Does the learner profiler successfully screen for neurodiversity and predict neuropsychological outcomes in high school learners?

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A minor dissertation submitted in *partial fulfilment* of the requirements for the award of the degree of Master of Arts (Clinical Psychology)

Supervisor: A/Prof. Leigh Schrieff-Brown
Minor Dissertation: February 2023
Words: 19 273

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Acknowledgments

Alhamdulillah, I praise and thank the Almighty, the most Gracious and the most Merciful, for the blessing of my studies and the completion of my thesis.

Thank you to my family for their unwavering love, support and prayers, without which I would not have been able to finish this thesis and the valuable contacts they provided for my data collection. Thank you to my parents for providing me the privilege of an education and for all the sacrifices they made to allow me to pursue my dream.

I would like to thank my supervisor, Dr. Leigh Schrieff, for her continued guidance, support and encouragement. Thank you for all the valued feedback and contributions you made to this thesis and for the resources and assistance you provided throughout each stage of the research.

To neuropsychology student Asheeqa Petersen thank you for generously allowing me to take over your originally proposed study.

Thank you to the National Research Foundation (NRF) for providing the financial support needed to pursue my studies and for the completion of this thesis.

Abstract

There has been a push for improved inclusive education for learners with learning difficulties and disabilities in SA due to the long-lasting detrimental consequences learning difficulties and disabilities have on learners' academic achievement and future outcomes. The importance of the screening and identification of learning difficulties and disabilities has been highlighted as the current screening policy in SA presents several issues and formal neuropsychological tests are time-consuming, costly, require expertise in administration, and lack language diversity. Therefore, computerized assessments, such as the Learner Profiler, have been put forward as a useful supportive tool to aid the screening for, and identification of, learning difficulties and disabilities. The current study investigated if the Learner Profiler, a computerized assessment tool, could successfully predict working memory, numeracy and literacy outcomes from formal neuropsychological pen and paper tests in a sample of high school learners. Participants were recruited from English-medium Cape Town high schools (N= 51). Participants first completed the Learner Profiler working memory, literacy and numeracy modules (stage 1) and then were later administered the KTEA-3 and the Working Memory Index from the WISC-IV (stage 2). It was found that the working memory outcomes from the Learner Profiler significantly predicted the overall Working Memory Index outcomes ($p < .001$) but not outcomes from the Digit Span Backwards and Letter-number Sequencing individual subtests ($p > .05$). The numeracy outcomes from the Learner Profiler did not significantly predict the outcomes from the numeracy neuropsychological pen and paper tests ($p > .05$). However, excluding one reading subtest ($p >.05$), the literacy outcomes from the Learner Profiler significantly predicted the literacy outcomes from the KTEA-3 ($p <.01$). Although the study was limited by a small sample size, the findings show the potential of the Learner Profiler to be a supportive tool to aid to the screening, identification, and possible diagnosis of learning difficulties and disabilities in SA.

Introduction

In 2001, South Africa (SA) introduced the Education White Paper 6: *special needs education, building an inclusive education and training system,* a framework document intended to usher in a new era of education highlighting inclusive education for learners with diverse learning needs (Nel & Grosser, 2016). Such inclusive education should also include learners with Learning Difficulties and Disabilities (LDDs), which are broadly defined as conditions typified by low academic performance and persistent problems in learning areas such as literacy and numeracy (Bellinger et al., 2008). LDDs can have long-lasting effects on school and academic achievement and have been associated with school dropout, high levels of anxiety and more frequent engagement in risk-taking behaviours (Francis et al., 2019; Gubbels et al., 2019; McNamara & Willoughby, 2010; Nakajima et al., 2018; Sainio, 2019). In SA, defining LDDs is complex, and screening and identification issues have been exacerbated by a policy that places most of the responsibility of LDD's screening on strained teachers who lack LDD expertise (Matolo & Rambuda, 2022; Mkhuma et al., 2014; Ntseto et al., 2021). Additionally, formal neuropsychological pen and paper tests typically used to diagnose LDDs are time-consuming, costly, and difficult to administer and score, making them unsuitable for the type of large-scale screening of LDDs needed in SA (Cole et al., 2018; Howieson, 2019). Computerized assessments of LDDs have been offered as a solution. One such assessment is the Learner Profiler, which is a multi-dimensional screening and assessment tool that can be used for the identification of LDDs.

Defining LDDs

LDDs have been defined broadly as conditions caused by interference in typical brain function or development that negatively affect an individual's academic performance (Bellinger et al., 2008). They may include deficits in learning and memory, lower IQ, developmental delays, and specific learning disabilities (Bellinger et al., 2008). According to the DSM-V, a specific learning disability is defined as a past or present demonstration of continuous difficulties in the acquisition of arithmetic, mathematical reasoning, writing, and reading skills during formal schooling (American Psychiatry Association, 2013). These include Dyslexia, Dyspraxia, Dysgraphia, and Dyscalculia. Dyslexia describes a pattern of learning difficulties characterized by poor spelling, issues with fluent and accurate word recognition and poor decoding (APA, 2013). Dyspraxia, also known as developmental coordination disorder, refers to fine and gross motor difficulties that hinder learning and academic achievement (Pierce, 2015). Dysgraphia is defined by a deficit in written expression through issues with handwriting that is incorrect or unrecognisable (Pierce, 2015).

Lastly, Dyscalculia describes a pattern of difficulties in numeracy such as problems with arithmetic fact memorization, calculation, math reasoning and number sense (Pierce, 2015).

LDD Prevalence

It is reported that globally 5-15% of the school-age population have impairments in maths, writing or reading (APA, 2013). UNICEF (2021) reports that 1 in 10 children worldwide has disabilities, with 16% of children aged 5-17 years reported as having one or more functional difficulties and 2% having a learning disability. In the US, prevalence rates of learning disabilities are reported at 7.66% with a reported increase of 17.1% over 12 years from 1997 to 2008 (Boyle, 2011). In India, it is reported that 3% of children in the 3rd and 4th grades have a learning disability with problems in reading, spelling, and writing being the most common reported learning difficulties (Padhy, 2015). In SA, it is reported that 2.5% of the child population are affected by some form of disability with children in rural areas being more likely to have a more detrimental disability than those from urban areas (Nel & Grosser, 2016). According to UNICEF (2012), 0.4% of the child population in SA is reported to have intellectual/learning difficulties, however, there are no other specific rates of LDDs reported for SA. These available prevalence rates are concerning as LDDs can have a wide range of detrimental effects on learning and academic achievement.

Consequences of LDDs

Experiencing learning difficulties and low academic achievement have been identified as risk domains for school dropout (Gubbels et al., 2019). A longitudinal study examining school dropout in India found that completing upper primary schooling and entering upper secondary school in later years largely relied on reading and writing skills at age 12 (Nakajima et al., 2018). This result indicates that literacy and reading skills can have long-lasting effects on later schooling. Similarly, learners with math difficulties were found to have a high likelihood of retaining their math difficulty in later years and, despite demonstrating growth in mathematic measures, and were academically behind their peers without math difficulty (Nelson & Powell, 2018). It was also found that identification of math difficulty was strongly related to later grade math performance with students with math difficulty demonstrating deficits in counting, applied problem solving, computation and fraction comparison (Nelson & Powell, 2018).

LDDs do not only have consequences for learning and academic achievement but they can also be related to psychosocial problems. Research has shown detrimental associations between LDDs and emotional problems such as high anxiety, low levels of hope, and internalising problems (Francis et al., 2019; Sainio, 2019). A study investigating longitudinal associations between academic achievement, academic emotions and LDDs in reading and math found that both learners with reading and math difficulties had higher anxiety and lower hope towards their respective subjects of learning difficulty (Sainio, 2019). Hence, students with learning difficulties had less positive and more negative emotions related to academics. Furthermore, a 34-study meta-analytic review investigating the association between poor reading and internalising problems found a significant difference between poor readers and typical readers on internalising problems ($d = 0.41$) and more specifically, that poor readers were at moderate risk for experiencing anxiety (Francis et al., 2019). Adolescents with LDDs have also previously been shown to engage more frequently over time in risk-taking behaviours such as acts of delinquency, acts of aggression, smoking and marijuana use than adolescents without LDDs, even when controlling for sex, age, and school (McNamara & Willoughby, 2010).

Further research on risk-taking behaviours found adolescents with LDDs to be at high risk for bullying, fighting and early sexual experiences but not for smoking, truancy, or drunkenness (Palfiova, 2016). Interestingly, family affluence and family composition did not have a moderating effect on the association between LDDs and risk-taking behaviour, however, LDDs were more prevalent in poor and non-intact families (Palfiova, 2016). Overall, these studies show that learners with LDDs may not only need academic assistance but also support to cope with negative emotions and in making decisions about risk-taking behaviour. The detrimental consequences of LDDs on a learner's academic achievement and psychosocial wellbeing indicate the importance of identifying learners with LDDs so they can receive the needed support for better future outcomes.

