# Using Working Memory to Predict Other Domains within the Learner Profiler in an Older Adolescent Sample

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## COMPULSORY DECLARATION

This work has not been previously submitted in whole, or in part, for the award of any degree. It is my own work. Each significant contribution to, and quotation in, this dissertation from the work, or works, of other people has been attributed, and has been cited and referenced.

Signature: _____ Date: 13 February 2023

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## Abstract

Learning difficulties and disabilities (LDD) are the most frequently diagnosed of childhood developmental disorders. In South Africa (SA), however, a standard and nationally accepted tool has not yet been established for assessing LDDs and thus, specific incidence rates are not known. An underlying factor which may be important to consider in the context of LDDs is working memory (WM) which has been reported as playing a crucial role in learning and WM deficits appear to be higher in the context of LDDs. Thus, it may be imperative to adopt, and adapt to, new technologies that are both cost-effective and easily accessible, addressing the gap in resource availability. The Learner Profiler (LP) is an example of one such computerised test, being relatively cost effective and accessible. It should be noted, however, that research on the LP test method is particularly limited due to both a scarcity in the literature and the use of small sample sizes in said literature. The aim of this research was to investigate whether a computerised tool of WM on the LP could predict scores on other computerised cognitive domains on the LP.

This quantitative study used a within-subjects experimental design to investigate the predictive value of LP WM module in other LP modules, namely, Visuospatial, Spelling, Missing Word, Word Choice, and New Word Spelling. The sample comprised of 1175 participants aged between 16 to 19 years old. At the time, participants attended a Technical Vocational Education and Training college (TVET) situated in an urban area in Gauteng, SA. The LP modules were administered during normal admissions processes at the college.

To assess the predictive value of the LP WM module, the scores of the modules were analysed using multiple regression analyses. The results of the regression analyses showed that the LP WM could predict scores on most of the other LP modules, barring one. The LP WM scores were able to significantly predict scores on the Visuospatial, Spelling, Missing Word, and New Word Spelling tasks with significance rates ranging between $p < .05$ and $p < .001$. The scores of the LP WM were not able to predict scores on the Word Choice task. Notably, however, the variances for the significant models were considerably small, ranging between 2% and 8%. When combined, these models account for about 20% of the variance. These results may, therefore, be considered negligible. Given these findings as well as issues that may have undermined the results, including the inconsistency in modality and issues that arose with computer-based testing, it can be concluded that the LP WM module was not predictive of scores of the other LP modules.

The findings of the current study contribute to the understanding the value of progressing to computer-based testing, generally, and specifically in the context of screening for deficits associated with LDDs. Moreover, it highlights the importance of appropriate resource implementation when using computer-based testing methods.

*Keywords:* Working memory, Learner Profiler, computer-based testing, adolescents, South Africa

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## Literature Review

Learning difficulties and disabilities (LDD) are the most frequently diagnosed of childhood developmental disorders, globally, with the prevalence of LDDs previously reported as being between 15% and 17% of school-aged children, globally (Farhad Pour et al., 2022). In South Africa (SA), however, a standard and nationally accepted tool has not yet been established for assessing LDDs and thus, specific incidence rates are not yet known (Nel & Grosser, 2016). There are many factors which contribute to defining and discussing LDDs within a SA context, including, but not limited to, the educational setting and socioeconomic landscape (Nel & Grosser, 2016). Given high estimates of LDDs globally, and given contextual vulnerabilities in the country, there is a need for a move toward establishing screening and assessment thereof in SA.

Neuropsychological testing and the importance thereof are becoming more apparent in this day and age, especially in assessing LDDs (Bracken et al., 2019; Charchat-Fichman et al., 2014). The assessment process involved in identifying LDDs, however, is oftentimes time-consuming and costly (Charchat-Fichman et al., 2014; Fletcher & Miciak, 2017). As a result, there may be many individuals who fall under the radar as the resources that are required to identify LDDs are not readily available or affordable. Hence, many individuals not identified as having a LDD, do not receive the necessary support and rehabilitation they require. Depending on the severity as well as other contributing factors, including the availability of rehabilitation resources, these deficits can have long-term effects to learning (Spaull, 2015). For all these reasons, it is imperative to adopt, and adapt to, new technologies that can screen for LDDs which may be more easily accessible and cost-effective. In this way, the gap in resource availability could potentially be addressed.

### Learning Difficulties and Disabilities (LDDs)

LDDs are typified by low achievement in school with the hallmark of low achievement in the areas of reading and mathematics (Johnson et al., 2014). Additionally, attentional difficulties are often concomitant and LDDs are often found to be co-morbid with Attention Deficit Hyperactive Disorder (ADHD; Fortes et al., 2016). LDDs are often grouped together as Specific Learning Difficulties, defined as cognitive processing deficits affecting the ability to learn and process information in an academic environment (Carvalho et al., 2016). LDDs do not occur as a result of an impairment in one or more of the following: disabilities in the visual, hearing or motor domains, and level of general intellectual functioning, or as a function of mental and emotional disorders (Hallahan et al., 2020). Additionally, the development of LDDs may be influenced by extrinsic factors such as

socioeconomic status (SES), access to appropriate education and support, and pedagogical factors such as flexible teaching and curriculum that is appropriate for all learners (Nel & Grosser, 2016). It has been found that there is a high incidence rate of LDDs in communities exposed to high levels of poverty (Cortiella & Horowitz, 2014).

**Prevalence of LDDs**

In Europe, the prevalence for specific domains has previously shown that rates for reading deficits were between 4% and 9% and rates for arithmetic deficits between 3% and 7% for children (Moll et al., 2014). In the United States (US), the prevalence of LDDs has previously been reported as 1.8% of the population aged 6 and older, which equates to 4.67 million Americans (Cortiella & Horowitz, 2014).

In a low- and middle-income country (LMICs) such as India, the general prevalence of LDDs was previously estimated to be between 15% and 20% of the population (Sridevi et al., 2015). In SA, it has been reported that for children aged five and older, the prevalence of cognitive difficulties such as remembering and concentrating, was approximately 4.2% in 2011 (Department of Education, 2014). Furthermore, in a previous report it was estimated that approximately 70% of children with a disability were not attending school and those who were attending were placed in a separate school for learners with special education needs (LSEN; Donohue & Bornman, 2018). Additionally, the global prevalence of attentional difficulties has been reported as 5% in children and specifically, in SA, the rate has been reported as being between 8% and 10% in children (Willis et al., 2017).

Overall, research studies on prevalence rates for LDDs appear to mostly focus on contexts in high-income countries such as the US and primary school-aged children. There is a scarcity in research studies specifically looking at adolescents from LMICs. As a result, prevalence rates are unknown, vulnerable groups such as adolescents often go under the radar (Nel & Grosser, 2016)

***Gender and LDDs***

Research studies have also investigated differences in the prevalence rates for gender in the context of LDDs. The prevalence rates were previously reported as males being more likely to have LDDs than females with a ratio of 1.8% to 1.5%, respectively, of the adult population. In school-aged children, this figure was previously reported to be approximately double, with 3.9% of boys and 2.0% of girls previously reported by families as having a LDD (Cortiella & Horowitz, 2014). Certain studies, however, have looked at specific differences in such difficulties between males and females. In a study conducted by Moll et al. (2014) who investigated isolated and combined LDDs in a sample of 1633 German-speaking children in

grades three and four, it was found that boys demonstrated more difficulties with both spelling and reading than girls. Moreover, it was found that girls had more difficulty with arithmetic than did boys. In contrast, in a study conducted by Morsanyi et al. (2018) in Northern Ireland, it was found that there were no significant differences between males and females with regards to difficulties with arithmetic. Notably, however, this study also found that those with arithmetic difficulties, also expressed difficulties with reading and/or writing.

Another study conducted by Cornoldi et al. (2019) in Italy investigated gender discrepancies in LDDs in a sample of 1624 children aged between seven and 16 years old using the Wechsler Intelligence Scale for Children Fourth Edition. It was found that males showed more difficulty in the verbal comprehension index which measures verbal reasoning and concept formation. No differences were found with regards to females and males in the perceptual reasoning index which measures non-verbal fluid reasoning abilities (Cornoldi et al., 2019). Moreover, the findings also demonstrated that across these two genders, difficulties within the working memory and processing speed indexes were also found (Cornoldi et al., 2019). In a similar and more recent study conducted by Giofrè et al. (2022) in Italy, similar differences were found regarding verbal comprehension performance and perceptual reasoning performance which were statistically significant, however, these differences were small.

## Current state of SA schooling system

In LMICs such as SA, the low achievement gap in the poorest schools is quite evident. In their SA study, Herrero Romero et al. (2018) reported that in the poorest schools, Grade nine learners were already five years behind in terms of their mathematical knowledge. Further, Spaull (2015) found that learners were not able to engage meaningfully with the curriculum by the time they reached Grade four. In another report by Spaull and Kotze (2015) it was noted that in the 2011 Trends in Mathematics and Science Study (TIMSS), 76% of Grade nine learners did not have a concrete understanding of basic mathematical concepts such as whole numbers and decimals. This has been termed as ‘silent exclusion’ – the idea of learners attending school and not learning / mastering what is required at that educational stage (Spaull & Kotze, 2015). This dire state of the schooling system in SA can be even more detrimental for learners who have LDDs.

### *Impact of LDDs on schooling*

Learning difficulties often begin in early schooling, which could affect an individual’s developmental and learning trajectory throughout their schooling career. Given that secondary schooling depends on understanding the basic skills in mathematics and reading

and intact attention facilitates learning and memory, deficits in these areas may pose a significant challenge for those with LDDs in school as they perform significantly below their enrolled grade-level (Boardman et al., 2016; Cortiella & Horowitz, 2014; Herrero Romero et al., 2019). For example, the academic performance of school-aged individuals with LDD was previously reported to be 3.4 years behind in reading and 3.2 years behind for mathematics for their enrolled grade-level (Cortiella & Horowitz, 2014). Further, attentional deficits affect higher-order cognitive functions impacting the ability to learn, especially in the areas of reading and mathematics (Ashkenazi et al., 2013; Maehler & Schuchardt, 2016). Consequently, this may also impact on behaviour because of the frustration and low self-esteem associated with the difficulty in following and/or understanding the information in the classroom (Claassens & Lessing, 2018; Cortiella & Horowitz, 2014).

Further, environmental factors, such as SES, may further undermine learners' ability to cope with such LDDs in the classroom given the association between SES and cognitive performance (van der Berg, 2015). This association is frequently reported in children from low SES backgrounds who are often affected by factors including overcrowded classrooms and lack of resources in schools as well as poor living conditions, lack of access to basic needs and undernourishment, to mention a few. These factors may in turn adversely impact learning as it may potentially place emotional stress on the child, ultimately disrupting engagement in learning activities (Uleanya, 2022). Furthermore, Hackman et al. (2015), state that there is a relationship between SES and cognitive ability as it was found that children from lower SES backgrounds performed worse on tasks of inhibitory control, working memory (WM), attention, and cognitive flexibility, all of which are domains related to learning. Moreover, it was found that the duration of poverty had an inverse relationship with WM. This finding therefore suggests that low SES may have chronic effects on cognitive development (Hackman et al., 2015). Given these reported prevalence rates of LDDs and the subsequent consequences thereof, it may be important to consider the underlying factors that may also be prevalent.

**WM and LDDs**

In the context of LDDs, it is important to consider underlying factors which may be impacting the ability to learn. One such factor is WM. WM is defined as the ability to hold information in mind, manipulate the information for a short period of time and respond appropriately to stimuli (Schneider & Niklas, 2017). WM is used in everyday settings as it allows for a space in which to mentally work with information. WM has been found to be a

robust measure of an individual's learning abilities over and above social and educational history (Friso-van den Bos & van de Weijer-Bergsma, 2020; Schneider & Niklas, 2017). A limited WM, however, has implications in understanding both simple and complex cognitive tasks such as those in arithmetic, literacy, and science (Friso-van den Bos & van de Weijer-Bergsma, 2020). Furthermore, WM as a measure of learning outcomes has been found to have more of an impact when general intellectual ability is accounted for as WM is implicated when learning new information (Schneider & Niklas, 2017). Despite difficulties in WM being seen in both typical (those without LDDs) and atypical (those with LDDs) student contexts, it appears to be more prevalent in the latter (Peng et al., 2018).

Previously, WM was thought to be synonymous with short-term memory. Short term memory was defined based on its limited duration and its involvement in brief storage of information (Baddeley, 2012; Chai et al., 2018). WM, on the other hand, while also limited in its capacity thought to be involved in more complex information processing (Angelopoulou & Drigas, 2021). The capacity for information held within WM is thought to be three or four objects or units of information for adults and two to 2.5 objects or units of information for preschool aged children (Angelopoulou & Drigas, 2021). There are two WM models that have become widely favoured, namely, the 'Multicomponent Model' and the 'Embedded Process Model'. These models were derived from an earlier theorisation and understanding of short-term memory which hypothesised that information is processed from sensory memory to short-term memory and then finally to long-term memory. Baddeley and Hitch (1974), however, state that these processes did not explain cognitive performance. For example, in a study conducted by Warrington and Shallice (1969 as cited in Cowan, 2012), it was found that individuals who were severely impaired on tests which assessed immediate recall of 2 items were able to perform adequately on other cognitive tests such as learning, memory and comprehension. Thus, it was previously understood that given the performance on the immediate recall test, individuals would have likely performed poorly on the other cognitive tests (Cowan, 2012). This, however, was clearly not the case as the participants demonstrated adequate abilities on other domains which beckoned the idea of another underlying construct other than short-term memory. Baddeley and Hitch (1974) noted that short-term memory did not account for differences between types of memory and interference. They noted that audio-verbal interference impacts other audio-verbal memory material more so than it impacts visuospatial arrangements and vice versa.

