddeley, 2000). The current findings further demonstrated that attention span was also associated with PS. This aligns with the resource theory in the literature review, which argues that WM is not constrained by PS only; there are other cognitive domains, such as attention and mental effort (Engle, 2002; Just & Carpenter, 1992). This underlies the significance of PS in successful cognitive functioning, particularly in tasks requiring attention switching and mental manipulation.

Similarly, PS was significantly positively associated with DS sequencing, LNS, and LLNS even when the LSM category and LSM group were included in the model. This strengthens former findings on the importance of PS on WM performance. However, in this context, it is suggested that PS contributed to WM performance independently of SES. These findings were consistent with PS theory (Salthouse, 1996) and indicated that SES may indirectly influence WM on SES. Also implies that PS consistently predicted WM performance, although no effect of SES was observed. Furthermore, PS plays an important role across SES, suggesting that better PS could help strengthen cognitive functioning no matter an individual's background. In contrast to the literature review, Hackman and Farah (2009) established that SES was a strong predictor of neurocognitive performance in executive function. Differences in SES exist in brain activities and could last for a lifetime, and those with higher PS may use more efficient neural pathways in executive tasks, which include WM. Collectively, these findings demonstrated that the current study met the objective of exploring the predictive role of PS on WM performance.

The indirect influence of age on WM measures in controlled SDMT-Oral aligns with the literature that found the decline in PS with increasing age negatively affects WM performance (Craik & Salthouse, 2000; Nettelbeck & Burns, 2009). Leonard et al. (2015) emphasised that low SES negatively impacts WM performance. Supporting this, Caplan and Waters (2005) reported poorer performance of older adults compared to young adults in all measures of WM and PS. This suggests that increased age is associated with poorer performance. Although these results imply that only age, LSM category, and LSM group indirectly influence WM measures, SDMT-Oral was a significant predictor. Therefore, SDMT-Oral may serve as the link among age, LSM, and WM performance. This indicates that age and LSM are mediated by the effect of SDMT-Oral on WM measures.

Additionally, gender had a significant relationship with SDMT-Oral and DS forward as well as LNS. This was evidenced by the findings that indicated a significant gender difference, with females performing better than males in SDMT-Oral and DS forward and LNS. This aligned the literature review with previous research that demonstrated a female advantage in verbal WM (Harness et al., 2008; Kaufman, 2007). Kiely et al. (2014) and Strober et al. (2020) demonstrated that PS (measured by SDMT) differs by age and gender. However, previous research on DS tests presents different findings concerning gender performance. Taborda et al. (2019) reported that males outperformed females in DS tests. Conversely, Robert and Savoie (2006) reported no differences in DS forward. These findings should be interpreted cautiously due to the unequal representation of the mean sample, as indicated earlier that females' mean age was greater than that of males. It is perhaps notable that a significant age gap between the genders could be a great explanation for these results. Importantly, females had fewer years of education compared to males, which suggests that the observed significant finding cannot be attributed to educational level. However, other factors, such as socioeconomic background, culture, might act as confounding variables, influencing the observed gender effects.

Lastly, current findings demonstrated that education and EFL may function as a strong interactive predictor. This could be explained by looking at the lifespan perspective, since the current study examined older adults. In particular, age-related decline in PS and WM has been recognised (Salthouse, 1996, 2005). In line with the literature review, age-related decline in this study demonstrated a similar pattern with other studies in cognitive constructs, particularly WM, PS, and executive function (Craik & Salthouse, 2000; Nettelbeck & Burns, 2009; Salthouse, 1996). This decline affects the ability to make proper decisions and other aspects of cognitive functioning (Banerjee et al., 2014). Nevertheless, the level of decline fluctuates based on compensatory aspects like cognitive reserve, which is associated with educational background (Stern, 2002). Those with a higher level of education may show better WM performance even in later life; this could be due to effective neural strategies and improved cognitive flexibility (Wang et al., 2017). Additionally, the first language further confuses this dynamic; for instance, individuals who do not speak EFL or the dominant language of testing may impose additional cognitive load in verbal WM tasks. These cognitive demands may limit the speed at which the information is processed or may display language processing delays. Following Bialystok and Craik (2010), bi/multilinguals frequently recruit dissimilar cognitive control processes in tasks requiring language rules and