LDDs in SA

Defining LDDs in SA is complex as there are internal and external barriers to learning. Internal barriers refer to developmental issues that may be physical or psychological, and external barriers are factors within the environment, such as socio-economic elements, that impact learning (Mazibuko et al., 2019). South African children may face both internal and external barriers, such as under-development, poverty, poor education quality, malnourishment, and poor living conditions, which can have detrimental effects on their physical and socio-emotional wellbeing and disrupt their learning (Nel & Grosser, 2016). With these issues in mind, there should be an emphasis on empowering ordinary teachers to be more inclusive in their teaching practices and classroom cultures so that learners with LDDs can be recognised and receive needed support. Teachers are considered to be fundamental in the identification of a learning disability, thus, they need to be well educated on the identifying characteristics of learners with possible learning difficulties and disabilities (Nel & Grosser, 2016). However, many teachers in SA feel unable to adequately identify and support learners with possible LDDs (Mkhuma et al., 2014; Nel & Grosser, 2016).

Issues with Screening for LDDs in SA

Teachers in SA are encouraged to follow a Screening, Identification, Assessment and Support (SIAS) policy that provides a guideline for the screening of LDDs. The SIAS policy states that teachers must screen all learners at admission using their admission form, health card, school reports, parent and teacher reports, and health programme reports, and record their findings in a learner profile (DBE, 2014). Subsequently, if a learner is identified as possibly having an LDD, the teacher must complete a Support Needs Assessment form 1 (SNA1) in collaboration with the learner's caregiver, which should include areas of concern, the learner's strengths and weaknesses across many learning areas, and an action plan for supporting the learner (DBE, 2014). Thereafter, a SNA2 form will guide the school-based support team which will review the teacher's identification process and provide a plan of action to strengthen the learner's support (DBE, 2014). This process for screening outlined by the SIAS places majority of the responsibility for the screening of LDDs on the teacher. It assumes that teachers will have the knowledge to identify learners with possible LDDs and adequately support their diverse learning needs.

Matolo and Rambuda (2022), using a seven-point semantic differential scale survey completed by 250 teachers, evaluated the application of the SIAS policy in SA schools and found that, despite the policy, teachers in primary and secondary schools do not screen for learning barriers, which is the first step in the policy's implementation. Research on the implementation of the SIAS policy revealed that many teachers lack the confidence, skills, and knowledge to implement strategies to identify and support learners with LDDs (Matolo & Rambuda, 2022; Mkhuma et al., 2014; Ntseto et al., 2021).

Teachers have reported that they could not implement the SIAS policy efficiently due to lack of resources, time and skill constraints, lack of knowledge about LDDs, lack of quality support and classroom overcrowding (Matolo & Rambuda, 2022; Mkhuma et al., 2014). Teachers are also affected by issues such as inadequate infrastructure, inadequate support services and a lack of sufficient learning support material (Nel & Grosser, 2016). They have also expressed that they need more training and practical strategies to help support students (Nel et al, 2016). Furthermore, teachers stated that they were committed to helping students, but when they cannot identify the learner's difficulties, they do not know how to proceed in assessing the learner's strengths and needs, which sometimes results in the learner dropping out of school (Mkhuma et al., 2014). Without proper identification, support strategies and plans, which all rely on the SNA1 forms from the SIAS policy, learner support assistants could not help learners with LDDs (Mkhuma et al., 2014). Overall, the SIAS policy, despite being intended to improve the identification and support of learners with LDDs, is not working as intended and places excessive responsibility on already strained teachers.

Neuropsychological tests

Other than the SIAS policy, which is meant to act as a guideline for teachers to identify and assess learners who require additional learning support, there is currently no nationally accepted tool for the screening of learning disabilities in South Africa (Nel & Grosser, 2016). Typically, LDDs are diagnosed through the use of formal neuropsychological pen and paper tests administered by trained professionals such as psychologists (Howieson, 2019). Formal pen and paper tests have gone through years of refinement and statistic-supported large-scale testing by professionals for the achievement of strong reliability, convergence and construct validity, sensitivity, and specificity (Howieson, 2019). These tests have also been standardised as large test batteries to obtain accurate normative data that is used to assess the performance of individuals completing the test (Howieson, 2019). Therefore, formal neuropsychological pen and paper tests are accurate and trustworthy assessments of LDDs, however, they do have some disadvantages.

Formal pen and paper neuropsychological tests are often costly, time-consuming due to lengthy administration and require proficiency in administration and interpretation (Cole et al., 2018; Howieson, 2019). A disadvantage that is particularly relevant for the SA context is that formal pen and paper tests are not available in diverse languages, they do not include sensitivity to cultural influences, and locally relevant norms are not available for most tests (Howieson, 2019). Formal tests are also unsuitable for repeat administration, particularly at frequent intervals (Gualtieri, 2004). There is a growing body of research investigating the use and feasibility of computerized assessments as a possible alternative to formal pen and paper tests, given these shortcomings (Howieson, 2019; Tomasik et al., 2018; Zygouris, 2017).

Computerized Assessments

Advantages to computerized tests include enhanced standardization in administration and scoring, greater cost efficiency in testing, ability to test large groups and to generate large databases, and the ability to administer tests in different languages (Gualtieri, 2004; Iverson et al., 2009). For example, a study investigating the feasibility of a web-based screener for Dyscalculia found that the internet could be used as a valuable first-pass screening tool for arithmetic learning difficulties (Zygouris, 2017). Billard et al (2021a; 2021b) assessed the predictive validity of a computerized adaptable test battery which assessed children's academic skills and cognitive functions in the domains of written language, oral language, mathematics' cognition, attention, and executive function. They found that that the results from the computerized test battery were highly predictive of the results from similar pencil-and-paper tests and the tests were moderately to strongly correlated depending on the section. Thus, they concluded that their computerized test battery for children aged 3-14 was a valuable first-line screening tool for LDDs. Computerized assessments of learning can allow teachers to administer continuous evaluations of learners' abilities and progress more efficiently than traditional tests which can be time-consuming and costly to generate, evaluate and interpret (Tomasik et al., 2018). This ease of use makes computerized assessments good for longitudinal comparability which, combined with their ability to provide aggregated scores and visualize information about groups of learners, can assist teachers in tracking the progress of the class (Tomasik et al., 2018).

However, computerized assessments also have some disadvantages. Those with less familiarity with computers tend to perform worse in computerized neurocognitive tests than those with self-reported frequent computer use (Iverson et al., 2009). There is also a risk that the testing environment for computerized tests is not optimal due to a lack of supervision (Gualtieri, 2004). Hence, performance on computerised assessments can be affected by various factors, which can affect the reliability of results if these are not controlled for. For example, Butterworth (2003) developed a self-administered, computer program Dyscalculia Screener aimed to provide a fast and reliable method of identifying dyscalculia. However, research found that the screener misidentified students with both false positives and negatives (Gifford & Rockliffe, 2012; Lewis et al., 2021). Further, computerized assessments may not be able to capture the qualitative value of the personal interaction involved in pen and paper tests and this may also decrease the participant's motivation to perform well (Howieson, 2019).

Although computerized assessments can never replace expert diagnoses, they can help to indicate within a large group who may need a referral for further assessment with a formal neuropsychological test. Thus, computerized assessments can be a useful supportive tool to aid the screening, identification, and possible diagnosis of LDDs. One such assessment is the Learner Profiler.

Learner Profiler

The Learner Profiler, previously known as the Do-It Profiler, was developed by Do-IT Solutions (United Kingdom) in collaboration with Shape the Learner (South Africa) and has been tested with over 50 000 SA learners (Pillay, 2021). It is a computerized, modular, multi-dimensional screening and assessment tool that can be used to provide personalised identification of LDDs (Kirby, 2016; Pillay, 2021; Smythe, 2016). The Learner Profiler provides a multidimensional assessment of a learner's academic skills, disability information, social context, study skills and strengths and weaknesses and can identify difficulties in multiple learning areas such as literacy, numeracy, attention, and motor coordination (The Learner Profiler, 2013; Smythe, 2016). This computerized assessment tool, which creates dynamic norms that are continuously updated using a SA database, can assess 1000s of learners simultaneously and does not require a trained professional for its administration (Smythe, 2016). Unlike formal pen and paper tests, the Learner Profiler is available in multiple languages including English, Afrikaans, Sotho, and isiXhosa. It is also being developed in other SA languages to include all the SA languages of learning and teaching areas (Smythe, 2016; Williamson, 2017).

The report produced by the Learner Profiler not only provides information about learning abilities but also provides strategies to assist the learner with their difficulties, allowing the creation of person-centred interventions based on the learner's needs, skills, and social context. The numeracy tests from the Learner Profiler have good internal consistency (Cronbach's a = 0.811; Pillay, 2021). Depending on the test, research shows that the reliability for the Learner Profiler ranges from *0.86-0.93* (Pillay, 2021). The numeracy tests used in the Profiler are presented by order of difficulty and the program assesses where the learner begins the assessment and where they finish, allocating a score according to their level of completion (Pillay, 2021).