### *Multicomponent Model of WM*

Based on these findings, in 1974, Alan Baddeley and Graham Hitch proposed the Multicomponent Model of WM. The Multicomponent Model was initially divided into three subcomponents (Chai et al., 2018; Cowan, 2012). Each of these subcomponents are regarded as modules as they are involved in the processing of information. These subcomponents are connected to one another within the broader scope of WM. These subcomponents are then also linked to other systems such as long-term memory and perception (Baddeley, 2012; Chai et al., 2018). The first subcomponent is the central executive which is defined as the attentional-controlling system and information processing (Schneider & Niklas, 2017). The central executive is thought to be responsible for sorting through and updating information to allow for shifting between response sets (Friso-van den Bos & van de Weijer-Bergsma, 2020). It is also responsible for co-ordinating information between the visuospatial sketchpad and the phonological loop. The second subcomponent is the visuospatial sketchpad which allows for the processing of a certain capacity of visual information and the third subcomponent is the phonological loop which is responsible for the rehearsal and processing of a certain capacity of audio-verbal information (Angelopoulou & Drigas, 2021).

This WM model was later revised to include a fourth subcomponent known as the episodic buffer which is involved in combining all the information across the three other subcomponents into chunks for memory storage. Given that WM is linked to long-term memory and perception, the episodic buffer is believed to act as a buffer store between these processes (Angelopoulou & Drigas, 2021). While this model accounts for processes of audio-verbal, visuospatial and attentional-control, researchers have argued against the separability of these processes as well as the exclusion of the influence from other modalities such as sensory information (Chai et al., 2018; Cowan, 2012).

### *Embedded Process Model of WM*

To account for the shortcomings of the Multicomponent Model of WM, Nelson Cowan proposed a revised model in 1988. This is known as the ‘Embedded Process Model’ which proposed that the visuospatial sketchpad and phonological loop temporarily activates processes of long-term memory while also processing sensory information from other modalities (Chai et al., 2018; Cowan, 2012). This model argues that the storage of information is dependent on the interference of the similarity between information within short-term memory. Furthermore, it states that the activation of memory includes a variety of processes such as sensory, phonological, orthographic, and semantic processes. This model also assumes that some of these processes are involved in attention (Chai et al., 2018; Cowan,

2012). The Embedded Process Model further proposed that the active information held in attention, activates existing information from the long-term memory. Using this active information, the long-term memory is able to interpret the information. A further consideration is the development of new pathways with the acquisition of new knowledge.

Similar to the Multicomponent Model, the Embedded Process Model also assumes that the central executive allows for the focus of attention. In the Embedded Process Model, however, the central executive also has the ability to search long-term memory. By doing so, new information from the focus of attention can be added or replaced to information within the long-term memory. Thus, the Embedded Process Model posited that WM operates at a functional level during which already established memories are activated by the information in the focus of attention. The information from the various modalities held in attention along with already established learned information can combine to form new pathways for the newly learned information which are then stored in long-term memory (Chai et al., 2018; Cowan, 2012). These activated functions both in attention and long-term memory are therefore able to assist in various cognitive tasks (Cowan, 2012, 2022). Based on the functioning of these models, it formed a basis onto which learning can be understood and the kinds of implications that impaired WM systems may have.

***Impact of WM on learning***

Numerous research studies have been conducted evaluating the predictive role of WM in the academic setting and the implications low WM may have on learning, for example, a longitudinal study by Ahmed et al. (2019) in which they examined the relationships between executive function components and academic achievement. WM, among other executive functions such as attention, planning and inhibition, was assessed at age 4.5 years and again at 15 years. The results of the study showed that only WM performance at 4.5 years was able to predict WM performance at age 15 years. Furthermore, it was also found that only WM significantly predicted achievement at 15 years of age. A study conducted by Napier (2015) investigated the predictive value of WM on academic achievement in three specific areas, namely, reading, mathematics and written expression. The sample consisted of adolescents aged 12 to 16 years with and without ADHD. Napier (2015) found that audio-verbal WM had significant predictive value on academic success and that visuospatial WM was significantly able to predict achievement in the areas of reading and mathematics only. Furthermore, deficits in WM were found to be more prevalent in the group with ADHD (Napier, 2015).

Additional implications have been shown for deficits in WM regarding academic achievement and drop-out rates. In a longitudinal study conducted by Fitzpatrick et al. (2015)

in a sample of 1824 children who were assessed at two- and three-years old, it was found that those who had low WM, had a higher risk of dropping out once they had reached high school. Comparatively, it was also found that for those had improved their WM scores overtime, the drop-out rate decreased by 26% (Fitzpatrick et al., 2015). A potential reason underpinning these difficulties may arise in the context of the classroom could be that as a result of poor WM abilities where lengthy instructions are often forgotten, and in turn, the ability to fully comprehend information is affected (Cowan, 2014).

Given these implications associated with WM, it is imperative to identify these difficulties early. Current screening and assessment measures, however, are not addressing these difficult (Nel & Grosser, 2016). Where these are available, such screening and assessment measures for domains such as WM are conducted in a way that is time-consuming and costly. Thus, a more efficient means of assessing WM may need to be adopted such as computerised measures for deficits in this area.

## Computer-based Testing and Pen-and-Paper Testing

Traditionally, many assessments, such as those used to assess cognitive deficits, make use of pen-and-paper neuropsychological tests. These tests are important for understanding and measuring complex cognitive processes (Casaletto & Heaton, 2017). The use of pen-and-paper based neuropsychological tools, however, are often time-consuming and costly, ultimately making them inaccessible (Casaletto & Heaton, 2017; Charchat-Fichman et al., 2014). It is for this reason that many traditional pen-and-paper neuropsychological tools have been converted to computerised versions resulting in a shift to using tools that are easily accessible and user-friendly (e.g., the Wechsler Adult Intelligence Scale [WAIS]; Wechsler, 2008).

Apart from conversions of existing tests, there has also been a move to more general use of computerised-based testing in neuropsychology (Casaletto & Heaton, 2017). The equivalence of computer-based testing and pen-and-paper testing have, however, often been questioned. To address this issue, the American Psychological Association (APA) formalised the Guidelines for Computer-based Testing and Interpretation in 1987 and highlighted the benefits of the shift. These benefits include self-administration and reducing administrative time (Canini et al., 2014; Feenstra et al., 2017).

### *Advantages and Disadvantages to using Computer-Based Testing*

There are many benefits and challenges when it comes to the use of computer-based testing. Some of the benefits of using computer-based testing include its accessibility and cost-effectiveness (Charchat-Fichman et al., 2014; Langenfeld, 2020). Traditional testing is

often conducted in a controlled setting to ensure accurate and meaningful results. This method, however, is often limited by the fact that it can only be conducted at a certain time and place. Where computer-based testing is accessible, individuals are at liberty to take tests at their own leisure which can be interrupted and continued at a later stage (Hagelkruys et al., 2016). Another advantage of computer-based testing is the ease of data collection. Traditional testing involves an expert supervisor scoring and making notes of the performance limiting the number of individuals that can be tested at one time. With computer-based testing, large numbers of individuals can be tested at any given time. Furthermore, storing data online allows one to compare and analyse large groups of data (Charchat-Fichman et al., 2014; Langenfeld, 2020). Another benefit of computer-based testing is the presentation of results as the system collates the data and elaborates on the results with graphs which aids in understanding the results (Hagelkruys et al., 2016). Additionally, computer-based testing is able to record response time more accurately than pen-and-paper testing (Charchat-Fichman et al., 2014; Hagelkruys et al., 2016).

Challenges of the using of computer-based testing include the lack of in-person supervision which is unique to traditional pen-and paper testing. As a result, there is a shift of responsibilities and roles. For example, the impact of this could lead to errors in execution such as clicking an incorrect response without the ability to self-correct (Hagelkruys et al., 2016). Furthermore, the qualitative aspect of testing is stripped away. In some cases, however, computer-based testing is able to analyse the behaviour of test-taker and generate a report by collating and analysing the data provided according to a database (Charchat-Fichman et al., 2014; Hagelkruys et al., 2016). Moreover, those unfamiliar with computers may have difficulty with executing the tests as a result of the user interface (Charchat-Fichman et al., 2014; Uleanya, 2022). While pen-and-paper testing and computer-based testing both have their flaws, these can be used in a complimentary fashion as they both have value in their testing. Furthermore, despite the challenges of computer-based testing, there are many programmes which are reportedly useful, such as the Learner Profiler (Do-It Profiler, 2016).

**The Learner Profiler**

The Learner Profiler (LP) is a computerised system that can be used for screening and assessment of LDDs. Initially, the LP was developed for educational settings and for induction into prisons in the United Kingdom (UK) to assess and capture information regarding any challenges an individual may have with learning (Do-It Profiler, 2016). Furthermore, it captures information regarding an individual’s demographics as well as

developmental and educational levels in relation to LDDs. Additionally, in its assessment of the individual, the LP takes account of the individual's social background (Do-It Profiler, 2016). In this way, the LP can deliver a person-centred approach.

The LP is based on pen-and-paper tools that have been translated into computerised versions (Kirby, 2016; Kirby & Saunders, 2015). It is software that has been developed by Ibis Consultants to assist in the identification of skills, strengths and weaknesses by monitoring and evaluating progress over time. Additionally, it also has an inbuilt Management Information System that provides multiple reports at person, group and institutional levels with recommendations based on the analysis of the information provided (Do-It Profiler, 2016; Kirby, 2014). Furthermore, the LP accounts for qualitative aspects by providing reports based on an individuals' responses while limiting the time taken for the screening to 30 minutes (Do-It Profiler, 2016). The LP is also able to assess an individual in their mother tongue (as it is can be made available in a range of languages, for example, Sepedi, Sesotho, isiXhosa, and isiZulu) and is disability accessible with a user-friendly interface. Despite success with its use in the UK, there is a dearth of literature investigating the predictive function of the LP for assessing LDDs both globally and within a SA population.

The LP has been used in four SA studies to date (see Appendix A for a summary of these studies). These studies investigate academic performance in relation to various factors such as the emotional aspects associated with academic achievement, housing conditions and the effects of school lunch predicting academic achievement (Pillay, 2017a, 2017b, 2018, 2021; Poh & Smythe, 2015). More closely, however and related to the current study, Poh and Smythe (2015) aimed to investigate the predictive ability of students' academic performance on the LP in a sample of FET college students. The study found that the LP was able to significantly predict academic performance as well as identify the variables that have predictive value such as access to daily running water, approaching lecturers for help, positive feelings towards the future; to mention a few (Poh & Smythe, 2015). While the LP has shown to have predictive value in academic performance, using WM scores to predict performance on other LP modules can provide further insight into the challenges learners and students may face and may also present a brief screening opportunity for such difficulties which could suggest the need for a more complete LP screen and consequent neuropsychological assessment. No studies to date have investigated whether WM predicts scores on other domains within the LP, however.

### Rationale

In summary, given the current state of the schooling system and the likely high rates of LDDs, screening for LDDs in schools is necessary in SA. This, however, may be challenging and impractical with formal one-on-one neuropsychological assessments. Although not without disadvantages, computerised testing presents an avenue for larger scaled screening for LDDs in schools. The LP is one such computerised screening tool. Overall, existing literature that has used the LP is limited and some of the sample sizes within existing studies, small. Thus, it may be beneficial to assess the usefulness of such a tool, especially in the context of LDDs and WM. WM has been shown to play a crucial role in learning and deficits in this area appears to be higher in the context of LDDs. There is one study demonstrating the predictive ability of the LP of academic outcomes, but none showing the predictive value of WM on other LP domains' scoring (Poh & Smythe, 2015). Thus, assessing the predictive ability of WM on other LP domains' scoring could assist in determining the overall capabilities of the LP as a screening measure for LDDs, and could potentially serve as a proxy (and briefer screen) for overall outcome on the LP.

## Aims and Hypotheses

The research aimed to report on a range of LDD LP domains for a sample of SA individuals attending a Technical Vocational Educational and Training (TVET) college (Part One) and to investigate whether the LP WM tool could successfully predict scores on other cognitive domains on the LP (Part Two). Thus, the hypothesis for Part Two was:

*The outcomes on the WM module on the LP can significantly predict outcomes on other computerised cognitive domains on the LP.*

## Method

The data for the current study was extracted from previously collected data, provided by Dt Ian Smythe from Ibis Consultants (owner of the LP). The reliance on such previously collected data was opted for after the original plan study, which relied on in-person data collection, was discontinued due to Covid 19 restrictions.

### Research Design and Setting

The study was quantitative in nature, with a within-subjects design. The data for the current study was collected in SA as part of the entry process into a Gauteng TVET college. The participants completed the LP WM, Visuospatial, Spelling, Word Choice, Missing Word, and New Word Spelling tasks on a computer during the normal admissions process at the

TEVT college. For Part One of the study, descriptive statistics were reported on for each of the LP outcomes. Additionally, between group differences were also reported on for each of the LP modules based on gender. For Part Two, multiple regression models were run with the scores on the LP WM as the predictor variable. The dependent variables are the scores for the Visuospatial, Spelling, Word Choice, Missing Word, and New Word Spelling tasks.

## Participants

The study participants were individuals aged 16 to 19 years, who were English-speaking and were recruited using convenience sampling. All participants were from SA and the TVET college which they attended is situated in an urban area. A total of 2142 participants aged 16 years and 21 years completed the LP. The participants also identified their preferred gender based on three categories, namely, female, male, and there was a third category for those who preferred not to disclose their gender. However, for the purposes of current study, the data for only 1175 participants were used as these participants had completed the WM module, obtained a score of more than zero (as those who scored zero either did not complete the WM module or completed it incorrectly) and matched the age criterion for the current study. I also decided to include an adolescents' cohort from the overall sample, first to limit the variation in age and also, because they are a vulnerable group who often go undetected in the context of LDDs (Boardman et al., 2016; Cortiella & Horowitz et al., 2014; Herrero-Romero et al., 2019). The exclusion criteria are based on whether participants completed the WM module on the LP and matched the age criterion.

These participants were invited to use the LP at the TVET with the potential of being accepted into their chosen college courses during normal admissions processes. Permission and access to the data for the current study was sought through Shaping the Learner (STL) which is the SA distributor for the LP. There is a contractual agreement between the college and STL as well as between STL and the Ibis Consultants (owner of the LP). Permission and access were done via personal communication.