attentional switching. Participants who did not speak EFL as their first language may suppress task performance, ascribing to decreased involuntariness and higher processing demands (Grundy et al., 2017). The interactive role of these variables may show a compound balance; older adults with fewer years of education and not speaking EFL may demonstrate confounded cognitive strain, whereas younger, educated participants with EFL may demonstrate improved WM capacity. These interactions highlight the importance of considering language and education when interpreting findings of cognitive performance in a diverse sample. This explanation could give a brief understanding of why these variables function as an interactive predictor.

Overall, there was a positive relationship between WM and PS, with SDMT-Oral being a significant predictor of WM and demographic variables. The results suggested that females who had a high level of education and spoke EFL exhibited superior PS and WM. An indirect influence of age, LSM, and SDMT-Oral was observed in the majority of WM tasks and attention span. Education and EFL significantly predicted certain WM measures.

5.7. Moderation of processing speed on the relationship between working memory and demographic variables

The hypothesis of this study was to determine whether PS moderates the relationship between WM and demographic factors. A set of regression analyses confirmed the moderating role of PS, as measured by SDMT-Oral. It was demonstrated that the inclusion of SDMT-Oral as a moderator variable, along with WM measures and significant demographic variables, led to a great deal of variance in WM. When all measures were considered, it was clear that attention spans moderated PS the most. It may be relevant to point out that WM and attention are closely linked, as mentioned earlier. However, SDMT-Oral demands efficiency and speed, which may be linked to WM (Benedict et al., 2017).

Moreover, attention is required in WM performance because, without sufficient attention, there is no success in processing information to WM for manipulation and encoding (Rhodes & Cowan, 2018). Therefore, for task completion, attentional capacity influences cognitive processing and impacts or guides additional cognitive input (Cowan, 1999). Another possible reason could be that the tasks rely on speed, which requires attention (Benedict et al., 2017). These two reasons explain how moderation occurred on attention spans, SDMT-Oral, and demographic variables.

This study's findings indicated that SDMT-Oral had a significant effect on the majority of WM tasks, where age is concerned. This means that age does not influence the performance of SDMT-Oral, but the fact that younger people are faster due to their processing efficiency, rather than age per se. Furthermore, a significant moderating effect of PS on the relationship between WM and demographic variables was observed. First, the moderation effect of PS was observed on the relationship between age, EFL, and LDSB. Second, PS moderated the relationship between age, LSM category, and LLNS. Lastly, PS moderated the relationship between age and LNS. This confirms the hypothesis that PS would moderate the relationship between demographic variables and WM. These findings demonstrate that demographic factors influence the performance of WM tasks, and this indirect effect depends on the performance of SDMT-Oral. Contrarily, years of education had no significant interaction with any of the WM tasks, and the main effect of SDMT-Oral was observed only in LLNS. This demonstrated that SDMT-Oral did not moderate the relationship between years of education and WM measures.

Although the current study did not examine language anticipatory movements, previous research has shown that PS explains the variance in such processes beyond WM (Huetting & Janse, 2015). Extending this, the current findings demonstrated a moderation effect of SDMT-Oral on EFL and LDSB, with the positive impact of EFL on LDSB performance being more substantial at higher PS. Further, this suggests that the higher SDMT-Oral score of EFL speakers was associated with their higher performance in LDSB compared to those whose first language was not English. These findings suggest that language proficiency may enhance efficient PS on complex WM tasks; PS also enhances WM. Such findings are aligned with the literature review on bilingual advantage frameworks, which suggests that language influences PS to improve executive functions (Bialystok & Feng, 2009). Grundy et al. (2017) further support this view by indicating that language dominance, switching, and exposure create strong cognitive processes and neural adaptation.