The Learner Profiler has previously been used in SA to assess literacy and numeracy; specifically, the relationship between literacy and child abuse, housing, bullying and hope for the future, as well as the relationship between numeracy and bullying (Pillay, 2016; Pillay, 2017a; Pillay, 2017b; Pillay, 2017c; Pillay, 2021). The Profiler has also been used successfully in a study aimed at predicting FET college student performance to understand the possible influence of familial context, environment, and socio-economic status on student performance (Poh & Smythe, 2014). The predictive ability of the Learner Profiler is promising, as it could be used to help teachers improve teaching for learners who are predicted to have low performance due to barriers to learning such as LDDs. Furthermore, to utilize this possible predictive ability of the Learner Profiler, it would be beneficial to understand the relationship between the Learner Profiler and the typical assessments used to detect LDDs. Thus far, no studies have investigated the relationship between the Learner Profiler and outcomes from formal pen and paper neuropsychological tests used to identify and diagnose LDDs.

Conclusion

LDDs can have long-lasting detrimental consequences on learners' academic achievement and future outcomes. There has been a push for improved inclusive education for learners with LDDs in SA, which highlights the importance of the screening and identification of LDDs. Current SA policy places most of the responsibility of screening and identification on strained teachers who lack time, resources, and training in LDDs (Matolo & Rambuda, 2022; Mkhuma et al., 2014; Ntseto et al., 2021). Formal neuropsychological pen and paper tests, despite being invaluable instruments used for the diagnosis of LDDs, are time-consuming, costly, require expertise in administration and lack language diversity (Cole et al., 2018; Howieson, 2019). Computerized assessments, such as the Learner Profiler, on the other hand, have been put forward as a useful supportive tool to aid the screening for and identification of LDDs. There is a dearth of literature using the Learner Profiler in SA with only one study assessing the Learner Profiler's ability to predict the academic performance of college students (Poh & Smythe, 2014). To date, no studies have investigated the Learner Profiler's ability to predict outcomes from formal neuropsychological pen and paper tests typically used to diagnose LDDs. If the results from the Learner Profiler can accurately predict outcomes on similar measures from more formal pen and paper neuropsychological tests, it could be considered an easier, more affordable and time efficient alternative that could be helpful in addressing issues with LDD screening and identification in SA and reducing strain on SA teachers.

Problem Statement

There is a dearth of literature on the Learner Profiler's ability to predict outcomes from formal neuropsychological pen and paper tests typically used to diagnose LDDs.

Research Aims & Hypotheses

The current study investigated if the Learner Profiler, a computerized assessment tool, could successfully predict working memory (WM), numeracy and literacy outcomes from formal neuropsychological pen and paper tests in a sample of high school learners. Therefore, it was hypothesized that:

The outcomes from the working memory, numeracy and literacy domains of the Learner Profiler can significantly predict outcomes from related measures on formal pen and paper neuropsychological tests.

Method

Research Design and Setting

The current study was cross-sectional and quantitative, with a within-subjects design, conducted at high schools in Cape Town. The study was completed in 2 stages: an LDD screening stage and a neuropsychological pen and paper test stage. For stage 1, participants who agreed to and had the necessary assent and consent to participate in the study, completed the Learner Profiler on a computer at their school computer laboratory or at home. Approximately 1 week afterwards, for stage 2 of the study, participants who agreed to and had the necessary assent and consent to continue their participation in the study, were contacted and a time was arranged for them to complete the Working Memory Index (WMI) subtests from the Wechsler Intelligence Scale for Children, Fourth Edition (WISC-IV) and the Kaufman Test of Educational Achievement, Third Edition (KTEA-3). For the current study, the outcomes from the Learner Profiler's literacy and numeracy domains were the predictor variables and the relevant outcomes from the formal neuropsychological pen and paper tests were the dependent variables.

Participants

Prior to sampling, G*Power (Version 3.1.9.4) was used to conduct an a priori power analysis that indicated a minimum sample size of 104 participants for a target power of .80 and a medium effect size (Cohen's $f2 = .15$) with $\alpha = .05$ (Faul, Erdfelder, Lang, & Buchner, 2007). A systematic review and meta-analysis on retention strategies revealed that a mean retention rate of 73.5% (SD = 20.1%), with 4.6 waves (SD = 8.0), over 4.3 years (SD = 5.0) was reported in longitudinal cohort studies (Teague, et al. 2018). Thus, for the current study, a retention rate of 76 participants was expected which would have ensured that the study was sufficiently powered given the minimal number of predictors. However, the study did not reach this target and there were only 51 participants. Recruitment for participants began in the second and third school terms. This may have resulted in the small sample size as many schools explained that they could not accommodate the study due to their learners' assignments and workload. Additionally, some schools were unable to participate as their learners were already taking part in other research studies.

The participants for the current study included 13- to 16-year-old learners ($M = 14.63$; $SD = 0.9$), attending Cape Town high schools. The age range was restricted to 13-16 years as this is the average age for students in their first years of high school without grade retention. The sample included both boys and girls. All participants were fluent in English. Participants were recruited using convenience sampling from English-medium high schools in Cape Town due to the language constraints of the neuropsychological tests chosen for Stage 2 of the study.

Inclusion criteria were that participants were 13-16 years and attending an English-medium Cape Town high school. Further, students who assented and were given parental consent were allowed to participate in Stage 1. For stage 2, only those students who assented, were given parental consent, and completed stage 1, were allowed to participate.

Measures

Computerized Assessment

The Learner Profiler. This is a person-centred computerized assessment and screening tool for LDDs. The Learner Profiler is available in English, Afrikaans, Sotho, and isiXhosa. The demographic information, Maths, Reading Comprehension, Missing Word, Spelling, Non-Word Spelling and WM modules were used in the study. The reliability for the Learner Profiler, depending on the test, ranges from *0.86-0.93* (Pillay, 2021). The numeracy tests from the Learner Profiler have good internal consistency (Cronbach's *a* = 0.811; Pillay, 2021). The Learner Profiler has previously been used in SA studies to assess literacy and numeracy (see Pillay, 2016; Pillay, 2017a; Pillay, 2017b; Pillay, 2017c; Pillay, 2021) and to predict FET college student performance (see Poh & Smythe, 2014).

Neuropsychological tests

Wechsler Intelligence Scale for Children (WISC-IV). This neuropsychological pen and paper test is a measure of intellectual ability for children aged 6 to16 years (Kaufman et al., 2006; Weschler, 2003). The WISC-IV contains 15 subtests; however, only the WMI subtests from the WISC-IV were used. The WMI contains the Digit Span Forwards, Digit Span Backwards and Letter-Number Sequencing subtests. The WISC-IV provides separate scores for the Digit Span backwards and Digit Span forwards components of the test which allow for the separate measures of WM and basic attention span, respectively (Kaufman et al., 2006). The Letter-Number Sequencing task also measures working memory. The WMI is reported to have an internal consistency of *.92* (Kaufman et al., 2006). The Digit Span subtest has previously been used in SA (see Mphahlele et al., 2021; Peltzer & Phaswana-Mafuya, 2012; Sherr et al., 2017).

Kaufman Test of Educational Achievement, Third Edition (KTEA-3). This neuropsychological test assesses academic achievement and skills in individuals aged 4 to 25 years old (Frame et al., 2016). The KTEA-3 contains 6 subtests that assess skills in mathematics, reading, and written and oral language (Frame et al., 2016). The 6 subtests include math concepts and applications, math computation, letter and word recognition, reading comprehension, written expression and spelling. All 6 subtests were used to assess literacy and numeracy abilities of the participants. The split-half reliability for the KTEA-3 ranges from good to excellent depending on the subtest. The mean split-half reliability for all grades indicates that the reliability is excellent for the math concepts and applications (*.96*), math computation (*.95*), letter and word recognition (*.97*), and spelling (*.95*) subtests and the reliability is good for the written expression (*.86*) and reading comprehension (*.88*) subtests (Kaufman & Kaufman, 2014). The KTEA-3 has been used to assess children's academic progress and skills performance in studies internationally (see Geoffroy et al., 2010; Hamner et al., 2021; Hein et al., 2014) and in an unpublished South African study (see Van Der Walt, 2022).

Procedure

Obtaining Ethical Approval

The method of this study was previously proposed by a Neuropsychology Masters student, Asheeqa Petersen, who was granted ethical approval by the Psychology Department's Research Ethics Committee and the Faculty of Health Sciences Human Research Ethics Committee. However, due to Covid and time constraints at the time of approval, Asheeqa Petersen was unable to carry out the study. No data had been collected at the time. Approval to take over the study was sought and obtained from the Psychology Department's REC (Appendix G), PSY2022-009, and FHS HREC (Appendix F)

Recruitment

Cape Town schools were contacted for recruitment after the Western Cape Department of Education (WCED) gave permission to conduct the study in schools in 2022 (Appendix H). The schools were sent a Participant Flyer (Appendix A) and Participant Information Sheet (Appendix B) via email and asked to forward the flyer and information sheet to parents of learners of relevant ages. Out of 57 schools contacted to participate in the study, only three schools agreed to participate and distributed the flyers to parents. One principal from the three schools requested a meeting which was arranged to discuss the nature and purpose of the proposed study and once the school agreed to participate in the study flyers were sent to the parents. Once recruitment from schools was exhausted, convenience sampling through distributing the flyer via WhatsApp was used. Parental consent forms (Appendix C) were sent to all parents who responded to the school email or WhatsApp Flyer, and indicated that their children were interested in participating in the study. Upon receiving those, I sent participant assent forms (Appendix D) for their children to complete before they participation in the study. The consent and assent forms were distributed electronically via RedCap, and parental consent and participant assent were obtained via valid electronic signatures or scanned copies of the signed consent and assent forms which were emailed or given to me. 88.2% of participants were recruited via schools and 11.7% of participants were recruited via community sampling (word-of-mouth, snowball sampling).