## Measures

### *Computerised screening measure*

**Learner Profiler.** The LP is a computerised screening measure developed by Professor Ian Smythe. The LP originally formed part of the Do-IT Profiler screening tools which was mainly used in educational settings in prisons in the United Kingdom. More recently, the LP has been used during induction programmes such as at TVET colleges under

the LP domain-name alongside STL. The LP screens for and identifies challenges associated with LDDs through use of modules assessing areas such as English and Math skills as well as WM and visuospatial skills. Additionally, it is also able to gather demographic information regarding social background and developmental, educational, and current functioning (Do-It Profiler, 2016). The LP has been used in a few SA studies (see Pillay, 2017a, 2017b, 2018, 2021; Poh & Smythe, 2015). The feedback provided by the LP concerns ADHD, Autism Spectrum Disorder, Developmental Coordination Difficulties/Dyspraxia, Dyslexia, and developmental language difficulties. Although, a specific profile related to dyscalculia is not generated, such outcomes can be customised with the LP developers of the study.

For the current study, I focused on WM, language, and visuospatial. The WM task is audio-verbal which takes the form of a backward digit span. The LP WM module consists of 12 trials with each span of digits administered twice. Therefore, for each trial, the score can be translated into the number of digits recalled (i.e., the raw digit span). A score between one and two is a recalled list of two digits, three and four is a recalled list of three digits, five and six is a recalled list of four digits, seven and eight is a recalled list of five digits, nine and ten is a recalled list of six digits and lastly, 11 -12 is a recalled list of seven digits. The language modules consisted of spelling known and new words as well as a Word Choice and Missing Word tasks in which participants are required to choose or fill in an appropriate word. The visuospatial task involved showing 3D shapes of various angles with options of other shapes to match the ones shown on screen. For these remaining modules the scores are based on the total score for all items presented for that task. The tests of the LP has high reliability which ranges from 0.86 to 0.93 (Pillay, 2021). More specifically, the numeracy tests have good internal consistency with a Cronbach's *a* of 0.811 (Pillay, 2021). In SA studies, the LP has previously been used to assess literacy and numeracy abilities (see Pillay, 2017a, 2017b, 2018, 2021). It has also been used in another SA study to predict FET academic performance (see Poh & Smythe, 2015).

**Procedure**

Data was collected from participants upon entry into the TVET college by a group of UK researchers using the LP in SA TVET college setting. The participants were invited to complete the LP. The participants were not preselected for the current study and those who had completed the modules at the point of data collection during the normal admissions process at the TVET and met the criteria were included in this study. The participants were assessed in English at the time of data collection. All the participants ticked a box acknowledging their agreement to participate and complete the LP at the beginning of the

assessment. For those participants who were below the age of 18 years at the time of data collection, parental consent was sought during the admission process. In the agreement, all the known risks and benefits as well as issues of confidentiality were addressed.

## Data Analysis

The RStudio version 3.6.2 software was used to collate and analyse the data. The significance level or alpha was set at $p < .05$. For Part One, descriptive statistics have been provided for each of the modules on the LP. Additionally, descriptive statistics have also been provided for gender. Univariate analyses were also conducted between all the variables as well as between all the variables within each specific gender category. For Part Two, multivariate regression analyses were used to determine whether the WM module on the LP can successfully predict other outcomes within the LP. Before analyses was commenced, the data was checked and cleaned.

## Ethical Considerations

This study received ethical clearance from UCT's Department of Psychology Research Ethics Committee (reference number: PSY2020-034; see Appendix B). The data was collected as part of an entry process in to the TVET college. Permission for the use of the data was sought through Shaping the Learner (STL) which is the SA distributor for the LP. There is a contractual agreement between the college and STL as well as between STL and the Ibis Consultants (owner of the LP).

### *Informed consent and assent process*

Before the commencement of the data collection, all the participants ticked a box acknowledging their agreement to participate and complete the LP at the beginning of the assessment. For those participants who were below the age of 18 years at the time of data collection, parental consent was sought during the admission process. In the agreement, all the known risks and benefits as well as issues of confidentiality were addressed.

**Potential risks and benefits.** There were no added risks for the current study as the data had already been collected and was done so as part of normal admissions process to the TVET college. The benefit of participating in the data collection was for the potential to enter into their chosen courses.

**Confidentiality.** All students tick a box that acknowledges that all parties and their agents will have access to the data in order to act as "Data Processors" and that all data collected may be anonymised and analysed for research purposes. All of this is in compliance with the Protection of Personal Information Act (POPIA). All the data that has been provided

to the current study was anonymised and participants were given an identification number which does not contain any potential identifying information. The data was held on a password-protected laptop to avoid breach of confidentiality.

## Results

### Part One:

#### *Descriptive Statistics for All Study Variables*

The sample size for this study was $N = 1175$. The descriptive statistics for the variables of interest for this study are presented in Table 1. The descriptive information includes means (M) and standard deviations (SD) and distributions for the numerical variables for all the variables. All the participants fell into the required age range, with the average age of the participants being $M = 18.42$ years (see Table 1). In terms of the breakdown in age, 0.8% of the participants were 16 years ($n = 9$), 10.6% of the participants were 17 years ($n = 124$), 34.8% of the participants were 18 years ($n = 409$), and 53.9% of the participants were 19 years ($n = 633$).

From Table 1, it is noted that while none of the standard deviations are particularly large, they do suggest extreme skewness in some of the variables within the dataset. As can be seen, a number of variables have wide ranges in their scores. Furthermore, as can be seen in Table 1, spelling score and New Word Spelling tasks have identical averages which were particularly low ($M = 2.17$; $M = 2.17$) given that these are based on a score out of 48 and 16 items, respectively. For the WM score on average, the participants were able to recall five digits backwards ($M = 8.28$).

**Table 1:**

*Descriptive Statistics (N = 1175)*

| | M | SD | Min | Max |
|---|---|---|---|---|
| Age | 18.42 | 0.71 | 16 | 19 |
| WMS[a] | 8.28 | 3.40 | 1 | 12 |
| VSS[b] | 21.76 | 2.88 | 15 | 29 |
| SPS[c] | 2.17 | 2.05 | 0 | 14 |
| WCS[d] | 26.04 | 4.52 | 0 | 30 |
| MWS[e] | 27.59 | 2.39 | 17 | 31 |
| NWSS[f] | 2.17 | 2.17 | 0 | 14 |

*Note.* WMS = Working Memory Score, VSS = Visuospatial Score, SPS = Spelling Score, WCS = Word Choice Score, MWS = Missing Word Score, NWSS = New Word Spelling Score; [a] = Numeric variable (raw score based on 12 items, scores of 1-2 = 2 digits recalled, scores of 3-4 = 3 digits recalled, scores of 5-6 = 4 digits recalled, scores of 7-8 = 5 digits recalled, scores of 9-10 = 6 digits recalled, scores of 11-12 = 7 digits recalled), [b] = Numeric variable (raw score based on 32 items), [c] = Numeric variable (raw score based on 48 items), [d] = Numeric variable (raw score based on 30 items), [e] = Numeric variable ( raw score based on 32 items), [f] = Numeric variable (raw score based on 16 items).

For this dataset, there was a large amount of missing data, specifically for the Visuospatial task and Missing Word task. Of those who had completed the WM module, 138 participants completed the Visuospatial module (12%), 1149 completed the spelling module (98%), 1175 completed the Word Choice module (100%), 213 completed the Missing Word module (18%) and 1148 completed the New Word Spelling module (98%; see Figure 1 below). The completed rates (i.e., those participants who completed the task), for those variables are 12% and 18%, respectively. This could be due to attrition-related issues during the administration of the LP as participants may not have completed all relevant modules.

**Figure 1:**

*LP module completion rates*

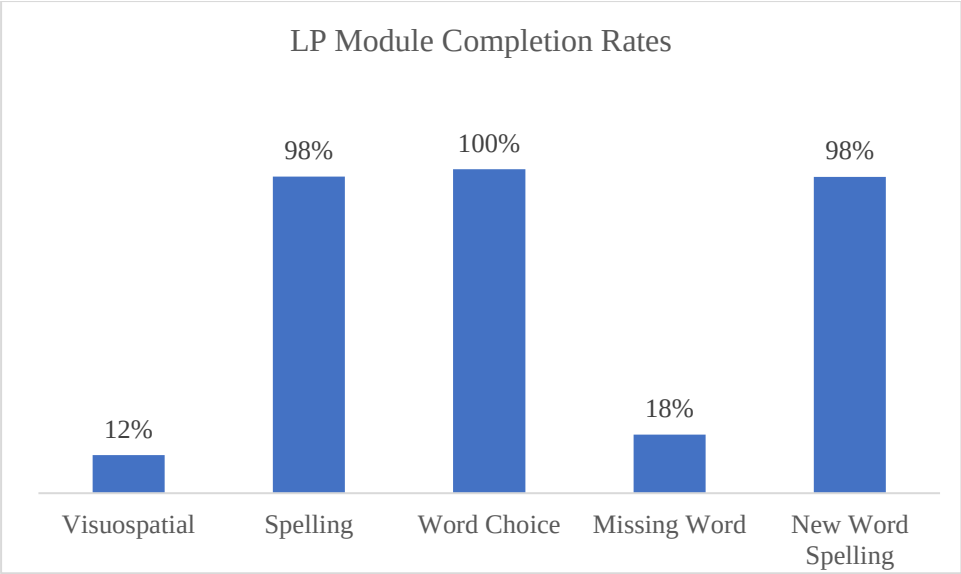
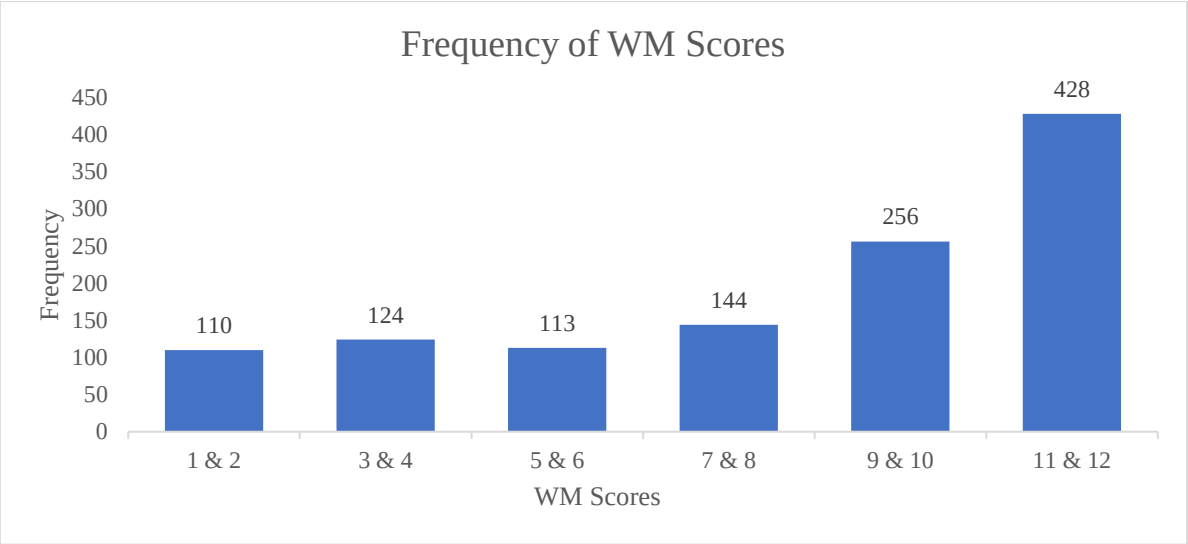



Figure 2 presents the frequency with which participants attained scores across each trial of the LP WM module. It can be noted that 12.3% of participants obtained a score between seven and eight which means that these participants were able to recall five digits. On the other hand, however, 36.4% of participants obtained a score between 11 and 12 which means that they were able to recall seven digits. On the lower end, 9.4% of participants obtained a score between one and two which means that these participants were able to recall only two digits, which suggests notable difficulties with WM.

**Figure 2:**

*Number of participants that scored in each category of the LP WM module*




The distribution plots (see Figures 3 to 8) showed that only Visuospatial scores are normally distributed. The scores for WM, Missing Word and Word Choice all have an extreme left skew which suggests that some participants seem to struggle on these tasks as they scored on the lower end of the spectrum. In contrast, the scores for the spelling task have an extreme right skew suggesting that some participants are much better at spelling than their peers who mostly scored quite low on this task (scoring zero or one).