Furthermore, attention span (LDSB) was not influenced by the SDMT-Oral score. This consistency with literature review suggesting that when an individual assessed in their first language, they tend to perform significantly better compare to those who are assessed in other languages than their first, as it easier to understand and respond in one's dominant language, disregarding the extra mental effort associated with switching (Mielicki et al., 2018; Oltshoorn et al., 2012). This statement supports Ardila's (2003) study on the retrieval of words and WM in bilinguals who spoke EFL and in English monolinguals. In brief,

participants were assessed in DS subtests, and there were no differences between monolinguals and bilinguals. This finding highlights the strength of the first language, as the two groups performed the same. These findings, however, should be interpreted with caution, since DS may not fully capture the complexities of language processing in bilingual individuals. As simple tasks like DS may not reveal the advantage of the first language as consistently, more complex tasks necessitate a higher level of processing. It could be that the cognitive demands of simple tasks may not sufficiently capture the resources where first language proficiency offers a significant advantage.

Moreover, the study design does not address the potential influence of PS, which may interact with language dominance to affect WM. As emphasised by Barrouillet et al. (2007), efficient processing allows verbal WM performance by supporting fast and continuous switching of cognitive resources from processing and maintenance, thereby allowing improved performance of WM tasks. These findings further extend this framework by demonstrating that higher PS can moderate the potential disadvantages associated with EFL, thus leading to strong WM performance, irrespective of language background.

Second, the GLM demonstrated a significant interaction between SDMT-Oral score and age on LDSB, suggesting that in young adults, a higher SDMT-Oral score was associated with increased LDSB score. This further highlighted that increased age has a negative effect on WM and PS. This is consistent with the literature that demonstrates that PS affects WM (Fournier, 2014; Kim & Park, 2018; Nettelbeck & Burns, 2009). The age-related decline in SDMT-Oral performance appears to influence WM task performance. Caplan and Waters (2005) assessed PS using a Digit Symbol and Digit Letter and WM in adults using different measures. Their evidence indicated an interaction of age and Digit Symbol with WM measures. This interaction suggests that the reason older adults do not perform better may be that PS affects WM in a way that is not directly related to PS. Park et al. (2002) demonstrated the decrease in WM and other cognitive constructs due to advancing age. These declines are said to last a lifetime. These are aligned with Nettelbeck and Burns (2009), who suggested that the increased age negatively impacts PS, which, in turn, affects WM. In support of this, Pliatsikas et al. (2018) reported that verbal WM declines with age, suggesting that when age increases, WM task performance declines. However, Pliatsikas et al. (2018) used a different WM task from that of the current study, and their variables were limited, whereas our study was extended to the PS.

Since other studies suggest a general decline in WM and PS as age increases (e.g., Park et al., 2002), it is important to consider the nuances of these age-related changes. Similarly, Myerson et al. (2003) examined the relationship between age and WM measures. The study compared DS subtests and LNS performance. The results indicated that as age increases, LNS scores decrease drastically compared to DS scores. These findings suggest that not all WM tasks are equally affected by age. Furthermore, a specific type of WM task can influence the observed age-related effects. However, findings by Hester et al. (2004) and Park et al. (2002) indicated that older adults have a habit of displaying a lower performance in DS forward and DS backward compared to that of younger adults, and this effect is worsened by lower PS. This raises a question of whether lower PS mediates the relationship between age and other cognitive constructs, or whether other factors play a role. These results indicate an interaction among PS, age, and WM. Future research should explore the effectiveness of cognitive training that is designed to improve WM and PS in adults.

In terms of the significant interaction between the SDMT-Oral score and age, LSM on LNS and LLNS, the results suggest that age and SES impact how quickly individuals respond to LNS and LLNS tasks. Although higher educational and SES background significantly influence the performance of these tasks, young adults with a higher LSM category and higher educational level performed better. This may be explained by the fact that individuals from low SES typically demonstrate fewer years of education. However, if an individual comes from a low SES background and has a higher level of education, their performance score improves. These findings suggested that the higher SDMT-Oral scores of those who were young and from higher SES were associated with increased SDMT-Oral performance, which influenced LNS and LLNS performance scores. These findings further highlight that increased age and low SES have a negative effect on WM and PS. This aligns with the literature. For example, findings of Myerson et al. (2003) on LNS highlighted that age-related decline in executive function led to difficulties in manipulating and maintaining information in WM.