Data Collection

For stage 1, participants whose parent/legal guardians provided consent and who had provided their assent were sent the link to the Learner Profiler and asked to complete it at home or at school on a laptop or desktop computer. Participants were provided with a 250MB data bundle for internet connectivity to complete stage 1. After completing the Learner Profiler assessment, participants were compensated with a R50 Checkers or Pick n Pay voucher. This was sent electronically.

Roughly one week after completing stage 1, participants who indicated they were interested in participating in stage 2, received parental consent and gave their assent to participate, were contacted to arrange a time to meet at school. During this in-person meeting, participants were administered the neuropsychological pen and paper measures which included the WMI from the WISC-IV and the KTEA-3. Participants were tested individually in an empty classroom or office on school premises. Although masks were no longer required in schools, all other Covid-related precautions such as social distancing and sanitising were adhered to for these in-person meetings.

After the neuropsychological pen and paper measures were completed, participants were compensated with a R50 Checkers or Pick n Pay card voucher.

Once both stages of the study were completed, the data from the Learner Profiler and neuropsychological pen and paper measures were collated, organised, analysed and stored on a password-protected computer and any hard copies of the measures were stored in a locked cabinet. Participants were sent the debriefing letter (see Appendix E) after the completion of both stages of the study.

Data Analysis

The data from the Learner Profiler and neuropsychological test measures were collated and analysed using RStudio version 3.6.2 software. The significance level or alpha was set at $p < .05$. The results of the Learner Profiler and neuropsychological test measures were summarized using descriptive statistics. Cross tabulations and Chi-square tests of Independence were conducted to analyse the impact of Age in the data. Thereafter, hierarchical multivariate regression analyses were conducted to ascertain if outcomes from the working memory, numeracy and literacy modules of the Learner Profiler, obtained in stage 1, could successfully predict outcomes from the neuropsychological pen and paper test measures, obtained in stage 2. These outcomes included the results from the WMI and its subtests from the WISC-IV and the results from the KTEA-3. Given the effects outliers can have on statistical analyses, and that these effects may be exacerbated in limited sample sizes, outliers were identified, and the analyses were run both with and without these outliers.

Ethical Considerations

Informed Consent and Assent

Ethical approval was obtained from the Department of Psychology's REC and the FHS HREC at UCT. Permission for the study was also obtained from the WCED. Further, informed consent from the parents / guardians of the participants, and assent from the participants was obtained before each stage of the study via RedCap using valid electronic signatures or a scanned copy of the signed forms. The consent and assent forms (Appendix C and Appendix D) provided a detailed outline of the nature and purpose of the study and stated that participation is voluntary, therefore, participants could withdraw from the study at any point without consequences.

Confidentiality

It was explained to participants, both in the consent and assent forms and in person (during the neuropsychological assessments), that all the information gathered in the study was only going to be used for the purposes of this study. It was also explained that information from both stages would remain anonymous and confidential. Furthermore, participants were told that information from the computerized Learner Profiler is protected by software that has a Secure Sockets Layer Certification (Smythe, 2016) and that information from both stages of the study, which was coded for anonymity, would be stored on a password protected computer. Finally, all hardcopies of the neuropsychological test measures were safely stored in a locked cabinet.

Benefits and Risks

As the study included minors, who are considered a vulnerable population, special care was taken to explain to the participants that all information gathered in the study would remain anonymous and confidential. Due to the nature of the pen and paper measures in stage 2 of the study, participants could become fatigued during the testing and were told that they could take breaks at any time during testing. They were also provided refreshments during testing to minimise fatigue. Participants were compensated with a R50 Checkers/ Pick n Pay voucher after each stage of the study and were provided with a summary of their strengths and needs from the Learner Profiler and neuropsychological test measures. Although masks were no longer required in schools, all other Covid-related precautions such as social distancing and sanitising were adhered to for in-person meetings.

Debriefing

Once both stages of the study were completed, participants were debriefed and provided with a debriefing letter (Appendix E) which contained the researcher's contact information if they had any questions or concerns about the study after participation.

Referrals

The current study investigated LDD prevalence; thus, if it was found that a participant was at risk for an LDD due their results from either stage of the study, they were given the option to be referred to the district educational psychologist or Groote Schuur Neuropsychology clinic for further testing and assessment.

Results

There were 51 participants in stage 1 who completed the LDD screening stage. From the 51 who participated in stage 1, 40 (78.4%) participated in stage 2: the neuropsychological pen and paper test stage. Of the 51 participants, 28 (54.9%) of these participants were female. The control variables were age and attention (Digit Span Forwards scores). Digit Span Forwards was labelled as attention in the study as the WISC-IV DSF is good measure of simple attention (Cullum, 1998). All WISC-V scores used were age scaled and all KTEA-3 scores used were scaled according to grade. Table 1 includes descriptive statistics for the control variables. The average age was 14.63 years (SD = 0.9, range = 3-15) and participants scored in the average range for attention (SD = 3.07, range = 13-16). Attention shared a moderate negative correlation with age (DSF: r = -0.3) indicating that as age increased, participants' attention decreased. Further analysis examining the cross tabulation between age and attention can be found in Appendix F. Below I present the results from descriptive statistics, cross tabulations, Chi-square tests of independence, correlational and hierarchical multivariate regression analyses for the WM variables followed by the numeracy variables and the literacy variables which are divided into written language and reading.

Working memory

Descriptive Statistics

Table 1 presents descriptive statistics, including means (M) and standard deviations (SD), for the WM variables. Participants scored, on average, in the low average range for Digit Span Backwards (M = 7.85, SD = 2.77) and Letter Number Sequencing (M = 7.92, SD = 2.44) subtest scaled scores. For WMI scores (M = 88.75, SD = 12.32) participants scored, on average, in the low average range. For the Learner Profiler WM module (M = 2.45, SD = 1.29) the average score fell into the Learner Profiler category *many challenges reported*.

Table 1

Descriptive Statistics for WM Variables (N = 51)

Variables	M	SD	Min	Max
Age	14.63	0.9	13	16
Attention [a]	9	3.07	3	15
DSB [a]	7.85	2.77	3	16
LNS [a]	7.92	2.44	2	16
WMI [b]	88.75	12.32	65	135
LPWM [c]	2.45	1.29	1	4

Note. Attention = Digit Span Forwards scaled scores, DSB = Digit Span Backwards scaled scores, LNS = Letter-Number Sequencing scaled scores, WMI = Working Memory Index, LPWM = Learner Profiler Working Memory Score; [a] = Numeric variable (<5 =borderline; 6-7 = low average; 8-11 = average, 12 – 13 = high average; 14-15 = superior; >16 = very superior); [b] = Numeric variable (<70 = extremely low; 70-79 = borderline; 80-89 = low average; 90-109 = average; 110-119 = high average; 120-129 = superior, > 130 = very superior)[c] = Categorical variable (1 = significant challenges reported; 2 = many challenges reported; 3 = reasonable skills; 4 = good skills).

Correlations

A summary of the correlational analyses is presented in Table 2. There were no statistically significant correlations between the Learner Profiler WM scores and the neuropsychological pen and paper WM test scores. Letter Number Sequencing shared a significant moderate positive correlation with Digit Span Backwards (LNS: $r = 0.54$, $p < .001$) which indicates that as Letter Number Sequencing scores increased, Digit Span Backwards scores also increased. Digit Span Backwards and Letter Number Sequencing shared a significant strong positive correlation with WMI (DSB: $r = 0.73$, $p < .001$; LNS: $r = 0.84$, $p < .001$). WMI shared a significant moderate positive correlation with attention (WMI: $r = 0.62$, $p < .01$). indicating that as WMI scores increased, attention scores also increased. Digit Span Backwards and WMI both shared a significant negative moderate correlation with age (DSB: $r = -0.32$, $p < .05$; WMI: $r = -0.41$, $p < .01$). In other words, as age increased, Digit Span Backwards and WM scores decreased. The relationship between age and the WM variables was further investigated using cross tabulations and Chi-squared tests of independence and showed a significant relationship between age and Letter Number Sequencing, $X^2(9, N=40) = 19.04$, $p = .02$. See Appendix F for a summary of the results of cross tabulations and Chi-squared tests of independence.