**Figure 3:**

*Histogram showing distribution of scores for the LP WM module*

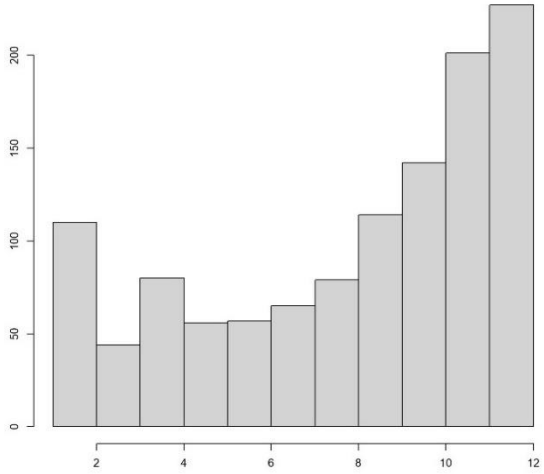



**Figure 4:**

*Histogram showing distribution of scores for the LP Visuospatial module*

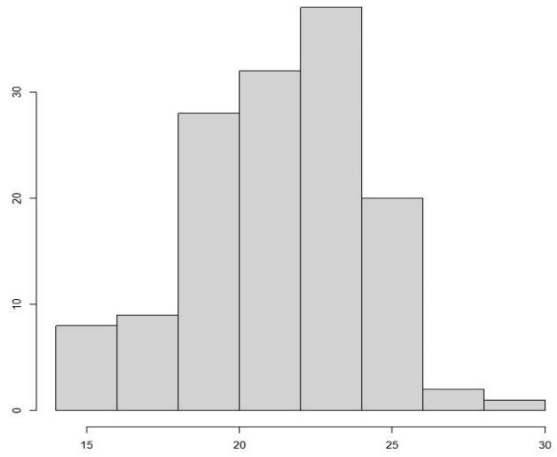



**Figure 5:**

*Histogram showing distribution of scores for the LP Spelling module*

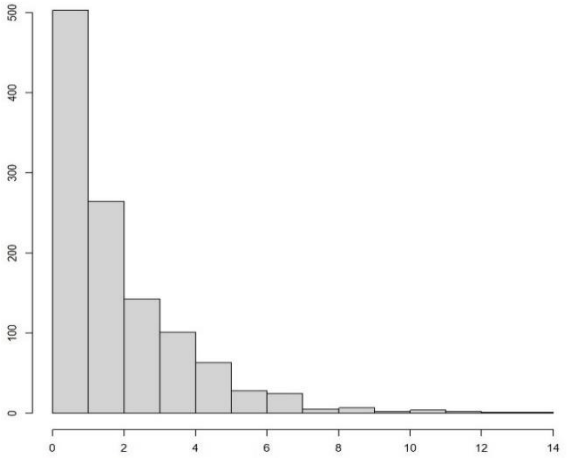



**Figure 6:**

*Histogram showing distribution of scores for the LP New Word Spelling module*

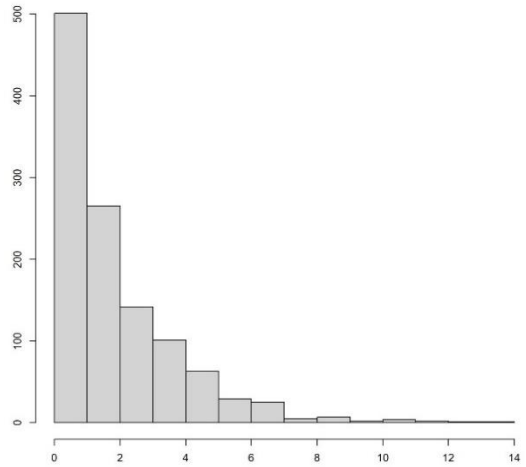



**Figure 7***:*

*Histogram showing distribution of scores for the LP Word Choice module*

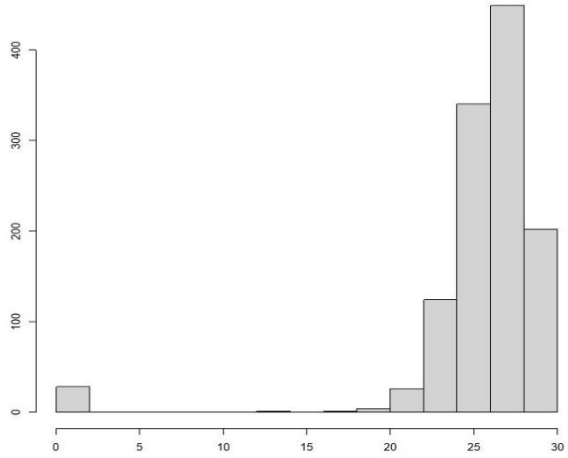
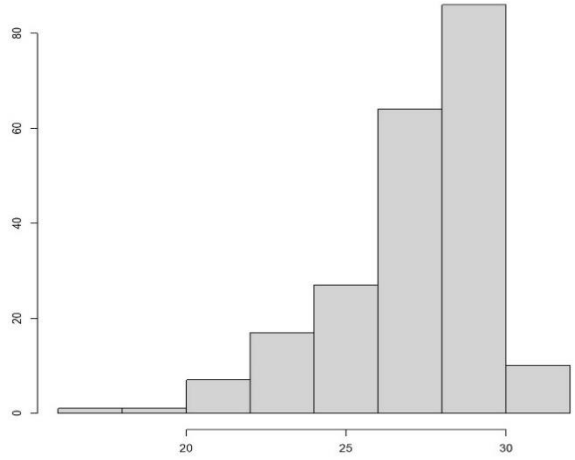



**Figure 8:**

*Histogram showing distribution of scores for the LP Missing Word module*



***Descriptive Statistics by Gender***

The descriptive statistics are reported for participants' gender across the study variables in Table 2. Regarding gender, participants in the study were requested to indicate whether they identified as female, male and or whether they preferred not to specify. The descriptive information includes means (M) and standard deviations (SD) and distributions for the numerical variables. Most participants were female (53,6%; *n* = 630/1175), and the least were preferred not to declare their gender (8,9%, *n* = 104/1175).

Overall, the averages for all the variables of interest grouped by gender were not particularly different from one another. For example, and specifically for WM, it can be noted that all participants, regardless of gender, were similar on average (*M* = 8.25; *M* = 8.16; and *M* = 8.97, respectively). The SDs for these groups are also relatively similar and are not particularly large or concerning but do suggest extreme skewness for some of the variables when grouped according to gender (WM scores and Word Choice scores).

**Table 2:**

*Descriptive statistics by gender*

| | Group | | | | | |
|---|---|---|---|---|---|---|
| | Female | | Male | | Prefer not to say | |
| | M | SD | M | SD | M | SD |
| Age | 18.40 | .70 | 18.39 | .74 | 18.64 | .52 |
| WMS[a] | 8.25 | 3.49 | 8.16 | 3.26 | 8.97 | 3.39 |
| VSS[b] | 21.58 | 2.61 | 23.50 | 2.71 | 21.52 | 2.89 |
| SPS[c] | 1.99 | 1.89 | 2.36 | 2.20 | 2.41 | 2.38 |
| WCS[d] | 26.19 | 3.82 | 25.88 | 4.94 | 25.80 | 6.26 |
| MWS[e] | 27.44 | 2.39 | 27.52 | 2.72 | 28.24 | 2.52 |
| NWSS[f] | 2.00 | 1.87 | 2.36 | 2.20 | 2.44 | 2.41 |

*Note.* WMS = Working Memory Score, VS = Visuospatial Score, SPS = Spelling Score, WCS = Word Choice Score, MWS = Missing Word Score, NWSS = New Word Spelling Score; [a] = Numeric variable (raw score based on 12 items, scores of 1-2 = 2 digits recalled, scores of 3-4 = 3 digits recalled, scores of 5-6 = 4 digits recalled, scores of 7-8 = 5 digits were recalled, scores of 9-10 = 6 digits recalled, scores of 11-12 = 7 digits recalled), [b] = Numeric variable (raw score based on 32 items), [c] = Numeric variable (raw score based on 48 items), [d] = Numeric variable (raw score based on 30 items), [e] = Numeric variable ( raw score based on 32 items), [f] = Numeric variable (raw score based on 16 items).

## Univariate Analyses

### *Correlational Analyses for LP Modules and Age*

Table 3 summarises the results of the correlational analyses. WM scores had the strongest association with Missing Word scores ($r = 0.26$, $p < 0.001$). This weak-moderate, significant, positive correlation suggests that there is some shared variance in performance on these tasks. This means that as WM scores increases, the participants were more likely to perform better on the Missing Word scores. However, the subtest completion rate, for Missing Word scores was 18%.

The other notable correlations were WM scores with spelling scores and new word spelling scores ($r = 0.09$, $p < 0.001$ for both), where the latter two variables appear to measure the same thing. These weak but significant correlations suggesting that some small proportion of variation in scores on spelling is associated with differences in WM scores. In other words, as WM score increases, participants were likely to perform better on the Spelling and New Word Spelling tasks. However, the high correlation between the two language domain variables (99%) suggests that either measure is sufficient but that using both is redundant. Regarding age, there were mostly weak correlations with the strongest being with the Visuospatial task; however, this association was still very weak and not significant ($r = -0.11$, $p > 0.99$).

**Table 3:**

*Correlations matrix*

| Variables | WMS | VSS | SPS | WCS | MWS | NWSS | Age |
|---|---|---|---|---|---|---|---|
| 1. WMS | - | | | | | | |
| 2. VSS | .18 | - | | | | | |
| 3. SPS | .10* | .15 | - | | | | |
| 4. WCS | -.02 | .03 | .13 | - | | | |
| 5. MWS | .27* | .04 | .32 | .39 | - | | |
| 6. NWSS | .10* | .14 | .99* | .12 | .32 | - | |
| 7. Age | .00 | -.11 | -.06* | .00 | .04 | -.06* | - |

*Note.* WMS = Working Memory Score, VS = Visuospatial Score, SPS = Spelling Score, WCS = Word Choice Score, MWS = Missing Word Score, NWSS = New Word Spelling Score. *$p$ <.05, **$p$<.001

### *Correlation Analyses for Gender*

For the correlational analyses for gender (see Appendix C), the outcome variables were split according to gender and analysed in that manner. It showed that for group differences by gender WM scores and Missing Word scores are correlated for the female participants ($r = 0.28$, $p = 0.002$) but not for male or participants who preferred not to disclose this. In other words, for those in the female category, when WM scores increased, these participants were likely to perform better on the Missing Word task. In contrast, Visuospatial scores are significantly related to WM scores for males ($r = 0.21$, $p = 0.003$) but not for female or prefer not to say participants. This means that for those in the male category, when WM scores increased, these participants were likely to performed better on the Visuospatial task. Given that the sample size for those who preferred not to declare their gender was small ($n = 104/1175$; 8.9%), significant weak correlations cannot be expected.

### *Analysis of Variance (ANOVA)*

Before conducting the ANOVA analyses, assumptions were explored, and it showed that the assumptions for homogeneity of variance and normality were only upheld for one dependent variable (Visuospatial) and not upheld for the remaining dependent variables and independent variable. In spite of the violations, ANOVAs were run as this test is robust against violations of this nature. However, it is important to note that generalisability of these findings to other populations is limited (Field, 2012; Tredoux & Durrheim, 2002). Effect sizes are reported for models that have reported significant main effects.

**Age.** The analysis detected significant main effect for gender, $F(2, 1172) = 5.88$, $p < 0.001$, $\eta_p^2 = 0.01$. A post-hoc Tukey's test showed that there was no difference between females and males, $p = 0.99$. Notably, both males and females were approximately 3 months younger than those who preferred not to disclose their gender; $p = 0.003$ and $p = 0.002$ respectively.

**WM.** The analysis detected no significant main effect for gender, $F(2, 1172) = 2.46$, $p = 0.08$. Given the skewness of the data, a logarithmic transformation was run for WMS and produced the same result, i.e., there was no significant main effect for gender, $F(2, 1172) = 1.29$, $p = 0.27$.

**Visuospatial.** The analysis detected a significant main effect for gender, $F(2, 135) = 3.41$, $p < 0.001$, $\eta_p^2 = 0.05$. A post-hoc Tukey's test showed that there was no difference between males and females, $p = 0.12$, and no difference between females and participants

who preferred not to state their gender, $p = 0.99$. However, there was a significant difference between males and participants who preferred not to state their gender with males scoring significantly higher on this task ($B = 1.98$, $p = 0.028$).

**Spelling.** The analysis detected a significant main effect in spelling across gender, $F(2, 1146) = 4.84$, $p < 0.001$, $\eta_p^2 = 0.01$. A post-hoc Tukey's analysis was run and showed that females had significantly lower scores than males ($B = -0.37$, $p = 0.012$). Given the skewness of the data, a logarithmic transformation was also run for SPS and produced a similar finding with a slightly smaller effect ($B = -0.16$, $p = 0.04$).

**Word Choice.** The analysis detected no significant main effect for gender, $F(2,1172) = 0.75$, $p = 0.47$.

**Missing Word.** The analysis detected no significant main effect for gender, $F(2, 210) = 1.49$, $p = 0.23$.

**New word spelling.** The analysis detected a significant main effect for gender, $F(2, 1145) = 4.89$, $p < 0.001$, $\eta_p^2 = 0.008$. A post-hoc Tukey's test shows that females scored significantly lower than males ($B = -0.36$, $p = 0.014$).

**Part Two:**

***Multiple Regression Analyses for the LP modules***

An initial linear model and multiple regression model was analysed and formed as preliminary findings (see Table 4). A linear regression model was run with working memory scores as the predictor and spelling scores as the outcome variable. The spelling task was chosen for the initial analyses because it had a significant, albeit weak, correlation with WM while also having a high completion rate (98%). The report for the preliminary model was predictive overall, $R^2 = 0.01$, $F(2,1146) = 7.71$, $p < 0.001$, as well as for the WM variable ($B = 0.06$, $p < 0.001$). This preliminary model suggests that WM can significantly predict spelling score, although, it only explains a small proportion of the variance which is less than 1%. Therefore, it may be that WM is not a good predictor of spelling ability. Additionally, based on the correlations reported for WM and gender, a second preliminary multiple regression model was run with WM and gender as the predictor variables, spelling score as the outcome variable and age as the control. The overall model has predictive value, $R^2 = 0.02$, $F(6, 1142) = 4.69$, $p < 0.001$. However, once gender and age are considered, WM loses its predictive value ($B = 0.03$, $p = 0.14$). Notably, males in the sample were better at spelling ($B = 0.38$, $p$

<0.001). In spite of this finding, the variance accounted for by this model is only 2% which is considerably low.

**Table 4:**

*First round of regression models*

| | | Model statistics | | | Coefficients | | | |
|---|---|---|---|---|---|---|---|---|
| | | $R^2$ | *F(df)* | *p* | *B* | *SE* | *t* | *p* |
| PrelimSPS | | .01 | 7.71 (2, 1146) | <.001** | | | | |
| | PrelimWMS | | | | .06 | .17 | 3.33 | .04* |
| | Age | | | | -.17 | .08 | -2.08 | .04* |
| PrelimSPS | | .02 | 4.69 (6, 1142) | <.001** | | | | |
| | PrelimWMS | | | | .03 | .02 | 1.49 | .14 |
| | Gender | | | | .38 | .13 | 2.97 | <.001** |
| | Age | | | | -.18 | .08 | -2.18 | <.03* |

*Note.* PrelimSPS = preliminary analyses for Spelling Score, PrelimWMS = preliminary analyses for Working Memory Score, *$p$ < .05, **$p$ <.001

Given the large sample size, it is possible for significant correlations and regressions to be produced purely on this basis. Additionally, only one variable (Visuospatial) appears to meet assumptions of normal distributions while others have extreme skewness to either the left or right. Therefore, based on these factors undermining the correlations and regressions, a smaller sample was selected to investigate whether there would in fact be a difference between a larger sample and a smaller sample. The smaller sample was chosen based on the those who scored 0 on the spelling task excluded. On this basis, the smaller sample size was $n$ = 899.