Moreover, the findings revealed that this is a non-linear effect where age is concerned, given that the age range was limited between 18 and 60 years. This explains why young adults performed better than older adults. However, the finding on the effect of education was supported by Guerra-Carrillo et al. (2017), who revealed that higher levels of educational achievement contribute to a higher PS. This larger-scale investigation of over 196,000 participants utilised slightly different sample sizes, which involved participants from 15 to 60

years, compared to ours. In other words, they included participants who were still developing in terms of cognitive development. Their results indicated that the level of education moderated the PS and reasoning ability. They utilised a longitudinal approach for 100 days of cognitive training to examine the relationship between learning and education. The current study adopted a cross-sectional approach. These findings extend existing research by demonstrating how PS interacts with age and SES to predict WM.

These findings are consistent with the literature; for instance, Steptoe and Zaninotto (2020) and Zhang et al. (2015) confirm that being older and from low SES harms PS. Meijer et al. (2009) assert that older adults with more years of education perform better than those with fewer years of education. The current findings further suggest that verbal WM indicates a decline with age, and, thus, WM might deteriorate as age increases. However, years of education and SES play a crucial role. In support of this, Oshri et al. (2019) demonstrate that individuals from low SES exhibit lower performance in WM and lower response in the dorsolateral prefrontal cortex. A possible reason for this would be that WM is associated with a brain region. If there are dysfunctions in the brain region, the storage and manipulation of information are compromised.

Additionally, low performance in LNS and LLNS may be explained by the fact that the participants were predominantly second language English speakers with a low level of education. This put them at a disadvantage compared to their peers. The task was administered in English, which disadvantaged those from low SES with a different first language and a low level of education. This aligned with the literature, which confirms that SES interacts with the level of education, and both education and language contribute to an individual's performance score (Wijeakumar et al., 2019; Zhang et al., 2020).

Remarkably, PS moderated the relationship between age and LNS, showing that the negative impact of increasing age on LNS performance was less severe for those with higher PS. This finding aligns with PS theory by Salthouse (1996), which states that declines in PS influence other cognitive ageing effects. It suggests that higher PS is a shielding factor in older adults, allowing them to maintain higher WM function despite age. This suggests that a person can be old but maintain higher PS and WM. These findings were unexpected since it is well recognised that PS and WM decline with age, although education is a protective factor in maintaining cognitive functioning. The literature review demonstrated that the white matter naturally changes as an individual's age increases. This deterioration weakens

cognitive functions, including PS, which affects WM (Bartzokis et al., 2003). However, the moderation findings indicate that if PS is at a higher level, it could influence WM performance; the natural decline could be less pronounced in adults, and other factors, such as education or language proficiency, could enhance both PS and WM.

Collectively, these findings highlight the importance of language experience on test performance, as the assessments demanded WM. Supporting this, a recent study by Immanuel et al. (2024) used DS forward, DS backward, and DS sequencing and reported the advantage of the first language in task performance. The disadvantage of second language speakers could be that WM involves the demand to manipulate information, which, in turn, requires the efficiency of PS and delayed response. These assessments demanded WM, which enables efficient individual performance in task performance, which explains the moderating effect of PS on the relationship between demographic variables and WM performance.

5.8. Theoretical implications

These findings support Cowan's (1999) embedded process theory, which suggests that WM depends on attention that facilitates the process and filters information through WM, by extending it through PS. According to the current findings, if PS moderates the efficiency of the attention span, this could mean that the decline in PS can produce more impairment in retrieving information from WM. The moderation of age and EFL on LDSB suggests that high PS demonstrated by young adults and those who spoke EFL could enhance the retrieval and encoding of information, thereby supporting the high-performance score in LDSB and LNS. This is aligned with previous research suggesting that verbal WM tasks depend on the phonological loop to manipulate information (Baddeley, 2003). In support of this, Bialystok (2008) assumes that bilinguals depend on executive control to manage language.