Table 2

Correlations Between WM Variables. (N = 40)

Variables	Age	Attention	DSB	LNS	WMI	LPWM
1.Age	-					

2.Attention	-0.30	-				
3.DSB	-0.32*	0.20	-			
4.LNS	-0.22	0.22	0.54***			
5.WMI	-0.41**	0.62**	0.73***	0.84***	-	
6.LPWM	-0.16	0.04	0.26	0.28	0.28	-

Note. WMI = Working Memory Index, Attention = Digit Span Forwards, DSB = Digit Span Backwards, LNS = Letter-Number Sequencing, LPWM = Learner Profiler Working Memory Score; *p < .05. **p < .01. ***p < .001.

Hierarchical Multivariate Regression (including outliers)

Preliminary analyses indicated that for the Digit Span Backwards and WMI models the assumptions of linearity, normality and homoscedasticity were met. For Letter Number Sequencing the assumption of linearity was violated. All VIF values were just above 1 (VIFmax = 1.12) indicating no issues with multicollinearity. Additionally, model diagnostics did not indicate any possible influential cases or outliers. In step 1, the first control variable age were put into 3 models with Digit Span Backwards, Letter Number Sequencing and WMI as the respective dependent variables. In step 2, the second control variable attention (Digit Span Forwards) was added to the models. In step 3 the Learner Profiler WM variable was added to the models. As attention and WMI scores are not independent of each other, a high variance was expected. Thereafter, an ANOVA (Analysis of Variance) was conducted to assess if there were any significant differences in the models after steps 2 and 3. A summary of the multivariate analyses is presented in Table 3.

Digit Span Backwards.

Step 1. The first control variable age accounted for 10% of the variance in Digit Span Backwards scores. This model was found to be significant, thus, age does significantly predict Digit Span Backwards scores, $F\ (1,38) = 4.41$, $p = .04$.

Step 2. The second control variable attention was added to the model and explained a further 2% of the variance. However, this model was not found to be significant, thus, attention and age does not significantly predict Digit Span Backwards scores, $F\ (2,37) = 2.44$, $p = .10$.

Step 3. The Learner Profiler WM scores were added to the model and explained a further 4% of the variance in Digit Span Backwards scores. However, this model was also not significant and thus all variables failed to significantly predict Digit Span Backwards scores, $F\ (3,36) = 2.32$, $p = .09$. The AVOVA indicated that step 2 did not differ significantly from step 1, F (1, 37) = 3.6 $p = 0.47$ and step 3 did not differ significantly from step 2, F (1, 36) = 13.7, $p = 0.16$.

Letter Number Sequencing.

Step 1. The first control variable age accounted for 2% of the variance in Digit Span Backwards scores. However, this model was not significant and age did not significantly predict Letter Number Sequencing scores, F (1,38) = 0.93, $p = .34$.

Step 2. The second control variable attention was added and accounted for 3% of the variance in Letter Number Sequencing scores. However, this model was not significant and the control variables did not significantly predict Letter Number Sequencing scores, F (2,37) = 0.88, $p = .42$.

Step 3. The addition of Learner Profiler WM scores explained a further 6% of the variance in Letter Number Sequencing scores, however, this model was not significant and the variables failed to significantly predict Letter Number Sequencing scores, F (3,36) = 1.41, $p = 0.25$. The AVOVA indicated that step 2 did not differ significantly from step 1, F (1, 37) = 4.95 $p = 0.35$ and step 3 did not differ significantly from step 2, F (1, 36) = 13.52, $p = 0.13$.

Working Memory Index.

Step 1. The first control variable age accounted for 12% of the variance in WMI scores. This model was significant and age significantly predicts WMI scores F (1,38) = 5.20, $p<0.05$.

Step 2. The second control variable attention was added and accounted for an additional 28% of the variance in WMI scores. This model was significant and the control variables did significantly predict WMI scores, F (2,37) = 12.37, $p < 0.05$.

Step 3. The addition of Learner Profiler WM scores explained a further 5% of the variance in WMI scores and this model was also significant. Therefore, the Attention, Age and Learner Profiler WM variables did significantly predict WMI scores, F (3,36) = 9.91, $p < 0.05$. An AVOVA indicated that step 2 differed significantly from step 1, F (1, 36) = 18.43, $p < .001$ through the addition of the attention scores but step 3 did not differ significantly from step 2.

Table 3

Multiple Regression Analyses Predicting Digit Span Backwards, Letter-Number Sequencing, and WMI Scores from Learner Profiler WM Scores Including Outliers (N = 40)

	Working Memory					
	DSB		LNS		WMI	
Predictors	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1		0.10		0.02		0.12^{*}
Age	-0.78		-0.19		-1.96	
Step 2		0.02		0.03		0.28^{***}
Attention	0.11		0.12		2.18^{***}	
Step 3		0.04		0.06		0.05^{***}
LPWM	0.46		0.45		2.12	
	$R^2 = 0.16$		$R^2 = 0.11$		$R^2 = 0.45$	
	Adj.$R^2 = 0.09$		Adj.$R^2 = 0.03$		Adj.$R^2 = 0.41$	

Note. WMI = Working Memory Index, , DSB = Digit Span Backwards, LNS = Letter-Number Sequencing, Attention = Digit Span Forwards, LPWM = Learner Profiler Working Memory Score.
**p* < .05. ***p* < .01. ****p* < .001.

Analyses (Excluding Outliers)

To assess if there were outliers in the dependent variables, boxplots were created (figures 1, 2 and 3 in Appendix F). These showed 6 outliers. As noted in the Method section, given the effect that such outliers can have on analyses, especially with a limited sample size, I reran all analyses without the outliers. There were some differences between the original models and the models with the outliers removed.

For Digit Span Backwards the original model explained a further 10% of the Digit Span Backwards scores (original: $R^2 = 0.16$, $F\ (3,36) = 2.32$, $p = .09$) compared to the model without outliers ($R^2 = 0.06$, $F\ (3,30) = 0.65$, $p = .59$) and neither model was significant. For Letter and Number Sequencing scores the original model explained 4% more of the variance in LNS scores (original: $R^2 = 0.11$, $F\ (3,36) = 1.41$, $p = .25$) compared to the model without outliers ($R^2 = 0.07$, $F\ (3,30) = 0.77$, $p = .51$) and neither model was significant. However, for the WMI scores the model with the outliers excluded explained a further 16% of the variance in WMI scores ($R^2 = 0.61$, $F\ (3,29) = 15.36$, $p < .001$.) compared to the original WMI model (original: $R^2 = 0.45$, $F\ (3,36) = 9.91$, $p < 0.05$) and both models were significant. Additionally, the ANOVA for the outliers-removed WMI model indicated that step 3 differed significantly from step 2 (F (1, 29) = 7.7, p = < .01) through the addition of the Learner Profiler WM scores while the ANOVA for the original WMI model indicated that step 3 did not differ significantly from step 2 (original: F (1, 36) = 3.4, p = .07). Furthermore, differing from the original model (original: t = 1.84, p = .07), the individual slope coefficient for Learner Profiler WM scores was significant in the outliers-removed WMI model (t = 2.78, p < .01). The results from the hierarchical multivariate regression analyses excluding outliers are presented in table 4.

Table 4

Multiple Regression Analyses Predicting Digit Span Backwards, Letter-Number Sequencing, and WMI Scores from Learner Profiler WM Scores Excluding Outliers (N = 34)

	Working Memory					
	DSB		LNS		WMI	
Predictors	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1		0.02		0.01		0.19
Age	-0.39		-0.18		-2.55*	
Step 2		0.01		0.01		0.32***
Attention	-0.05		-0.04		1.3***	
Step 3		0.03		0.05		0.10***
LPWM	0.31		0.23		1.68**	
	$R^2 = 0.06$		$R^2 = 0.07$		$R^2 = 0.61$	
	Adj.$R^2 = -0.03$		Adj.$R^2 = -0.02$		Adj.$R^2 = 0.57$	

Note. WMI = Working Memory Index, , DSB = Digit Span Backwards, LNS = Letter-Number Sequencing, Attention = Digit Span Forwards, LPWM = Learner Profiler Working Memory Score.
*p < .05. **p < .01. ***p < .001.

Numeracy

Descriptive Statistics

Table 5 presents descriptive statistics, including means (M) and standard deviations (SD), for the Mathematics variables. For Math Computation (M = 75.63, SD = 8.65), Math Concepts and Applications (M = 78.13, SD = 7.31) and Math composite (M = 75.2, SD = 15.27) participants scored, on average, in the below average range. For the Learner Profiler math module (M = 1.5, SD = 0.88) the average score indicated many challenges reported.

Table 5

Descriptive Statistics for Numeracy Variables (N = 51)

Variables	M	SD	min	max
MC [a]	75.63	8.65	59	109
MCA [a]	78.13	7.31	62	97
Math	75.2	15.27	59	94
LPMATH [b]	1.5	0.88	1	4

Note. MC = Math Computation , MCA = Math Concepts and Applications , Math = Math Composite, LPMATH = Learner Profiler Math Score; [a] = Numeric variable (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high) [b] = Categorical variable (1 = significant challenges reported; 2 = many challenges reported; 3 = reasonable skills; 4 = good skills).