For the reasons discussed above, a second round of multiple regressions were run. The first model was run with WM and gender as the predictor variable and spelling as the dependent variable and age as the control variable using the smaller sample size, $N$ = 899. This constituted as the first model. While the model reported that there was a significant relationship, the overall variance accounted for was negligible; $R^2$ = 0.02, $F$(6, 1142) = 4.68, $p$<0.001. This suggests that the significance of this model represents an artifact of the sample size rather than a representation of the relationships within the data. Therefore, it was determined that multiple linear regression models needed to be run on the untransformed data

for all the study variables to investigate the significance of the relationships between the predictor variable and the outcome variables. Overall, most models reported significant relationships, except Word Choice. Furthermore, age was also only found to be predictive for Spelling ($B$ = 0.18, $p$ = 0.03), however, it only accounts for 1.8% of the variance which is considerably small. Each model will be explained and is summarised in Table 5. For each separate multiple regression model, the variables WM and gender were used as predictor variables and age was used as a control variable. The remaining variables were the dependent variables.

The second model reported that WM was able to predict scores on Visuospatial, $R^2$ = 0.09, $F$(6, 131) = 2.32, $p$ = 0.03. However, the overall variance of this model is 9% which is small but slightly better than the variances for the other variables. This model is, however, problematic as it beckons the plausibility of a confounding factor playing a role. For example, possible attrition-related confounds could have affected the results as 1000 participants were excluded due to missing scores. Furthermore, this model also showed that gender predicted performance on the Visuospatial task more so than WM task.

The third model reported that WM scores does not predict scores on Word Choice, $R^2$ = 0.002, $F$(6, 1168) = 0.44, $p$ = 0.85. Therefore, scores on the WM task does not predict the scores on the Word Choice task. However, this model also only accounts for less than 1% of the variance which is significantly small.

The fourth model reported that WM scores was able to predict scores on Missing Word, $R^2$ = 0.08, $F$(6, 206) = 3.07, $p$ = 0.006. This model reports that scores on WM task does determine scores on the Missing Word task. Overall, this model explained 8% of the variance, which is slightly better than the other models, however, it is small. Furthermore, 962 participants were excluded from this model due to missing scores which is also problematic.

The fifth model reported that WM scores was able to predict scores on new word Spelling, $R^2$ = 0.02, $F$(6, 1141) = 4.70, $p$ < 0.001. Therefore, scores on the WM task are able to determine the outcomes on the new word Spelling task. However, this model explained about 2% of the variance.

While most of these models produced significant results, these models are not useful in determining whether the scores on the LP WM module is in fact a good predictor variable for determining outcomes on other LP modules as the variance that is accounted for in each model is significantly small. Preliminary findings also showed that while WM is predictive for outcomes on other variables, the variance is low. Furthermore, when gender is accounted

for, WM loses its predictive value. Therefore, a smaller sample ($n$ = 899), with those who scored zero on the Spelling task excluded, was derived from the larger sample to investigate whether significant results would have been produced. While this did in fact produce significant results, the variance was negligible. Thus, during the second round, subsequent models were reverted to include all the untransformed data within the larger sample, and the results showed that WM scores significantly predicted scores on the Visuospatial, Missing Word, and new word Spelling tasks. However, the variances for each were small. Together, the significant models only explain about 21% of the variance which is still considerably low. Furthermore, these models violate assumptions of normal distributions and homoscedasticity, suggesting that they have poor model fit. For those models which did produce significant results and can therefore be considered the 'best' models, the only characteristic for those models is that they have complete data, i.e., that most participants completed the task. Those models with completed data explain less than 4% of the variance which is very low.

**Table 5:**

*Second round of regression models*

| | | Model statistics | | | Coefficients | | | |
|---|---|---|---|---|---|---|---|---|
| | | $R^2$ | *F(df)* | *p* | *B* | *SE* | *t* | *p* |
| SPS | | .02 | 4.69 (6, 1142) | <.001** | | | | |
| | WMS | | | | .03 | .02 | 1.49 | .14 |
| | Gender | | | | -.12 | .33 | -.36 | .71 |
| | Age | | | | -.18 | .08 | -2.18 | 0.03* |
| VSS | | .09 | 2.31 (6, 131) | .03* | | | | |
| | WMS | | | | .09 | .24 | .38 | .70 |
| | Gender | | | | 2.02 | .99 | 2.04 | .04* |
| | Age | | | | -.50 | 0.44 | -1.14 | .25 |
| WCS | | .002 | .0.44 (6, 1168) | .84 | | | | |
| | WMS | | | | -.003 | .05 | -.06 | .95 |
| | Gender | | | | -.39 | .28 | -1.12 | .26 |
| | Age | | | | .02 | .19 | .11 | .91 |
| MWS | | .08 | 3.07 (6, 206) | .006* | | | | |
| | WMS | | | | .18 | .06 | 3.07 | .002** |
| | Gender | | | | -.02 | .35 | -.06 | .95 |
| | Age | | | | .16 | .28 | .59 | .55 |
| NWSS | | .02 | 4.70 (6, 1141) | <.001** | | | | |
| | WMS | | | | .03 | .02 | 1.48 | 0.14 |
| | Gender | | | | .37 | .12 | 2.93 | 0.003** |
| | Age | | | | -.18 | .08 | -2.12 | .03* |

*Note.* WMS = Working Memory Score, VSS = Visuospatial Score, SPS = Spelling Score, WCS = Word Choice Score, MWS = Missing Word Score, NWSS = New Word Spelling Score. * $p$ <.05, **$p$ <.001

Based on these results, a final set of models were considered with transformed logarithmic data (see Table 6). Overall, the models reported significant relationships with WM scores predicting scores on new word spelling ($R^2$ = 0.009, $F$(1, 897) = 4.36, $p$ = 0.03), Spelling ($R^2$ = 0.005, $F$(1, 897) = 4.33, $p$ = 0.04), Word Choice ($R^2$ = 0.007, $F$(1, 1145) = 8.43, $p$ <0.001), and Missing Word ($R^2$ = 0.089, $F$(1, 211) = 20.7, $p$ <0.001). However, the variances explained by these models are very small. Thus, it can be concluded that despite transforming the data, the models are not predictive as the models have no predictive value and violates all assumptions. Furthermore, transforming the data has had no noticeable effect on the models which suggests that skewness is not the issue. Rather, it seems that the variables are not strongly related, and that they do not co-vary. As such, scores on the LP WM module not predictive of scores of the other modules on the LP.

**Table 6:**

*Regression on log transformed variables*

| Dependent variable | Predictors | *B* | *SE* | 95% CI | | *p* | $R^2$ |
|---|---|---|---|---|---|---|---|
| | | | | *LL* | *UL* | | |
| LogNWSS | LogWM | .23 | .07 | .08 | .37 | <.001** | .009 |
| LogSPS | LogWM | .07 | .04 | .00 | .14 | .04* | .005 |
| LogWCS | LogWM | .01 | .00 | .01 | .01 | <.001** | .007 |
| SqRMWS | LogWM | .08 | .02 | .06 | .10 | <.001** | .089 |

*Note.* Log NWSS = logarithmic transformation of New Word Spelling Score, Log SPS = logarithmic transformation of Spelling Score, LogWCS = log transformation of Word Choice Score, SqRMWS = square root of Missing Word Score, Log WM = logarithmic transformation of Working Memory Score, *$p$ <.05, **$p$ <.001

## Discussion

LDDs have become the most frequently diagnosed of the childhood developmental disorders with prevalence rates ranging between 15% and 17% (Farhad Pour et al., 2022). Notably, however, prevalence rates in SA remain undetermined. A potential reason for this is arguably that there are no known standardised and nationally accepted tools to screen for and identify those with LDDs. Moreover, SA is also characterised by numerous contextual vulnerabilities which may be construed as contributory factors to defining LDDs. Common

contextual vulnerabilities may include challenges in the educational setting, such as overcrowded classrooms, a lack of adequately trained teachers, and resource-constrained schooling facilities which may in turn impact a child's ability to learn within the classroom. Moreover, the unequal socioeconomic landscape of the country, which results in poor living conditions, under-nourishment, and a lack of access to basic services for parts of the population, may also disrupt learning, as it places emotional stress on a child, ultimately causing a disruption in engagement with learning (Nel & Grosser, 2016). These vulnerabilities may, therefore, pose further obstacles to diagnosing LDDs, further contributing to the uncertainty of prevalence rates. Given the global prevalence rates and commonality of LDDs, prevalence rates in SA may, therefore, arguably be as high, if not higher, particularly in circumstances where numerous contextual vulnerabilities are likely to be at play.

Notwithstanding the contextual and socioeconomic considerations, there are also cognitive factors to consider in the context of LDDs. WM has been reported in the literature as playing a crucial role in learning and, similarly WM deficits have previously been reported to be high in the context of LDDs (Friso-van den Bos & van de Weijer-Bergsma, 2020) . As WM is closely related to attention, it therefore plays a role as a gateway function to other cognitive functions (Angelopoulou & Drigas, 2021). Against this background, screening for LDDs is evidently necessary, but in particular, in SA schools. This, however, poses challenges of its own given a lack of resources to support such screening and thus the formal diagnoses of LDDs.

One such challenge, which is particularly common, is the issue of costs. Neuropsychological assessments are often conducted on an individual basis and can, therefore, be time-consuming and costly. Computer-based testing, on the other hand, however, presents an avenue for screening of LDDs on a larger and thus more cost-effective scale, rendering it particularly useful in settings such as schools. The LP is an example of such computer-based testing. It should be noted, however, that research on the LP test method is particularly limited due to both a scarcity in the literature and the use of small sample sizes in said literature.

The aim of this research was, therefore, to report on a range of LDD LP domains in a sample of SA individuals attending a TVET college, noting any gender related differences. Further, it aimed to investigate whether the WM module of the LP could successfully predict scores on other computerised cognitive domains on the LP. Although research has often demonstrated that WM does indeed predict learning outcomes on a range of other cognitive

domains, there is a notably scarcity in of literature specifically looking at the LP and more so, in the context of SA.

**Summary of Results**

In terms of the descriptive characteristics, a substantial proportion of the sample scored above what is typically expected for an audio-verbal WM task which is four units of information for the adult population. The score or number of digits recalled for this sample was five digits. Approximately, 12% of the sample were able to recall five digits in a backward fashion. There was, however, a significant percentage of participants in the sample (36%), who were able to recall seven digits in a backward fashion. Among those who could be identified as having difficulties with WM, approximately 9% participants were only able to recall two digits.

In terms of the other domains that were investigated, the participants who completed the Spelling and new word spelling tasks scored poorly, on average, obtaining scores of approximately two out of 48 and 16, respectively. The scores on these tasks may, however, not be a true reflection of the participants' performance as many participants scored 0 on these tasks suggesting a lack of engagement or completion thereof. As previously discussed, the completion rates for Visuospatial and Missing Word were significantly low with only 12% and 18% of the participants completing these tasks, respectively. The scores obtained on these tasks were, however, on average, 21 out of 32 and 27 out of 31. While the poor completion rate for these tasks reduces the variability given the reduced sample sizes and given the ranges in the scores on other tasks where a higher percentage of the sample completed it, the measures of Visuospatial, Missing Word, Spelling and New Word Spelling may not accurately reflect the true performance of the sample. The question of attrition-related confounds therefore arises which may arguably be the reason for the measure outcomes as opposed to what their actual performance should reflect had those confounds been addressed.

In terms of how these domains compare across gender, for all the categories (female, male, and those who preferred not to specify) participants scored within the same range for the WM. Hence, there were no differences across gender. These scores suggest that on average, the participants were able to recall five digits backwards. Notably, however, for the Visuospatial task, males performed significantly better than those who preferred not to specify their gender. Moreover, on both the Spelling and new word spelling, males performed significantly higher than females. For the Word Choice and Missing Word, no significant differences were found in performance across gender.

The regression analyses for the effect of age on the LP modules demonstrated that age was significantly capable of predicting scores on the Spelling task. Specifically, it demonstrated that younger participants were likely to perform better than older participants. The explained variance, however, was considerably small, accounting for less than 1%. The regression analyses for the LP WM and the other LP modules indicated that WM was able to significantly predict scores on the Visuospatial, Spelling, Missing Word, and New Word Spelling tasks. It also indicated that WM does not predict scores on the Word Choice task. However, for each of the regression analyses, the variances produced were significantly small. Age only significantly scores on the Spelling task, however, the variance accounted for was considerably low. This suggests that there may be other factors which account for the variance within each model. I discuss each of the main findings for each domain in relation to current literature below. In addition, I discuss possible attrition-related confounds that may have influenced the results of this research.

**WM as a Predictor Variable**

Research on WM has produced mixed findings in terms of its predictive value in other cognitive domains. For example, some research findings report positive outcomes in terms of WM predicting outcomes in other cognitive domain (Bigozzi et al., 2021; Meneghetti et al., 2016; Stipek & Valentino, 2015; Wang et al., 2018) and others do not (Haring, 2016; Paz-Baruch, 2022; Peng et al., 2018). These findings may, in part, be due to the administration modality (e.g., either audio-verbal or visual) used to predict outcomes on other cognitive domains. WM is believed to be a multicomponent system which is made up of domain-general components (such as the central executive and episodic buffer) and domain-specific components (such as the audio-verbal and visuospatial; Baddeley, 2012). The assessments used to evaluate WM, therefore, appear to tap into the different components of WM. For example, the Digit Span backward test, as the one used in the current study, taps into the phonological loop as it is based on audio-verbal information whereas the Spatial Span test, used in other research studies, taps into the visuospatial component (Wang & Carr, 2019). The findings from relevant literature further demonstrates that while WM can predict outcomes on other cognitive domains, these findings may not consider modality. In other words, the modality used within testing needs to be consistent in order to evaluate the predictive value of WM.

**WM and Visuospatial Skills**

Findings from existing literature show that WM plays a role in visuospatial skills (Meneghetti et al., 2016; Wang et al., 2018). Although, the current study has demonstrated

that the LP WM task was able to predict performance on the Visuospatial tasks, the variance accounted for, albeit significant, was small.