5.9. Conclusion

This study aimed to observe how PS influences the relationship between WM measures and demographic factors like age, years of education, SES, and gender. This was done by examining combined cognitive functions and demographic variables. In addition, the current investigation results were able to confirm previous research on the influence of demographic variables on WM and the moderating role of PS. In the findings, an association between PS and WM was demonstrated, and an interaction was observed. Additionally, education had a greater effect than age and EFL on SDMT-Oral, but PS did not moderate the relationship

between education and WM. Older adults demonstrated significantly lower performance compared to younger adults in terms of both WM and PS performance.

All WM and PS measures were positively and significantly correlated. Demographic variables, such as age, significantly negatively correlated, while years of education, EFL, and SES significantly positively correlated with specific WM and PS tasks. Gender was significantly correlated with one WM measure. The best predictive models were model 3, which means that PS, as measured by SDMT-Oral, moderates significantly the relationships between demographic variables, such as age, EFL, LSM, and LDSB, LLNS, but not between years of education, gender, and DS forward, DS backward, DS sequencing, DS total, LNS, as well as LLNS. The overall findings suggest that there is a common relationship between WM and PS. Despite the different effects of these two cognitive factors on demographic variables, they confirmed the moderation of PS on these variables. These results were similar to those found in other countries, indicating the usefulness of these assessments as a valid cognitive assessment in South Africa. This study presented both its strengths and limitations, which will be described in detail below.

5.10. Limitations, Strengths, and Recommendations of the study.

This section outlines limitations, strengths, recommendations, and contributions identified in the current study. Firstly, the sample size was smaller than the size that was initially determined to have sufficient statistical power. The smaller sample size reduced the power of the study to identify minor effects. The change in sample size occurred as a result of limitations imposed by the time framework allocated to data collection. The sample is also not representative of the South African population, which limits the generalisability of the findings. Moreover, the sample on gender was unbalanced in terms of sample size, age, and level of education, with females constituting 66% compared to males 34%. Females ranged between 18 and 60 years, while males were between 18 and 49 years, which could reduce statistical power or impose biases in the findings. Additionally, three people collected data for this study, which could introduce an administration bias. Although we tried to control for it by strict adherence to the test administration, it is still possible. The sample was not stratified by language background, which resulted in an imbalance between monolinguals and bi/multilinguals. Although participants indicated fluency in English, this could have imposed bias, especially for those who speak other languages as their first language other than English, as language proficiency was self-reported. This reliance on self-report limited the study's ability to measure language experience precisely.

Another limitation concern was the use of SDMT in a language-diverse sample. Although this was a reliable test for PS, the oral version depends on an oral output, which might disadvantage participants who were not EFL speakers or dominant in the language used for testing. This could lead to slower responses or reflect challenges in language processes rather than an accurate PS measure. The oral version of SDMT may have bias, especially for bi/multilingual participants, given the finding that SDMT-Oral correlated strongly with most demographic and cognitive variables. This could demonstrate a true PS measure or a language confound. Future research to investigate this further. This concern applies to DS and LNS subtests, which were also restricted to English. Specifically, LNS requires participants to be familiar with letters and numbers. Suppose one had less knowledge of the English alphabet; this could introduce further cognitive demands for those who do not speak EFL.

Moreover, all tasks were in English, which was set as an inclusion criterion. However, neither the examiners' nor the participants' accents were controlled in this study. This might have impacted the participants' performance, particularly second- or third-language English speakers. Variation in accents might have introduced additional processing demands, potentially slower responses, and affected task performance. Also, the study did not control for language proficiency but took a self-assessed measure for the language variables.

The main strength of this study is that it is one of the few studies conducted in a South African context that investigates the influence of PS on the relationship between WM and demographic variables. There was an obvious inclusion of numerous demographic factors that were identified as potentially influencing WM and PS test performance. Another important strength of the current study is the heterogeneousness of the sample group in their levels of education, SES, language experience, and age, which allowed for the exploration of the impact of demographic variability in test performance.