Correlations

A summary of the correlational analyses is presented in Table 6. There was a significant moderate positive correlation between Math Concepts and Applications and Learner Profiler math scores (MCA: $r = 0.36$, $p < .05$). Additionally, there was a moderate positive correlation between Math Computation and Learner Profiler math scores. Math computation and Math Concepts and Applications both shared significant moderate positive correlations with Math composite scores (MC: $r = 0.37$, $p < .05$; MCA: $r = 0.52$, $p < .01$). There was a significant moderate negative correlation between Learner Profiler math scores and age (LPMATH: $r = -0.42$, $p < .01$). The relationship between age and the numeracy variables was further investigated using cross tabulations and Chi-square tests of independence. The Chi-square analyses did not show any significant relationships between the numeracy variables and age. See Appendix F for a summary of the results of cross tabulations and Chi-square tests of independence.

Table 6

Correlations Between Numeracy Variables. (N = 40)

Variables	Age	Attention	MC	MCA	Math	LPMATH
1.Age	-					
2.Attention	-0.30	-				
3.MC	-0.01	-0.05	-			
4.MCA	-0.23	0.01	0.41**	-		
5.Math	0.00	0.04	0.37*	0.52**	-	
6.LPMATH	-0.42**	0.18	0.31	0.36*	0.11	-

Note. MC = Math Computation , MCA = Math Concepts and Applications , Math = Math Composite, LPMATH = Learner Profiler Math Score; *p < .05. **p < .01. ***p < .001.

Hierarchical Multivariate Regression (Including Outliers)

In step 1, for the hierarchical multivariate analyses, the control variable age was put into 3 models with Math Computation, Math Concepts and Applications and Math composite as the respective dependent variables. In step 2 the control variable attention determined by Digit Span Forwards scores was added to the models. In step 3 the Learner Profiler Math variable was added to the models. Thereafter, an ANOVA was conducted to assess if step 2 significantly differed from step 1 and if step 3 differed from step 2 in all 3 models. A summary of the multivariate analyses is presented in Table 7.

Math Computation.

Step 1. A model with the control variable age indicated that age accounted for 0.01% of the variance in Math Computation scores. This model was not significant; therefore, age fails to significantly predict Math Computation scores, F (1,38) = 0.01, p = .94.

Step 2. The addition of the Digit Span Forwards scores explained a further 0.01% of the variance in Math Computation scores. This model was not significant, therefore age and attention failed to significantly predict Math Computation scores, F (2,37) = 0.05, p = .95.

Step 3. The addition of Learner Profiler math scores explained a further 12% of the variance in Math Computation scores. The individual slope coefficient for Learner Profiler math scores was found to be significant, t = 2.17, p < .05. However, overall this model was not significant and the variables failed to significantly predict Math Computation scores, F (3,36) = 1.62, p = .2.

Diagnostics and analyses of this model indicated that the assumption of linearity and normality were not met but the assumption of homoscedasticity was met. An ANOVA indicated that there was a significant difference between the model in step 2 and step 3, F

(1,36) = 4.73, $p < .05$. Model diagnostics initially indicated an outlier which was subsequently removed to create a new model. However, this model did not significantly differ from the original model, thus the original model with the outlier was used.

Math Concepts and Applications.

Step 1. A model with the control variable age indicated that age accounted for 5% of the variance in Math Concepts and Applications scores. However, this model was not significant, therefore age fails to significantly Math Concepts and Applications scores, F (1,38) = 2.14, $p = .15$.

Step 2. The addition of the Digit Span Forwards scores explained a further 1% of the variance in Math Concepts and Applications scores. However, this model was not significant, therefore, age and attention failed to significantly Math Concepts and Applications scores, F (2,37) = 1.12, $p = .34$.

Step 3. The addition of Learner Profiler Math scores explained a further 8% of the variance in Math Concepts and Applications scores. However, this model was not significant and the variables age, attention and Learner Profiler Math scores failed to significantly predict Math Concepts and Applications scores., F (3,36) = 1.96, $p = .14$.

Diagnostics and analyses of this model indicated that the assumption of linearity, normality and homoscedasticity were met. An ANOVA indicated that there was no significant difference between the models in step 1, 2 or 3, F (31,36) = 3.49, $p = .06$.

Math Composite.

Step 1. A model with the control variable age indicated that age accounted for 2% of the variance in Math Composite scores. However, this model was not significant, therefore age fails to significantly predict Math Composite scores, F (1,38) = 0.68, $p = .42$.

Step 2. The addition of the Digit Span Forwards scores explained a further .001% of the variance in Math Composite scores. However, this model was not significant, therefore, age and attention failed to significantly Math Composite scores, F (2,37) = 0.03, $p = .97$

Step 3. The addition of Learner Profiler math scores explained a further 15% of the variance in Math Composite scores. The individual slope coefficient for Learner Profiler math scores in this model was found to be significant, $t = 2.55$, $p <.05$. However, this model was not significant and the variables failed to significantly predict Math Composite scores, F (3,36) = 2.47, $p = .08$.

Diagnostics and analyses of this model indicated that the assumption of linearity, normality and homoscedasticity were met. An ANOVA indicated that there was a significant difference between the model in step 2 and step 3 through the addition of Learner Profiler Math scores, F (1,36) = 6.53, $p <.05$.

Table 7

Multiple Regression Analyses Predicting Math Computation, Math Concepts and Applications, and Math Composite scores from Learner Profiler Math Scores Including Outliers (N = 40)

	Mathematics					
	MC		MCA		Math	
Predictors	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1		0.00		0.05		0.02
Age	1.18		-0.99		0.17	
Step 2		0.00		0.06		0.02
Attention	-0.21		-0.19		-0.18	
Step 3		0.12		0.08		0.15
LPMATH	3.58*		2.58		3.17*	
	$R^2 = 0.12$		$R^2 = 0.14$		$R^2 = 0.17$	
	Adj.$R^2 = 0.05$		Adj.$R^2 = 0.07$		Adj.$R^2 = 0.10$	

Note. MC = Math Computation , MCA = Math Concepts and Applications , Math = Math Composite, LPMATH = Learner Profiler Math Score,

*$p < .05$. **$p < .01$. ***$p < .001$.

Analyses (Excluding Outliers)

To assess if there were outliers in the dependent variables, boxplots were created (figures 4, 5 and 6 in Appendix F). These showed 4 outliers. Similar to the WM section, I reran the analyses without the outliers. There were no significant differences between the hierarchical models created with the outliers and those in which the outliers were excluded. For Math Computation, the model with the outliers excluded explained a further 1% of the Math Computation scores ($R^2 = 0.13$, F (3,32) = 1.61, $p = .21$) compared to the original model (original: $R^2 = 0.12$, F (3,36) = 1.62, $p = .2$) and neither model was significant. For Math Concepts and Application scores the model with the outliers excluded explained a further 5% of the variance in MCA scores ($R^2 = 0.19$, F (3,32) = 2.56, $p = .07$) compared to the original model ($R^2 = 0.14$, F (3,36) = 1.96, $p = .14$) and neither model was significant. Finally, for Math Composite scores the model with the outliers excluded explained a further 4% of the variance in Math Composite scores ($R^2 = 0.21$, F (3,32) = 2.88, $p = .05$) compared to the original model (original: $R^2 = 0.17$, F (3,36) = 2.47, $p = .08$) and neither model was significant. A summary of the hierarchical multivariate analyses excluding outliers is presented in Table 8.

Table 8

Multiple Regression Analyses Predicting Math Computation, Math Concepts and Applications, and Math Composite scores from Learner Profiler Math Scores Excluding Outliers (N = 36)

	Mathematics					
	MC		MCA		Math	
Predictors	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1		0.01		0.04		0.03
Age	-0.39		-1.23		-0.75	
Step 2		0.05		0.11		0.10
Attention	-0.39		-0.65*		-0.5	
Step 3		0.07		0.04		0.08
LPMATH	2.32		1.59		2	
	$R^2 = 0.13$		$R^2 = 0.19$		$R^2 = 0.21$	
	Adj.$R^2 = 0.05$		Adj.$R^2 = 0.12$		Adj.$R^2 = 0.14$	

Note. MC = Math Computation , MCA = Math Concepts and Applications , Math = Math Composite, LPMATH = Learner Profiler Math Score,

*$p < .05$. **$p < .01$. ***$p < .001$.

Literacy

Written Language

Descriptive Statistics. Table 9 presents descriptive statistics, including means (M) and standard deviations (SD), for the written language variables. 1 participant did not complete one of the written language modules of the Learner Profiler, therefore $N = 50$ for this section of the study. For Spelling, Written Expression and Written Language Composite scores participants scored in the average range. For the Learner Profiler Non-Word Spelling composite participants scored in the significant challenges reported range ($M = 1.82$, $SD = 0.72$). Participants scored many challenges report for Learner Profiler Spelling scores ($M = 2.9$, $SD = 1.18$). For Learner Profiler Missing Word, participant’s scores were in the reasonable skills range ($M = 3.38$, $SD = 0.95$).