A study conducted by Meneghetti et al. (2016) examined the relationship between visuospatial and spatial rotation abilities. Both Corsi blocks and Digit Span backward tasks were used, with the former assessing visuospatial WM and the latter assessing verbal WM. For that particular study, 83 female participants were firstly assessed on their visuospatial WM and verbal WM skills. Thereafter, they were required to learn three navigation routes in a garden on a video in which they needed to retrace and consolidate those routes, draw the routes on paper and then had to find a shortcut of all three routes when they are all assembled. This task was used to assess their spatial abilities (Meneghetti et al., 2016). The results showed that the performance on the Corsi blocks correlated with their visuospatial performance in learning to navigate. The Digit Span backward task, however, did not demonstrate any correlations with visuospatial performance, likely due to differences in modality. This may be the case for the current study, as the modalities used to assess WM and visuospatial performance were not consistent.

The findings of Meneghetti et al. (2016) are supported by Wang et al. (2018) who investigated the relationships between executive functioning, visuospatial WM, verbal WM and spatial ability in a sample of 144 adults. Spatial ability for this study was defined as mental rotation. This study made use of both Digit Span backward and a backward Spatial Span tasks to assess verbal WM and visuospatial WM, respectively. To assess mental rotation, it made use of the Vanderberg-Kuse Mental Rotation Test and the Tower Test which has a secondary visuospatial component. The findings from this study showed that visuospatial WM accounted for more variance than verbal WM on individual outcomes on the mental rotation task (Wang et al., 2018). This suggests that the domain-specific component, i.e., visuospatial WM does in fact play a role in tasks assessing visuospatial performance.

It is contended that verbal WM is involved in learning visuospatial information, however, it is not to the degree that visuospatial WM is involved in learning visuospatial information (Gras et al., 2013; Meneghetti et al., 2016). The WM task used in the current study took the form of an audio-verbal task, as the numbers are only dictated and do not appear on the screen and therefore, the WM score only partially accounted for some effect in the visuospatial performance. This may demonstrate that there are domain-specific constructs that are activated when a specific task is being performed.

To my knowledge, in the only SA study on this topic, conducted to date, Fisher (2008) found that WM abilities using computer-based neuropsychological tests, gave rise to a myriad of concerns with regards to the appropriateness of some of the WM tests, their outcomes, and their influence on other cognitive domains. One such concern was that the Digit Span Test, which is typically audio-verbal, may not have been appropriate for the context of the study. In other words, the Digit Span Test may not have translated well on a computerised version as it required the participants to type in their answers which ultimately threatened the validity of the test. Traditionally, in audio-verbal face-to-face Digit Span tests, participants are required to verbally reproduce their answers (Fisher, 2008). Similarly, this too may have been case for the current study as participants were also required to type their answers in a textbox rather than verbally reproducing their answers.

Another study conducted by Haring (2016) also raised similar concerns in investigating the predictive value of WM, intelligence, and mathematical performance using computer-based testing. Haring (2016) found that there was no correlation between these constructs. Therefore, it may also be that methodological confounds were at play such as making use of computerised versions of tests which are measuring domain-specific constructs of WM. Thus, for the current study, the LP WM task that was administered, may only be predictive of other cognitive outcomes which are similar in administration in terms of tapping either audio-verbal or visuospatial functions.

**WM and Literacy**

For the purposes of this study, the Spelling, Missing Word, New Word Spelling, and Word Choice tasks will be grouped together and discussed in the context of literacy. According to Peng et al. (2018), WM allows one to manipulate and decode verbal language into various parts such as syllables, phonemes, and graphemes which is known as phonological processing. At the same time, WM allows for simultaneous retrieval of phonological information (Peng et al., 2018). Deficits in these areas have implications for word reading and ultimately, comprehension as it could be difficult to access language-based information while simultaneously keeping visual or verbal information in mind (Alloway & Copello, 2013).

The results of the current study showed that WM was capable of predicting performance on the Spelling, Missing Word, and new word tasks, however, the results are negligible as the variance accounted for in this study was small. For the Spelling, Word Choice and new word Spelling tasks, each accounted for 2% of the variance and the Missing Word task accounted for 8% of the variance.

Following an initial assessment of the literature in which the association between WM and literature is considered, there have been mixed reports on the predictive value of WM. While certain studies appear to conclude that WM does indeed predict performance on literary tasks (Bigozzi et al., 2021; Stipek & Valentino, 2015), others conclude that the predictive value of WM on literacy performance is grade-dependent (Paz-Baruch, 2022; Peng et al., 2018).

Current literature reports that WM plays a role in the development of vocabulary which includes reading ability, spelling, and comprehension. A longitudinal study conducted by Stipek and Valentino (2015) investigated the associations between academic achievement, attention, and memory amongst six thousand learners from age five to age 14 years to track academic trajectories. The results showed that working memory was a robust predictor of reading skills (Stipek & Valentino, 2015).

Regarding spelling accuracy, a study conducted by Bigozzi et al. (2021) investigated the effects of WM on spelling accuracy in a sample of 112 grade two and three learners. By looking at the number of homophone errors made by grade two learners, they found that visuospatial WM in particular played a significant role in spelling accuracy. Bigozzi et al. (2021) state that increased skills in WM is linked to higher spelling accuracy as it is a necessary skill that allows individuals to avoid making errors. Specifically, visuospatial WM is needed for choosing the correct orthographic representations of auditory and/or verbal information. However, for grade three learners, it was found that WM does not to appear to predict spelling accuracy. These learners were assessed one year later, and the same result was found – WM did not predict spelling accuracy. A potential conclusion on the disparity between these results was that by grade three, writing skills has started becoming automatised requiring less WM demands (Bigozzi et al., 2021). Of course, these results cannot be generalised to the current study given the differences in the average age of the samples.

Further, Alloway and Gregory (2013) investigated the predictive role of WM in the intelligence in a sample of participants aged 17 to 58 years. The results showed that WM still plays a role across multiple literacy skills such as word reading and spelling in the adult population, making the largest contribution to spelling skills. It is stated that this finding may be due to unfamiliar words used in their measures. This is supported by Peng et al. (2018) who conducted a meta-analysis and found that WM was strongly associated with word-reading of non-words. A possible explanation for this finding could be that more resources are being employed to decode the non-word into their grapheme, phoneme, and syllables (Peng et al., 2018). Moreover, it is stated that the contribution made by WM is modest and

that by adulthood, processes such as word-reading and spelling become automatised (Alloway & Gregory, 2013). This may be the case for the current study as for this sample of adolescents, WM only accounted for a small amount of variance. The discrepancy in these results could be due to many reasons.

One such reason that has been put forth in the literature is that the role played by WM may be grade dependent (Paz-Baruch, 2022). Researchers have argued that WM's role is more significant in early years compared to later adolescence and adulthood. According to Peng et al. (2018), the role WM plays in phonological processing is most prevalent in early childhood. Peng et al. (2018) state that in early childhood, verbal knowledge is still undergoing development and therefore literacy skills are less automatised. Thus, during early childhood, significantly more WM resources are being employed to build foundations for phonological awareness such as coding and decoding processes. This process appears to be most prominent before grade four and then become less prominent in grade four and beyond (Paz-Baruch, 2022; Peng et al., 2018). Therefore, it could be suggested that by adolescence and adulthood, the use of WM in literacy domains become less of a demand.

Given that the current sample was made up of adolescents, this may be a possibility for the findings produced as the variance accounted for within each literacy subtest was small. This suggests that the skills employed for literacy have become automatised and participants required less WM demands. Apart from WM, there are many other factors which predict literacy skills and performance. These include both cognitive factors as well as environmental and social factors. For example, for the cognitive factor, other than WM, there are also other executive functions that predict literacy performance such as inhibition and planning skills (Dekker et al., 2017). Regarding social and environmental factors, these include the background of an individual such as socioeconomic status, quality of education received, exposure to educational experiences (Arrimada et al., 2020; Bakken et al., 2017; Webb & Williams, 2018). Furthermore, for the current study, the tasks used to assess literacy (i.e., Spelling, Missing Word, Word Choice and new word Spelling) were measured using different modalities. Thus, the inconsistency in modality may have also influenced the results of the current study.

**Gender Differences**

The current study found that there were no differences for WM across gender categories, a finding, which to an extent, is in line with existing literature. For example, in a study conducted by Wang and Carr (2019) wherein they investigated differences between gender, WM and spatial ability, it was found that there were no gender differences in terms of

WM and spatial ability outcomes. However, this finding may have been due to methodological issues in relation to the measures used. Wang and Carr (2019) state that differences may not have been elicited as they made use of a simple backward spatial span which may have been less cognitively demanding. Another study conducted by Saylik et al. (2018) showed that there were gender differences in their results, but that these differences were only apparent when certain conditions of WM were assessed. From their findings, it appears that men performed better on a spatial WM task. However, the difference in performance was not significant. Like the previous study, a significant difference may not have been elicited due to the nature of the task used, which in this case was a simple spatial WM span.

Despite the lack of differences in gender for WM outcomes, the current study found that there were some significant differences in the tasks administered across the three categories for gender for visuospatial, Spelling, and new word Spelling tasks.

Regarding the differences in Visuospatial scores, this was only apparent between males and those who preferred not to specify their gender, with males performing significantly better. There was no significant difference between males and females which contradicts existing literature. In a study conducted by Barel and Tzischinsky (2018), which looked at gender differences in visuospatial abilities in a sample 157 adults of which 80 were female and 70 were male, a 3D mental rotation task was administered to the adult sample similar to the one administered in the current study. It was found that males significantly outperformed females. This finding is supported by Castro-Alonso and Jansen (2019) who conducted a meta-analysis on gender differences for multiple spatial assessments and found that only on 3D mental rotations task, males tendered to outperform females but not on other 2D mental rotation tasks.

Regarding the differences in gender for the Spelling and new word Spelling tasks, results showed that females obtained significantly lower results on these tasks of spelling than males. This finding contradicts current literature in which it is reported that women tended to outperform men on (Wilsenach & Makaure, 2018).

Notably, there is a scarcity of literature which specifically assessed isolated spelling tasks in the context of WM and gender and even more so for an adolescent population. Moll et al. (2014) conducted a study which considered the prevalence rates of LDDs as well as gender differences amongst boys and girls in relation to specific constructs associated with LDDs. For spelling specifically, it was found that boys had more difficulties with isolated spelling than girls (Moll et al., 2014). It is important to note that these findings are not

generalisable to an adolescent population as the sample looked at primary school learners. While a significant difference for gender was found in this study, participants performed poorly across genders for the literacy tasks. Thus, the outcomes produced on these tasks may not reflect true performance as the scores produced on the Spelling and new word spelling tasks suggests a lack of engagement with the task.

**Age as a Predictor**

As noted, age only significantly predicted scores on the Spelling task and with minimal variance explained. I have already discussed the diminishing effects of age as a predictor for literacy performance (Bigozzi et al., 2021) and the fact that there are multiple factors that predict the outcomes investigated, such as cognitive factors, namely, executive functions and social and environmental factors. Last, the age group included were all older adolescents and the lack of variance in age might also contribute to its low predictive power.

**Implications for Computerised Assessments**

Computer-based testing provides many advantages, including but not limited to, cost-effectiveness, time efficiency, mass assessments, recording of accurate response times, and storage of data. These advantages in turn can address many resource-stricken issues. At the same time, however, computer-based testing can also pose many challenges.

A potential issue which may have influenced the findings of this research was the administration of computer-based versions of traditional pen-and-paper neuropsychological tasks. This may in turn introduce a confound known as construct-irrelevant variance (Boevé et al., 2015). Construct-irrelevant variance, in short, means that third variables account for more variance than actual performance. An example of this is exposure to information technology. Particularly within the SA context, online assessments are relatively new and so raises many concerns around exposure to technology (Bryant, 2017; Fisher, 2008). These concerns include how performance on online assessments could be influenced by factors such as experience using a computer and test anxiety, which can ultimately impact test engagement. In the SA study conducted by Fisher (2008) investigating the efficacy of computer-based neuropsychological WM tasks, the findings showed that approximately 32% of the female participants and 24% of the male participants reported being inexperienced with computers.

The aforesaid findings are further supported by Uleanya (2022) who reviewed the current state of learning challenges within in an SA and Nigerian context. Uleanya (2022) states that low level of exposure to information technology compromises learning and performance (Oyedemi & Mogano, 2018; Schlebusch, 2018; Thurlow et al., 2010). This can

result in test-takers not participating or not fully engaging with the assessment. This is one explanation for the current research in which some tasks were left incomplete by participants. For the current study, while all participants were from SA, and attended a TVET college situated in an urban area, I did not have a measure of their levels of experience with computerised assessments.

Computer-based assessments can also introduce construct-irrelevant variance related to disengagement with the testing. For this study, this is one possibility that may have resulted in attrition within this sample. According to Wise (2019), obtaining valid results is related to the effort put in by those taking the test. When testing disengagement occurs, it becomes challenging to tease apart whether it is a true reflection of performance or if test-takers have sufficiently and efficiently engaged with the test. Another factor that overlaps with testing disengagement is testing motivation which can also result in poor performance. According to Wise (2019), unmotivated test-takers tended to underperform by more than a half standard deviation compared to motivated test-takers. Both present as possibilities as to why certain tasks within the assessment for this study were incomplete or not sufficiently answered. The implications of these issues result in not being able to tease apart those who are struggling and those who did not engage with the tasks.

**Limitations and Directions for Future Research**

A number of limitations of the research design and study method could affect the generalisability of the findings. The first limitation is the use of a computerised audio-verbal WM tool to predict performance on other computerised versions of neurocognitive domains which made use of a different (i.e., visual) modality. Hence, modalities within the assessment were not consistent. For example, Fisher (2008) states that the Digit Span backwards task was found to produce significant findings when associated with domain-general content. However, when used in the context of domain-specific content, it is not able to produce similar findings. Therefore, future research should tailor the WM tasks to the specific content which is being assessed and make use of consistent modalities across measures.

Another limitation of this research is the use of secondary data and high incompletion rates as a result thereof. The use of secondary data introduces a few confounds to the design of the research as there are many factors that cannot be controlled for, for example, the setting in which the LP was administered. Given that the LP was administered to a large group of participants at a time, it is possible that the administration of the LP was not fully proctored. This could have resulted in the attrition-related confounds such as a lack of test-

engagement or addressing any concerns the participants may have had regarding the instructions of the tasks. While this research made use of a large sample size, the completion rates within each module differed. This resulted in some of the modules such as Visuospatial and Missing Word only having completion rates of 12% and 18%, respectively. This undermined the results produced by this research. While non-proctored testing is often considered an advantage of computer-based testing, this may not the case for testing using the LP as it may have affected the completion rates of the data. Therefore, it is important that online computer-based testing in the context of formal testing, such as at a TVET college, employ proctoring to ensure that all participants complete and understand the instructions of the task. In addition, measures were not taken to enhance the reliability and validity of the findings.