Employing a longitudinal study design would enable the clarification of the precise and separate functions of sociodemographic factors. Specifically, implementing effective measures that accommodate a diverse community, such as South Africa, is essential. This might involve creating new standardised measures that align with African language and cultural diversity or adjusting current cognitive assessments. Also, future research is recommended to utilise larger sample sizes and incorporate a wider range of age cohorts to improve their ability to identify significant effects. Also, include participants from rural areas

to understand the distinct influences of PS, WM, and the impact of age, education, and language experience on cognitive performance. This may facilitate the generalisation of findings to the broader rural community and, therefore, enhance the cultural diversity of the results. Future studies should increase the sample size to maintain statistical power. They should include a broader range of WM and PS assessment tools and establish normative data for cognitive instruments that are specifically designed for the South African demographic. Additionally, future research would benefit from more language background assessment and the inclusion of comparison groups to understand better how cognitive constructs may be differentially influenced by language experience. Finally, this study further contributed to the South African research community by providing insight into the use of cognitive measures and how demographic factors influence these measures.

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Appendices

Appendix A: Demographic Questionnaire

Demographic Questionnaire

Name: _____

Surname: _____

Age: _____

Date of Birth:

D	D	M	M	Y	Y	Y	Y

Gender: _____

Ethnicity: _____

Home Language: _____

Highest Level of Education: _____

Have you ever failed a grade in school? If so, which one?

_____

Have you ever required intervention from a language specialist?

_____

Have you ever been diagnosed with a neurological, metabolic or psychiatric illness?

_____

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:	

Subjective experience of financial resources (fiscal appraisal)

Income comparison

1. At present, how would this household classify its financial situation?

   5-point scale ("Much above average income" to "Much below average income").

1	2	3	4	5
Much above average income		Average income		Much below average income

2. How would you classify your household in terms of income, compared with other households in your community?

   5-point scale ("Very comfortable" to "Extremely poor")

1	2	3	4	5
Very comfortable		Comfortable		Extremely Poor

Subjective standing

Please imagine a ten-step ladder where the poorest people in South Africa stand on the bottom (the first step) and the richest people in South Africa stand on the highest step (the tenth step). On which step are you on today?

10-point scale

Appendix B: Living Standards Measure

Living Standards Measure:

Please answer the below questions according to your current circumstances.

Question	Answer	
1. I have the following in my household		
TV Set	True	False
Swimming pool	True	False
DVD player	True	False
M-Net/DStv subscription	True	False
Air conditioner	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 or on the plot:		
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
Question	**Answer**	
6. I live in a rural area outside Gauteng	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 C: Shortened Version of Language Experience and Proficiency Questionnaire (LEAP-Q-SV)

Participant No: _____

The Language Experience and Proficiency Questionnaire (LEAP-Q)

1. What languages do you know?

   Language A: _____

   Language B: _____

   Language C: _____

2. Language A:

   This is my _____ (First, second, third) language. All questions below refer to your knowledge of language A.

2.1 Age when you...

   Began acquiring this language: _____

   Became fluent in this language: _____

   Began reading in this language: _____

   Became fluent reading in this language: _____

2.2 Please circle your level of proficiency in speaking, understanding, and reading in this language:

Speaking

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

Understanding Spoken Language

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

Reading

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

3. Language B:

This is my _____ (First, second, third) language. All questions below refer to your knowledge of language B.

3.1 Age when you...

Began acquiring this language: _____

Became fluent in this language: _____

Began reading in this language: _____

Became fluent reading in this language: _____

3.2 Please circle your level of proficiency in speaking, understanding, and reading in this language:

Speaking

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

Understanding Spoken Language

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

Reading

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

4. Language C:

This is my _____ (First, second, third) language. All questions below refer to your knowledge of language C.