Table 9

Descriptive Statistics for Written Language Variables (N = 50)

Variables	M	SD	min	max
Age	14.63	0.9	13	16
Attention	9	3.07	3	15
SP [a]	87.55	14.31	65	119
WE[a]	93.7	9.25	75	118
WLC [a]	89.85	10.53	71	119
LPSP [b]	2.9	1.18	1	4
LPNW [b]	1.82	0.72	1	4
LPMW[b]	3.38	0.95	1	4

Note. SP = Spelling , WLC = Written Language Composite, LPSP = Learner Profiler Spelling Score; LPNW = Learner Profiler Non-Word Spelling Composite; LPMW = Learner Profiler Missing Word, [a] = Numeric variable (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high) [b] = Categorical variable (1 = significant challenges reported; 2 = many challenges reported; 3 = reasonable skills; 4 = good skills)

Correlations. A summary of the correlational analyses is presented in Table 10. Spelling and Written Language composite both share significant strong positive correlations with Learner Profiler Spelling scores (SP: $r = 0.64$ $p < .001$; WLC: $r = 0.65$, $p < .001$). Spelling, Written Expression and Written Language Composite all share a significant moderate positive correlation with Learner Profiler Non-Word Spelling composite scores (SP: $r = 0.37$ $p < .05$; WE: $r = 0.45$, $p < .01$; WLC: $r = 0.44$, $p < .01$). Learner Profiler Spelling scores share a significant moderate correlation with Learner Profiler Non-Word spelling composite scores (LPSP: $r = 0.47$, $p < .001$). Learner Profiler Non-Word spelling scores share a significant moderate correlation with Learner Profiler Missing Word scores (LPNW: $r = 0.48$, $p < .001$). Learner Profiler Missing Word scores share a significant moderate correlation with Learner Profiler Spelling scores (LPSP: $r = 0.55$, $p < .001$).

Although they were weak, age shared negative correlations with some of the written language variables. The relationship between age and the written language variables was further investigated using cross tabulations and Chi-square tests of independence. The Chi-square results for age and Written Language Composite showed that age had a significant relationship with Written Language Composite, $X^2(6, N=40) = 13.83$, $p = .03$). See Appendix F for a summary of the results of cross tabulations and Chi-squared tests of independence.

Table 10

Correlations between Written Language Variables. (N = 40)

Variables	Age	Attention	SP	WE	WLC	LPSP	LPNW	LPMW
1.Age	-							
2.Attention	-0.30	-						
3.SP	0.00	0.26	-					
4.WE	-0.13	0.01	0.55^{***}	-				
5.WLC	-0.07	0.19	0.93^{***}	0.82^{***}	-			
6.LPSP	0.04	-0.03	0.64^{***}	0.5^{**}	0.65^{***}	-		
7.LPNW	-0.18	-0.25	0.37^{*}	0.45^{**}	0.44^{**}	0.47^{***}	-	
8.LPMW	0.02	-0.13	0.47^{**}	0.44^{**}	0.51^{***}	0.55^{***}	0.48^{***}	-

Note. SP = Spelling , WE = Written Expression, WLC = Written Language Composite, LPSP = Learner Profiler Spelling Score; LPNW = Learner Profiler Non-Word Spelling Composite; LPMW = Learner Profiler Missing Word , *p < .05. **p < .01. ***p < .001.

Hierarchical Multivariate Analyses. In Step 1, for the hierarchical multivariate analyses, the control variable Age was put into 3 models with Spelling, Written Expression and Written Language composite scores as the respective dependent variables. In step 2 the control variable attention determined by Digit Span Forwards scores was added to the models. In Step 3 the Learner Profiler Spelling variable was added to the models. In step 4 the Learner Profiler Non-Word Spelling variable was added to the models. Finally, in step 5 the Learner Profiler Missing Word variable was added to the models. Thereafter, ANOVAs were conducted to assess if there were significant differences in the models after each step in all 3 models. Preliminary analyses indicated that for the Spelling, Written Expression and Written Language Composite models the assumptions of linearity, normality and homoscedasticity were met. Additionally, all VIF values were just above 1 (VIFmax = 1.52) indicating no issues with multicollinearity. Model diagnostics showed no significant outliers in any of the 3 written language models. A summary of the multivariate analyses is presented in Table 11.

Spelling.

Step 1. A model with the control variable Age indicated that age accounted for 0% of the variance in Spelling scores. This model was not significant and age fails to significantly predict Spelling scores, F (1,38) = 0.00, p = .98.

Step 2. The addition of the Digit Span Forwards scores accounted for an additional 7% of the variance in Spelling scores. This model was not significant and attention failed to significantly predict Spelling scores, $F\ (2,37) = 1.48,\ p = .24$.

Step 3. The addition of Learner Profiler Spelling scores explained a further 42% of the variance in Spelling scores. This model was significant and Age and Learner Profiler Spelling scores significantly predict Spelling scores, $F\ (3,36) = 11.50,\ p < .05$.

Step 4. The addition of Learner Profiler Non-Word Spelling scores explained a further 4% of the variance in Spelling scores. This model was significant and the variables age, attention, Learner Profiler Spelling and Non-Word Spelling scores significantly predict Spelling scores, $F\ (4,35) = 9.83,\ p < .05$.

Step 5. The addition of Learner Profiler Missing Word scores explained a further 1% of the variance in Spelling scores. This model was significant and age, attention, Learner Profiler Spelling and Non-Word Spelling and Missing Word scores significantly predict Spelling scores, $F\ (5,34) = 8.09,\ p < .05$.

An ANOVA indicated that there was a significant difference between step 1 and step 2 with the addition of the Digit Span Forwards scores ($F\ (1, 37) = 5.52\ p <..05$) and a significant difference between step 2 and step 3 with the addition of the Learner Profiler Spelling scores ($F\ (1, 36) = 30.92, p <.001$). Therefore, Learner Profiler Spelling scores predict Spelling scores.

Written Expression.

Step 1. A model with the control variable Age indicated that age accounted for 2% of the variance in Written Expression scores. This model was not significant, therefore age fails to significantly predict Written Expression scores, $F\ (1,38) = 0.64,\ p = .43$.

Step 2. The addition of the Digit Span Forwards scored accounted for a further 0.1% of the variance in Written Expression scores. This model was not significant, therefore attention fails to significantly predict Written Expression scores, $F\ (2,37) = 0.33,\ p = .72$.

Step 3. The addition of Learner Profiler Spelling scores explained a further 25% of the variance in Written Expression scores. This model was significant and Learner Profiler Spelling scores significantly predict Written Expression scores, $F\ (3,36) = 4.44\ \ p <.05$.

Step 4. The addition of Learner Profiler Non-Word Spelling scores explained a further 5% of the variance in Written Expression scores. This model was significant and Learner Profiler Spelling and Non-Word Spelling composite scores significantly predict Written Expression scores, $F\ (4,35) = 4.21, p < .05$.

Step 5. The addition of Learner Profiler Missing Word scores explained a further 4% of the variance in Written Expression scores. This model was significant and Learner Profiler

Spelling, Non-Word Spelling and Missing Word scores significantly predict Written Expression scores, $F(5,34) = 3.78$, $p < .05$.

An ANOVA indicated that there was only a significant between step 2 and step 3 with the addition of the Learner Profiler Spelling scores $F(1, 36) = 13.37$, $p < .001$. Therefore, Learner Profiler Spelling scores predict Written Expression scores.

Written Language Composite.

Step 1. A model with the control variable Age indicated that age accounted for 1% of the variance in Written Language Composite scores. This model was not significant, therefore age fails to significantly predict Written Language Composite scores, $F(1,38) = 0.19$, $p = .66$.

Step 2. The addition of the Digit Span Forwards scored accounted for a further 2% of the variance in Written Language Composite scores. This model was not significant, therefore attention fails to significantly predict Written Language Composite scores, $F(2,37) = 0.67$, $p = .52$.

Step 3.The addition of Learner Profiler Spelling scores explained a further 44% of the variance in Written Language Composite scores. This model was significant and Learner Profiler Spelling scores significantly predict Written Language Composite scores, $F(3,36) = 10.66$ $p < .001$.

Step 4. The addition of Learner Profiler Non-Word Spelling scores explained a further 5% of the variance in Written Language Composite scores. This model was significant and Learner Profiler Spelling and Non-Word Spelling composite scores significantly predict Written Language Composite scores, $F(4,35) = 9.48$, $p < .001$.

Step 5. The addition of Learner Profiler Missing Word scores explained a further 3% of the variance in Written Language Composite scores. This model was significant and Learner Profiler Spelling, Non-Word Spelling and Missing Word scores significantly predict Written Language Composite scores, $F(5,34) = 8.21$, $p < .001$.

An ANOVA indicated that there was only a significant between step 2 and step 3 with the addition of the Learner Profiler Spelling scores $F(1, 36) = 32.7$, $p < .001$. Therefore, Learner Profiler Spelling scores predicts Written Language Composite scores.