Last, another limitation of this research is that there was a lack comparable data, such as school reports, which could have provided information on factors such as school performance or highest grade level obtained prior to attending the TVET college. This limits the results of the research as the participants' performance on the entrance assessment conducted in this study cannot be compared to previous academic performance, which could possibly have formed as baseline scores, prior to attending the TVET college. Given that this was secondary data, this may not have been included in the initial data collection for this sample. Thus, future research should obtain comparable information from the participants such as level of education, grades or conduct pen-and-paper neuropsychological assessments.

**Conclusion**

The current research investigated whether a computer-based WM task on the LP could predict outcomes on other computer-based neuropsychological tasks on the LP, as one might expect, given that many cognitive tasks rely on intact WM function. Investigating the predictive value of a computerised WM task, could address a myriad of concerns that arise with traditional pen-and-paper assessments such as cost and efficiency. Progressing to computer-based testing could essentially address issues screening for deficits associated with LDDs.

The findings of this research demonstrated that the LP WM task was able to predict outcomes on some of the other LP tasks. However, these findings were negligible as the variance accounted for was small. Therefore, based on these findings, it can be concluded that the LP WM may not be a good predictor of the performance on the other LP tasks. The findings produced by this study may have been undermined by factors concerned with the

administration of the tasks. In other words, due to inconsistency in modality across the tasks of the LP, the predictive value of the LP WM could not be fully explored. Moreover, it is also important to consider the methodological issues that can be introduced when making use of computerised versions of traditional pen-and-paper neuropsychological tests. These include issues such as construct validity of the tests as well as construct-irrelevant factors accounting for variance such as lack of exposure to information technology, testing disengagement and motivation.

The findings of this research study, therefore, reinforce the importance of moving towards computer-based testing as a means of addressing issues within resource-constraint contexts such as South Africa. It further highlights the importance of appropriate resource implementation when utilising computer-based testing methods such as the LP to ensure successful screening of deficits associated with LDDs. Notwithstanding this, the obstacles and challenges identified and discussed within the context of computer-based testing cannot readily be overlooked and ought to be addressed during the implementation of the testing method.

## References

Ahmed, S. F., Tang, S., Waters, N. E., & Davis-Kean, P. (2019). Executive function and academic achievement: Longitudinal relations from early childhood to adolescence. *Journal of Educational Psychology*, *111*(3), 446–458. https://doi.org/10.1037/edu0000296

Alloway, T. P., & Copello, E. (2013). Working memory: The what, the why, and the how. *Australian Educational and Developmental Psychologist*, *30*(2), 105–118. https://doi.org/10.1017/edp.2013.13

Alloway, T. P., & Gregory, D. (2013). The predictive ability of IQ and Working Memory scores in literacy in an adult population. *International Journal of Educational Research*, *57*, 51–56. https://doi.org/10.1016/j.ijer.2012.10.004

Angelopoulou, E., & Drigas, A. (2021). *Working memory, attention and their relationship: A theoretical overview*. *5*(10), 1–8. https://doi.org/http://dx.doi.org/10.33448/rsd-v10i5.15288

Arrimada, M., Torrance, M., & Gardner, S. (2020). Factors affecting learning to write in first grade. *Psychology Department, School of Social Sciences, Nottingham Trent University*, *0*(0), 1–25. https://doi.org/10.31234/osf.io/sa4g7

Ashkenazi, S., Black, J. M., Abrams, D. A., Hoeft, F., & Menon, V. (2013). Neurobiological underpinnings of math and reading learning disabilities. *Journal of Learning Disabilities*, *46*(6), 549–569. https://doi.org/10.1177/0022219413483174

Baddeley, A. (2012). Working memory: Theories, models, and controversies. *Annual Review of Psychology*, *63*, 1–29. https://doi.org/10.1146/annurev-psych-120710-100422

Baddeley, A. D., & Hitch, G. (1974). Working Memory. *Psychology of Learning and Motivation - Advances in Research and Theory*, *8*(C), 47–89. https://doi.org/10.1016/S0079-7421(08)60452-1

Bakken, L., Brown, N., & Downing, B. (2017). Early childhood education: The long-term benefits. *Journal of Research in Childhood Education*, *31*(2), 255–269. https://doi.org/10.1080/02568543.2016.1273285

Barel, E., & Tzischinsky, O. (2018). Age and sex differences in verbal and visuospatial abilities. *Advances in Cognitive Psychology*, *14*(2), 51–61. https://doi.org/10.5709/acp-0238-x

Bigozzi, L., Malagoli, C., Pecini, C., Pezzica, S., Vezzani, C., & Vettori, G. (2021). Attention components and spelling accuracy: Which connections matter? *Children*, *8*(7), 1–19. https://doi.org/10.3390/children8070539

Boardman, A. G., Vaughn, S., Buckley, P., Reutebuch, C., Roberts, G., & Klingner, J. (2016). Collaborative strategic reading for students with learning disabilities in upper elementary classrooms. *Exceptional Children*, *82*(4), 409–427. https://doi.org/10.1177/0014402915625067

Boevé, A. J., Meijer, R. R., Albers, C. J., Beetsma, Y., & Bosker, R. J. (2015). Introducing computer-based testing in high-stakes exams in higher education: Results of a field experiment. *PLoS ONE*, *10*(12), 1–13. https://doi.org/10.1371/journal.pone.0143616

Bracken, M. R., Mazur-Mosiewicz, A., & Glazek, K. (2019). Trail Making Test: Comparison of paper-and-pencil and electronic versions. *Applied Neuropsychology:Adult*, *26*(6), 522–532. https://doi.org/10.1080/23279095.2018.1460371

Bryant, W. (2017). Developing a strategy for using technology-enhanced items in large-scale standardized tests. *Practical Assessment, Research and Evaluation*, *22*(1), 1–10.

Canini, M., Battista, P., Della Rosa, P. A., Catricalà, E., Salvatore, C., Gilardi, M. C., & Castiglioni, I. (2014). Computerized neuropsychological assessment in aging: Testing efficacy and clinical ecology of different interfaces. *Computational and Mathematical Methods in Medicine*, *2014*. https://doi.org/10.1155/2014/804723

Carvalho, M. C., Lima, R. F. de, Souza, G. G. B. de, Pires, T. C., Pierini, R., Rodrigues, S. das D., Simão, A. N. P., & Ciasca, S. M. (2016). Characterization of school-related problems and diagnoses in a Neuro-Learning Disorder Clinic. *Estudos de Psicologia (Campinas)*, *33*(1), 161–171. https://doi.org/10.1590/1982-027520160001000016

Casaletto, K. B., & Heaton, R. K. (2017). Neuropsychological assessment: Past and future. *Journal of the International Neuropsychological Society*, *23*(9-10 Special Issue), 778–790. https://doi.org/10.1017/S1355617717001060

Castro-alonso, J. C., & Jansen, P. (2019). Visuospatial Processing for Education in Health and Natural Sciences. In *Visuospatial Processing for Education in Health and Natural Sciences* (Issue August). https://doi.org/10.1007/978-3-030-20969-8

Chai, W. J., Abd Hamid, A. I., & Abdullah, J. M. (2018). Working memory from the psychological and neurosciences perspectives: A review. *Frontiers in Psychology*, *9*(MAR), 1–16. https://doi.org/10.3389/fpsyg.2018.00401

Charchat-Fichman, H., Uehara, E., & Santos, C. F. (2014). New technologies in assessment and neuropsychological rehabilitation. *Temas Em Psicologia*, *22*(3), 539–553. https://doi.org/10.9788/tp2014.3-01

Claassens, T., & Lessing, A. C. (2018). Young adult learners with dyslexia: their socio-emotional support needs during adolescence. *Journal of Psychology in Africa*, *25*(1), 32–36. https://doi.org/10.1080/14330237.2015.1007599

Cornoldi, C., Di Caprio, R., De Francesco, G., & Toffalini, E. (2019). The discrepancy between verbal and visuoperceptual IQ in children with a specific learning disorder: An analysis of 1624 cases. *Research in Developmental Disabilities*, *87*(November 2018), 64–72. https://doi.org/10.1016/j.ridd.2019.02.002

Cortiella, C., & Horowitz, S. H. (2014). The state of learning disabilities: Facts, trends and emerging Issues. *National Center for Learning Disabilities*, 1–52. http://gradnation.org/sites/default/files/The State of Learning Disabilities.pdf

Cowan, N. (2012). Multiple concurrent thoughts: The meaning and developmental neuropsychology of working memory. *Developmental Neuropsychology*, *35*(5), 447–474. https://doi.org/10.1080/87565641.2010.494985.Multiple

Cowan, N. (2014). Working memory underpins cognitive development, learning, and education. *Educational Psychology Review*, *26*(2), 197–223. https://doi.org/10.1007/s10648-013-9246-y

Cowan, N. (2022). Working memory development: A 50-year assessment of research and underlying theories. *Cognition*, *224*(March), 105075. https://doi.org/10.1016/j.cognition.2022.105075

Dekker, M. C., Ziermans, T. B., Spruijt, A. M., & Swaab, H. (2017). Cognitive, parent and teacher rating measures of executive functioning: Shared and unique influences on

school achievement. *Frontiers in Psychology*, *8*(JAN), 1–13. https://doi.org/10.3389/fpsyg.2017.00048

DOE. (2014). *Report on the Annual National Assessment of 2014 gr 1 to 6 & 9*. 112.

Do-It Profiler. (2016). Criminal Justice System. *Do-It Profiler*. http://www.learningdisabilities.org.uk/help-information/learning-disability-a-z/c/criminal-justice-system/

Donohue, D., & Bornman, J. (2018). The challenges of realising inclusive education in South Africa. *Learning and Teaching Around the World: Comparative and International Studies in Primary Education*, *34*(2), 120–126. https://doi.org/https://doi.org/10.15700/201412071114

Farhad Pour, R., Azmodeh, M., Seyed, Tabatabaei, M., & Nasab, D. H. (2022). Modeling of loneliness in mothers with children having Specific Learning Disorders based on coping strategies with the mediating role of self-efficacy. *Women. Health. Bull*, *9*(1), 17–23. https://doi.org/10.30476/WHB.2022.93185.1149.1.

Feenstra, H. E. M., Vermeulen, I. E., Murre, J. M. J., & Schagen, S. B. (2017). Online cognition: factors facilitating reliable online neuropsychological test results. *Clinical Neuropsychologist*, *31*(1), 59–84. https://doi.org/10.1080/13854046.2016.1190405

Field, A. (2012). Discovering statistics using R. *Choice Reviews Online*, *50*(04), 50-2114-50–2114. https://doi.org/10.5860/choice.50-2114

Fisher, K. N. (2008). Working memory in South Africa: Performance on a selection of computer-based neuropsychological tests. An unpublished Master's Dissertation. *Unpublished*.

Fitzpatrick, C., Archambault, I., Janosz, M., & Pagani, L. S. (2015). Early childhood working memory forecasts high school dropout risk. *Intelligence*, *53*, 160–165. https://doi.org/10.1016/j.intell.2015.10.002

Fletcher, J. M., & Miciak, J. (2017). Comprehensive cognitive assessments are not necessary for the identification and treatment of learning disabilities. *Archives of Clinical Neuropsychology*, *32*(1), 2–7. https://doi.org/10.1093/arclin/acw103

Fortes, I. S., Paula, C. S., Oliveira, M. C., Bordin, I. A., de Jesus Mari, J., & Rohde, L. A. (2016). A cross-sectional study to assess the prevalence of DSM-5 specific learning

disorders in representative school samples from the second to sixth grade in Brazil. *European Child and Adolescent Psychiatry*, *25*(2), 195–207. https://doi.org/10.1007/s00787-015-0708-2

Friso-van den Bos, I., & van de Weijer-Bergsma, E. (2020). Classroom versus individual working memory assessment: predicting academic achievement and the role of attention and response inhibition. *Memory*, *28*(1), 70–82. https://doi.org/10.1080/09658211.2019.1682170

Giofrè, D., Allen, K., Toffalini, E., Mammarella, I. C., & Caviola, S. (2022). Decoding gender differences: Intellectual profiles of children with specific learning disabilities. *Intelligence*, *90*(July 2021). https://doi.org/10.1016/j.intell.2021.101615

Gras, D., Gyselinck, V., Perrussel, M., Orriols, E., & Piolino, P. (2013). The role of working memory components and visuospatial abilities in route learning within a virtual environment. *Journal of Cognitive Psychology*, *25*(1), 38–50. https://doi.org/10.1080/20445911.2012.739154

Hackman, D. A., Gallop, R., Evans, G. W., & Farah, M. J. (2015). Socioeconomic status and executive function: Developmental trajectories and mediation. *Developmental Science*, *18*(5), 686–702. https://doi.org/10.1111/desc.12246

Hagelkruys, D., Böhm, C., Motschnig, R., Kertzman, S., Sirota, A., Lerer, B., & Gyarmathy, É. (2016). Adapting a stand-alone computerized cognitive test battery for online use - A case-study in the context of users with special needs. *Computers in Human Behavior*, *63*, 757–768. https://doi.org/10.1016/j.chb.2016.05.069

Hallahan, D. P., Pullen, P. C., Kauffman, J. M., & Badar, J. (2020). Exceptional Learners. *Oxford Research Encyclopedia of Education*, *April 2021*. https://doi.org/10.1093/acrefore/9780190264093.013.926

Haring. (2016). *The predictive value of working memory and creativity in average performing and gifted children*. Utrecht.