4.1 Age when you...

Began acquiring this language: _____

Became fluent in this language: _____

Began reading in this language: _____

Became fluent reading in this language: _____

4.2 Please circle your level of proficiency in speaking, understanding, and reading in this language:

Speaking

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

Understanding Spoken Language

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

Reading

0	1	2	3	4	5	6	7	8	9	10
None	Very Low	Low	Fair	Slightly less than adequate	Adequate	Slightly more than adequate	Good	Very Good	Excellent	Perfect

Appendix D: Ethical Clearance Certificate

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/23/02**
PROJECT TITLE:	The relationship between working memory and processing speed: The influence of demographic variables on test performance in the South African sample.
INVESTIGATOR	Celie Thobekile (2750813)
SCHOOL/DEPARTMENT OF INVESTIGATOR	SHCD/Psychology
DATE CONSIDERED	14 June 2023
DECISION OF THE COMMITTEE	Approved unconditionally
RISK LEVEL	Low Risk
EXPIRY DATE	31 December 2025
ISSUE DATE OF CERTIFICATE 03 June 2023	**CHAIRPERSON** (Dr Aline Ferreira Correia)

cc: Dr Aline Ferreira Correia (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 **Date** 29/07/2023

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

Appendix E: Permission to Conduct Research

AFCI
ARK FELLOWSHIP CENTRE INTERNATIONAL

Phone +27 60 611 6462
Email Zamani.malunga@icloud.com
Address Ark Fellowship Centre International-KwaMakhutha
30 Nhlanhla Avenue
Kwamakhutha Township
Durban
4126

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

Re: Permission to collect data

Dear Thobekile Cele

Please note that your request has been accepted.

Should you need any further assistance on this, please contact Ps Malunga on the above details.

Sincerely

Z Malunga

Signature .....

Date 29 July 2023

Appendix F: Wits Permission to Conduct Research

UNIVERSITY OF THE WITWATERSRAND JOHANNESBURG
SCHOOL OF HUMAN AND COMMUNITY DEVELOPMENT
PSYCHOLOGY

14 August 2023

Thobekile Cele

TO WHOM IT MAY CONCERN

"The relationship between working memory and processing speed: The influence of demographic variables on test performance in the South African sample"

This letter serves to confirm that the above project has received permission to be conducted on University premises, and/or involving staff and/or students of the University as research participants. In undertaking this research, you agree to abide by all University regulations for conducting research on campus and to respect participants' rights to withdraw from participation at any time.

As Head of the Department of Psychology, I grant permission for you to approach staff in order to invite Psychology students to participate in your research.

Ethical clearance has been obtained. (Protocol number: MAPSYC/23/02)

Yours sincerely,



Prof Carol Long, Head of Department, Psychology
☎ +2711 717 4510 ✉ carol.long@wits.ac.za

Appendix G: Advertisement to Recruit Participants

Volunteers needed for research study



As part of my research study, you are invited to participate in a study that comprise cognitive assessment for working memory and processing speed. It will take 60 minutes to complete the assessment. Participants will be compensated R90 upon completion of assessment.

You may participate, if you:

- Are a South African between the ages of 20-60 years
- bi/multilingual and have 7 to 15 years of public school education
- do not suffer from any neurological impairment or linguistic disorder or any sort of addiction
- have no history of loss of consciousness
- do not suffer from any metabolic or psychological illness

If you wish to take part or would like to get more information
please contact me on: 0829588939 or
email: 2750813@students.wits.ac.za

Appendix H: Participant Information Sheet

Psychology

School of Human and Community Development

University of the Witwatersrand

Private Bag 3, Wits, 2050

Tell: (011) 717 4500

Fax: (0110) 717 4559

Participant Information Sheet

Dear Sir/Madam

My name is Thobekile Cele. I am psychology research master's student at the University of the Witwatersrand. I am conducting research which forms part of a larger project entitled. *"Exploring the Relationship between Demographic Factors and the Performance in Cognitive Tests: Exploring the Mediating Power of Speed of Processing".* The title of my study is: "*The Relationship between Working Memory and Processing Speed: The Influence of Demographic Variables on Test Performance in a South African Sample".* The aim of my study is to investigate the relationship between demographic variables (age, language, education and socioeconomic status) and cognitive variables (working memory and speed of processing).

I would like to invite you to participate in my study which will require you to answer questions, solve problems, and complete pencil and paper activities. Prior to data collection, you will need to sign a formal consent form, agreeing to participate in this study. You will then need to complete a demographic questionnaire and a battery of cognitive tests.