Herrero Romero, R., Hall, J., & Cluver, L. (2019). Exposure to violence, teacher support, and school delay amongst adolescents in South Africa. *British Journal of Educational Psychology*, *89*(1), 1–21. https://doi.org/10.1111/bjep.12212

Herrero Romero, R., Hall, J., Cluver, L., & Meinck, F. (2018). Can supportive parenting protect against school delay amongst violence-exposed adolescents in South Africa? *Child Abuse and Neglect*, *78*(September), 31–45. https://doi.org/10.1016/j.chiabu.2017.09.025

Johnson, E. S., Humphrey, M., Mellard, D. F., Woods, K., Lee, H., & Swanson, H. L. (2014). *Cognitive processing deficts and students with specific learning disabilities : A selective meta-analysis of the literature. 33*, 3–18.

Kirby, A. (2014). *Do-IT*.

Kirby, A. (2016). Using data driven decision systems to deliver person-centred approaches in developmental disorders : one example of complexity - the criminal justice system. *Hillary Place Papers*, *3*. http://hpp.education.leeds.ac.uk/wp-content/uploads/sites/131/2016/02/HPP2016-3-Kirby.pdf

Kirby, A., & Saunders, L. (2015). A case study of an embedded system in prison to support individuals with learning difficulties and disabilities in the criminal justice system. *Journal of Intellectual Disabilities and Offending Behaviour*, *6*(2), 112–124. https://doi.org/10.1108/JIDOB-09-2015-0036

Langenfeld, T. (2020). Internet-based proctored assessment: Security and fairness issues. *Educational Measurement: Issues and Practice*, *39*(3), 24–27. https://doi.org/10.1111/emip.12359

Maehler, C., & Schuchardt, K. (2016). The importance of working memory for school achievement in primary school children with intellectual or learning disabilities. *Research in Developmental Disabilities*, *58*, 1–8. https://doi.org/10.1016/j.ridd.2016.08.007

Meneghetti, C., Zancada-Menéndez, C., Sampedro-Piquero, P., Lopez, L., Martinelli, M., Ronconi, L., & Rossi, B. (2016). Mental representations derived from navigation: The role of visuo-spatial abilities and working memory. *Learning and Individual Differences*, *49*, 314–322. https://doi.org/10.1016/j.lindif.2016.07.002

Moll, K., Kunze, S., Neuhoff, N., Bruder, J., & Schulte-Körne, G. (2014). Specific learning disorder: Prevalence and gender differences. *PLoS ONE*, *9*(7). https://doi.org/10.1371/journal.pone.0103537

Morsanyi, K., van Bers, B. M. C. W., McCormack, T., & McGourty, J. (2018). The prevalence of specific learning disorder in mathematics and comorbidity with other developmental disorders in primary school-age children. *British Journal of Psychology*, *109*(4), 917–940. https://doi.org/10.1111/bjop.12322

Napier, D. E. (2015). Predicting adolescents' academic achievement: The contribution of attention and working memory. *Dissertation Abstracts International: Section B: The Sciences and Engineering*, *76*(4-B(E)). http://www.redi-bw.de/db/ebsco.php/search.ebscohost.com/login.aspx%3Fdirect%3Dtrue%26db%3Dpsyh%26AN%3D2015-99200-013%26site%3Dehost-live

Nel, M., & Grosser, M. M. (2016). *An Appreciation of Learning Disabilities in the South African Context*. *14*(1), 79–92.

Oyedemi, T., & Mogano, S. (2018). The Digitally disadvantaged: Access to digital communication technologies among first year students at a rural South African university. *Africa Education Review*, *15*(1), 175–191. https://doi.org/10.1080/18146627.2016.1264866

Paz-Baruch, N. (2022). The role of gender and cognitive mechanisms in mathematical and reading performance. *Educational Studies*, *00*(00), 1–18. https://doi.org/10.1080/03055698.2022.2091406

Peng, P., Barnes, M., Wang, C. C., Wang, W., Li, S., Swanson, H. L., Dardick, W., & Tao, S. (2018). Meta-analysis on the relation between reading and working memory. *Psychological Bulletin*, *144*(1), 48–76. https://doi.org/10.1037/bul0000124

Pillay, J. (2017a). Is school lunch connected to literacy achievement in primary school children? A South African perspective. *International Journal of Psychology & Behavior Analysis*, *3*(1). https://doi.org/10.15344/2455-3867/2017/125

Pillay, J. (2017b). The relationship between housing and children's literacy achievement: Implications for supporting vulnerable children. *South African Journal of Education*, *37*(2), 1–10. https://doi.org/10.15700/saje.v37n2a1268

Pillay, J. (2018). Hope for the future and literacy achievement in a sample of impoverished South African primary school children. *Africa Education Review*, *15*(2), 32–48. https://doi.org/10.1080/18146627.2016.1224601

Pillay, J. (2021). Bullying prevalence and numeracy performance among primary school children in Johannesburg: Implications for school-based interventions. *South African Journal of Childhood Education*, *11*(1), 1–10. https://doi.org/10.4102/sajce.v11i1.956

Poh, N., & Smythe, I. (2015). To what extend can we predict students' performance? A case study in colleges in South Africa. *2014 IEEE Symposium on Computational Intelligence and Data Mining, Proceedings*, 416–421. https://doi.org/10.1109/CIDM.2014.7008698

Saylik, R., Raman, E., & Szameitat, A. J. (2018). Sex differences in emotion recognition and working memory tasks. *Frontiers in Psychology*, *9*(JUN). https://doi.org/10.3389/fpsyg.2018.01072

Schlebusch, C. L. (2018). Computer anxiety, computer self-efficacy and attitudes towards the internet of first year students at a South African university of technology. *Africa Education Review*, *15*(3), 72–90. https://doi.org/10.1080/18146627.2017.1341291

Schneider, W., & Niklas, F. (2017). Intelligence and verbal short-term memory/working memory: Their interrelationships from childhood to young adulthood and their impact on academic achievement. *Journal of Intelligence*, *5*(2), 1–19. https://doi.org/10.3390/jintelligence5020026

Spaull, N. (2015). Schooling in South Africa: How low-quality education becomes a poverty trap.Pdf. *South African Child Gauge 2015*, *12*. https://doi.org/10.2139/ssrn.2973766

Spaull, N., & Kotze, J. (2015). Starting behind and staying behind in South Africa. *International Journal of Educational Development*, *41*, 13–24. https://doi.org/10.1016/j.ijedudev.2015.01.002

Sridevi, G., George, A. G., Sriveni, D., & Rangaswamy, K. (2015). Sacred Heart Hospital, Paynkulam, Thodupuzha, Idukki, Kerala, 3 Formerly professor of Clinical Psychology, Sweekaar Rehabilitation Institute for Handicapped. *Clinical Psychologist*, *1*(1), 4–9.

Stipek, D., & Valentino, R. (2015). Memory, Attention and Academic Achievement. *Journal of Educational Psychology*, *107*(3), 771–788.

Thurlow, M., Lazarus, S. S., Albus, D., & Hodgson, J. (2010). Computer-based Testing : Practices and Considerations. In *Special Education*.

Tredoux, C., & Durrheim, K. (2002). *Numbers, hypotheses and conclusions: A course for social science* (Eds.). UCT Press.

Uleanya, C. (2022). Rural undergraduate university students' learning challenges in Africa: case study of Nigeria and South Africa. *African Identities*, *20*(1), 89–117. https://doi.org/10.1080/14725843.2020.1813083

van der Berg, S. (2015). What the annual national assessments can tell us about learning deficits over the education system and the school career year. *Ssrn*, *5*(2), 28–43. https://doi.org/10.2139/ssrn.2693697

Wang, L., Bolin, J., Lu, Z., & Carr, M. (2018). Visuospatial working memory mediates the relationship between executive functioning and spatial ability. *Frontiers in Psychology*, *9*(DEC), 1–13. https://doi.org/10.3389/fpsyg.2018.02302

Wang, L., & Carr, M. (2019). Gender, working memory, strategy use, and spatial ability. *North American Journal of Psychology*, *21*(3), 601–618.

Webb, G. L., & Williams, C. J. (2018). Factors affecting language and literacy development in Australian Aboriginal children: Considering dialect, culture and health. *Journal of Early Childhood Research*, *16*(1), 104–116. https://doi.org/10.1177/1476718X17693417

Wechsler, D. (2008). *Wechsler Adult Intelligence Scale - Fourth Edition Administration and Scoring Manual*. Pearson.

Willis, R., Dhakras, S., & Cortese, S. (2017). Attention-Deficit/Hyperactivity Disorder in looked-after children: a Systematic review of the literature. *Current Developmental Disorders Reports*, *4*(3), 85–85. https://doi.org/10.1007/s40474-017-0119-9

Wilsenach, C., & Makaure, P. (2018). Gender effects on phonological processing and reading development in Northern Sotho children learning to read in English: A case study of Grade 3 learners. *South African Journal of Childhood Education*, *8*(1), 1–12. https://doi.org/10.4102/sajce.v8i1.546

Wise, S. L. (2019). Controlling construct-irrelevant factors through computer-based testing: disengagement, anxiety, & cheating. *Education Inquiry*, *10*(1), 21–33. https://doi.org/10.1080/20004508.2018.1490127

# Appendix A

*Existing literature that has used the Learner Profiler*

| Authors | Aim(s) | Research Design & Sample Characteristics | Measures | Findings | Limitations & Potential Gaps |
|---|---|---|---|---|---|
| Poh & Smythe (2015) | Investigate the possibility of predicting students' performance through using an online assessment platform. | Quantitative survey<br>Gauteng FET colleges<br>2012 – 2013<br>*N* = 7 989 | Learner Profiler: Demographics, SES, academic performance, and cognitive evaluations. | Found that it is possible to predict academic performance as well as explain the variables that are likely to be useful in the prediction. | Does not assess LDD in a sample that is representative of SA population as it can be assumed that students attending FET colleges may be above-average achievers. |
| Pillay, J. (2017a) | Investigate the association between school lunch and literacy achievement. | Quantitative survey<br>School in Soweto township<br>Primary school learners (Grades 5 -7), *N* = 160<br>Boys = 93, girls = 67<br>Age range: 12 – 14 | Self-report measures (Do-It Profiler & Shape the Learner)<br>DV: Five literacy categories<br>IV: Questions about taking lunch to school (IV, included in the Learner Profiler assessment) | Found that learners who did not have lunch obtained significantly lower marks than those who had some form of lunch. | Small sample size & One school which may not be representative of the population in Soweto or country;<br>Did not account for factors such as having lunch but not eating it at school because of preference opposed to lack of financial or social assistance. |
| Pillay, J. (2017b) | Investigate the association between | Quantitative survey | Learner Profiler | Found that children from low SES families | Small sample size and one school which may not |

| | | | | | |
|---|---|---|---|---|---|
| | outlook on the future and literacy achievement by investigating feelings associated with the future. | School in Soweto township<br>Primary school learners (Grades 5 – 7), *N* = 160<br>Boys = 93, females = 67<br>Age range: 12 – 14 | DV: five literacy categories<br>IV: Questions were included that related to feelings of the future<br>Shape the Learner. | performed poorly in certain literacy tasks and that there is an association between feeling positive about the future and literacy achievement. | be representative of the population. |
| Pillay, J. (2018) | Examines the relationship between housing conditions and literacy achievement at a school in SA. | Quantitative survey<br>School in LMIC SES setting<br>Primary school learners (Grade Five learners), *N* = 160<br>94 boys, 66 girls<br>Medium of instruction: English and Sesotho | Learner Profiler Survey<br>Section A – F which focused on learner demographics, SES, exposure to school-based violence, study skills, and substance abuse in relation to school literacy.<br>IV: Items which focused on housing conditions (3)<br>DV: five literacy tests (Section B - F)<br>Non-word spelling (30 B items)<br>Reading fluency (8 C items)<br>Spelling-type sounded word correctly (25 D items) | Found that there is a relationship between housing conditions and literacy achievement: learners that lived in informal settings performed poorly in literacy tests as compared to those who live in conventional ‘brick’ houses.<br>Furthermore, it was also found that learners who have chores perform poorly in literacy tests as compared to those that have less responsibilities. | Small sample size and one school which may not be representative of housing provisions in high density areas. |

| | | | | | |
|---|---|---|---|---|---|
| | | | Spelling (30 E items)<br>Nonwords (24 F items) | | |
| Pillay, J. (2021) | Aimed to investigate the prevalence of school bullying and numeracy performance in SA | Quantitative survey<br>Schools in Johannesburg<br>Primary school learners (Grades 1 – 7), *N* = 435<br>56.5% girls, 43.7% boys | Self-report measure for bullying<br>Do-It Profiler Learner Survey for numeracy testing | High prevalence of bullying was found,<br>Bullying was more prevalent in high SES schools than low SES schools,<br>Found that that there is an association between bullying experiences and numeracy performance; reports of bullying experiences were most commonly reported for children aged 10 years who consequently also had the lowest numeracy scores. | Sample only comprised of 10% of the population and therefore may not be a true representation,<br>Relied on self-report measures. |

**Appendix B**

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14 December 2021

Asheeqa Petersen
Department of Psychology
University of Cape Town
Rondebosch 7701

Dear Asheeqa

I am pleased to inform you that ethical clearance has been given by an Ethics Review Committee of the Faculty of Humanities for the amendments to your study, *Using working memory to predict other domains within the learner profile in an older adolescent sample*. The reference number remains PSY2020-034.

I wish you all the best for your study.

Yours sincerely

Signed by candidate

Lauren Wild (PhD)
Associate Professor
Chair: Ethics Review Committee

## Appendix C

*Correlation matrix for LP variables by gender*

| | Female | | | | | | Male | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 4 | 5 | 6 |
| 1. Working Memory | - | | | | | | - | | | | | |
| 2. Visuospatial | .10 | - | | | | | .21* | - | | | | |
| 3. Spelling | .07 | -.03 | - | | | | .09 | .15 | - | | | |
| 4. Missing Word | .28** | -.03 | .31** | - | | | .15 | .23 | .24 | - | | |
| 5. Word Choice | .00 | .11 | .17** | .41** | - | | .00 | .03 | .17 | .56** | - | |
| 6. New Word Spelling | .07 | -.03 | .99** | .31** | .17** | - | .10 | .14 | .99** | .27 | .18 | - |

*Note.* * $p < .05$, ** $p < .001$. Correlations are not reported for the group who preferred not to declare their gender as the sample size ($n$ = 145/1175) is too small to expect weak significant correlations.