Your participation will be confidential and only my supervisor and I will have access to your identifying information. Your personal information will be assigned a participant number which will ensure anonymity. The data obtained from this study will be stored on a password protected device and the results will be available on the Internet (World Wide Web) via the

University's library website and potentially be published in scientific journals and presented at conferences. If you wish to have access to the results, please contact me or my supervisor using the details below.

If you decide to take part in the research study, it should be because you want to volunteer. You can withdraw from participation at any point without any penalties. You do not have to answer any questions if you do not want to. You will not get any direct benefits if you choose to join the research study. You will not lose any services, benefits, or rights you would normally have if you decided not to join. Taking part in the research study will not cost you anything. You will be compensated a total of R90, 00 to cover any transport costs you may incur.

If you have any concerns or complaints about the ethical procedures of this research study, you can contact the University Human Research Ethics Committee (Non-Medical) via the details indicated below.

Human Research Ethics Committee (Non-Medical)

Telephone: 011 717 1408

Email: hrecnon-medical@wits.ac.za

If you have any questions about this research study, feel free to contact me or my supervisor using the contact details provided below.

Thobekile Cele
Researcher
Email: 2750813@students.wits.ac.za
Cell: 082 958 8939

Dr Aline Ferreira-Correia
Research Supervisor
Email: Aline.FerreiraCorreia@wits.ac.za
011 717 9527

Appendix I: Informed Consent Form

Psychology

School of Human and Community Development

University of the Witwatersrand

Private Bag 3, Wits, 2050

Tell: (011) 717 4500

Fax: (0110) 717 4559

Informed Consent Form

Name of researcher: Thobekile Cele

Supervisor: Dr Aline Ferreira-Correia

I, ……., am above the age of 21, I confirm that I have read and understood the information sheet and agree to participate in this research project entitled: "*The Relationship between Working Memory and Processing Speed: The Influence of Demographic Variables on Test Performance in a South African Sample",* which forms part of a larger project entitled: *"Exploring the Relationship Between Demographic Factors and the Performance in Cognitive Tests: Exploring the Mediating Power of Speed of Processing".*

I agree to the following:

(Please circle the relevant options below)

The research study was explained to me. I understand what this study is about.	YES/NO
I understand that participation in this study is voluntary.	YES/NO
I agree that my participation will remain anonymous (my name or other identifying data will not be used by the researcher in their research report).	YES/NO
I agree that other researchers may have access to the information obtained from this study, however, my name and any personal information will not be used or passed on.	YES/NO
I agree that any of the information that I provide can be stored by the supervisor and used as secondary data.	YES/NO
I understand that as a participant, I can withdraw from this study at any point without any prejudice/penalties.	YES/NO

…… (signature)

…… (name of participant)

…… (date)

…… (signature)

…… (name of researcher)

…… (date)

Appendix J: Summary of insignificant relationship between DS forward, DS total, and demographic variables

Insignificant relationship between demographic variables and DS forward and DS total

Model 1	Variable	F value	Pr > F
DS forward	Age	1.36	.2469
	Years of education	2.84	.0951
	LSM category	.5762	.5762
	LSM group	.02	.8775
	NL	1.06	.3516
	EFL	.32	.5701
DS total	Gender	.73	.3965
	LSM category	2.09	.0878
	LSM group	.87	.3522
	NL	1.87	.1599

Note. LSM = Living Standard Measure. NL = Number of languages. EFL = English as first language.

Appendix K: Summary of the main effect of SDMT-Oral on working memory measures and insignificant demographic variables

The main effect of SDMT-oral on DS backward, DS sequencing, and DS total on insignificant independent variables

Model 3	Variable	F value	Pr> F	p value
DS backward	Age	1.36	.2464	.26
	Years of education	.20	.6577	.26
	EFL	1.73	.1923	.28
DS sequencing	Age	.85	.3599	.29
	Years of education	1.80	18.31	.12
	LSM category	1.77	.1431	.19
	NL	.03	.9707	.27
	EFL	.41	.5223	> .99
DS total	Age	.98	.3254	.26
	Years of education	2.01	.1595	.25
	EFL	1.93	.1685	.11

Note. LSM = Living Standard Measure. NL = Number of languages. EFL = English as first language.