Table 11

Multiple Regression Analyses Predicting Spelling, Written Expression and Written Language Composite scores from Learner Profiler Spelling, Non-Word Spelling and Missing Word Scores Including Outliers (N = 40)

	Written Language					
	SP		WE		WLC	
Predictors	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1		0.00		0.02		0.01
Age	2.06		-0.88		0.31	
Step 2		0.07		0.00		0.02
Attention	1.7		0.15		0.91	
Step 3		0.42^{*}		0.25^{*}		0.44^{***}
LPSP	5.77^{***}		2.21^{***}		4.07^{***}	
Step 4		0.04^{*}		0.05^{*}		0.05^{***}
LPNW	3.27		2.13		2.4	
Step 5		0.01^{*}		0.04^{*}		0.03^{***}
LPMW	0.4		0.39		0.4	
	$R^2 = 0.54$		$R^2 = 0.36$		$R^2 = 0.55$	
	Adj.$R^2 = 0.48$		Adj.$R^2 = 0.26$		Adj.$R^2 = 0.48$	

Note. . SP = Spelling, WE = Written Expression , WLC = Written Language Composite, LPSP = Learner Profiler Spelling Score, LPNW = Learner Profiler Non-Word Spelling Score, LPMW = Learner Profiler Missing Word Score,
*$p < .05$. **$p < .01$. ***$p < .001$.

Analyses (Excluding Outliers). To assess if there were outliers in the dependent variables' boxplots were created (figures 7, 8 and 9 in Appendix F). There was 1 significant outlier. Similarly, to the previous sections, I reran the analyses without the outliers. There were no significant differences between the original hierarchical multivariate models and those created with the outliers excluded from the data set. For Spelling the original model explained an additional 1% of the variance in Spelling scores (original: $R^2 = 0.54$, F (5,34) = 8.09, $p < .05$) compared to the model with the outliers excluded ($R^2 = 0.53$, F (5,33) = 7.50, $p < .001$) and both models were significant. For Written Expression the model with the outliers excluded explained a further 1% of the variance in Written Expression scores ($R^2 = 0.37$, F (5,33) = 3.81, $p < .05$) compared to the original model (original: $R^2 = 0.34$, F (5,34) = 3.78, $p < .05$) and both models were significant. Additionally, the Written Expression model with the outliers excluded had a significant individual slope coefficient for Learner Profiler Non-Word Spelling scores, $t = 2.39$, $p < .05$. Finally, for Written Language Composite the model with the outliers excluded explained a further 1% of the variance in Written Language Composite scores ($R^2 = 0.56$, $F\ (5,33) = 8.47$, $p < .001$.) compared to the original Written Language composite model ($R^2 = 0.55$, $F\ (5,34) = 8.21$, $p < .001$) and both models were significant. The Written Language Composite model with the outliers excluded also differed from the original model as it had a significant individual slope coefficient for Learner Profiler Non-Word Spelling scores, $t = 2.71$, $p < .05$. The results for the hierarchical multivariate analyses excluding outliers is presented in table 12.

Table 12

Multiple regression analyses predicting Spelling, Written Expression and Written Language Composite scores from Learner Profiler Spelling, Non-Word Spelling and Missing Word Scores Excluding Outliers (N = 39)

	Written Language					
	SP		WE		WLC	
Predictors	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1		0.01		0.00		0.01
Age	2.95		0.43		1.6	
Step 2		0.04		0.02		0.00
Attention	1.6		-0.03		0.74	
Step 3		0.42^{***}		0.23^{**}		0.44^{***}
LPSP	5.2^{***}		1.71^{***}		3.43^{***}	
Step 4		0.06^{***}		0.11^{**}		0.10^{***}
LPNW	4.6		4.2^{*}		4.3^{*}	
Step 5		0.01^{***}		0.01^{**}		0.01^{***}
LPMW	2.25		1.11		1.62	
	$R^2 = 0.53$		$R^2 = 0.37$		$R^2 = 0.56$	
	Adj.$R^2 = 0.46$		Adj.$R^2 = 0.27$		Adj.$R^2 = 0.5$	

Note. . SP = Spelling, WE = Written Expression , WLC = Written Language Composite, LPSP = Learner Profiler Spelling Score, LPNW = Learner Profiler Non-Word Spelling Score, LPMW = Learner Profiler Missing Word Score,

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Reading

Descriptive Statistics. One participant did not complete the reading section of the Learner Profiler therefore N = 50. The average score for Learner Profiler Reading scores was significant challenges reported (M = 1.6, SD = 0.99). For Reading (M = 78.98, SD = 11.63) and Reading composite (M = 83.65, SD = 12.42) participants scored, on average, in the below average range. On average, Letter and Word recognition scores were in the average range (M = 91.3, SD = 15.32). A summary of the descriptive statistics is presented in Table 13.

Table 13

Descriptive Statistics for Reading Variables (N = 50)

Variables	M	SD	min	max
Age	14.63	0.9	13	16
Attention	9	3.07	3	15
LWR[a]	91.3	15.32	69	124
Reading [a]	78.98	11.63	58	109
RC[a]	83.65	12.42	63	117
LPREAD[b]	1.6	0.99	1	4

Note. LWR = Letter and Word Recognition; RC = Reading Composite, [a] = Numeric variable (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high) [b] = Categorical variable (1 = significant challenges reported; 2 = many challenges reported; 3 = reasonable skills; 4 = good skills).

Correlations. A summary of the correlational analyses is presented in Table 14. There was a significant moderate positive correlations between the Learner Profiler Reading scores and Letter and Word Recognition, Reading and Reading Composite scores (LWR: r = 0.4, p < .05; Reading: r = 0.5, p < .01; RC: r = 0.51, p < .001). Letter and Word Recognition scores shared a significant moderate positive correlation with Reading scores (Reading: r = 0.49, p < .01) and a significant strong positive correlation with Reading Composite scores (RC: r = 0.9, p < .001). Additionally, Reading scores shared a significant strong positive correlation with Reading Composite scores (RC: r = 0.82, p < .001). Learning Profiler Reading scores shared a moderate positive correlation with attention (LPREAD: r = 0.3).

Although they were weak, age shared non-significant negative correlations with all of the reading variables. The relationship between age and the reading variables was further investigated using cross tabulations and Chi-square tests of independence. The Chi-square results for age and the reading variables showed no significant relationship between age and Letter and Word Recognition, Reading or Reading Composite scores, respectively. See Appendix F for a summary of the results of cross tabulations and Chi-square tests of independence.

Table 14

Correlations Between Reading Variables (N = 40)

Variables	Age	Attention	LWR	Reading	RC	LPREAD
1.Age	-					
2.Attention	-0.03	-				
3.LWR	-0.05	0.25	-			
4.Reading	-0.24	0.07	0.49^{*}	-		
5.RC	-0.15	0.19	0.9^{***}	0.82^{***}	-	
6.LPREAD	-0.02	0.3	0.4^{*}	0.5^{**}	0.51^{***}	-

Note. LWR = Letter and Word Recognition; RC = Reading Composite, LPREAD = Learner Profiler Reading Score; *p < .05. **p < .01. ***p < .001.

Hierarchical Multivariate Regression. In Step 1, the control variable age was put into 3 models with Letter and Word Recognition, Reading and Reading Composite scores as the respective dependent variables. In Step 2 the second control variable attention (Digit Span Forwards Scores) was added to the models. Thereafter, in Step 3, the Learner Profiler Reading scores were added to the models and an ANOVA was conducted to assess if step 2 differed significantly from step 1 and if step 3 differed significantly from step 2. A summary of the multivariate analyses is presented in Table 15.

Letter and Word Recognition.

Step 1. A model with the variable age was created which accounted for 0% of the variance in Letter and Word Recognition scores. This model was not significant, and age does not significantly predict Letter and Word Recognition scores, F (1,38) = 0.11, p = .74.

Step 2. The addition of the Digit Span Forwards scored accounted for a further 6% of the variance in Letter and Word Recognition scores. This model was not significant, and attention does not significantly predict Letter and Word Recognition scores, F (2,37) = 1.20, p = .31.

Step 3. The Learner Profiler Reading scores were added to the model and accounted for an additional 12% of the variance in Letter and Word Recognition scores. The individual slope coefficient for Learner Profiler Reading scores was found to be significant, t = 2.26, p <

.05.However, this model was not significant and Learner Profiler Reading scores failed to predict Letter and Word Recognition scores, F (3,36) = 2.6, p = .07. An ANOVA indicated that there was a significant difference between Step 2 and Step 3, F (1,36) = 5.12 p = .02. This model met the assumptions of linearity, normality, and homoscedasticity.

Reading.

Step 1. A model with the control variable Age was created which explained 6% of the variance in Reading scores. However, this model was not significant, and Age does not predict Reading scores, F (1,38) = 2.41, p = .13.

Step 2. The addition of the Digit Span Forwards scored accounted for 0% of the variance in Reading scores. This model was not significant, and attention does not significantly predict Reading scores, F (2,37) = 1.17, p = .32.

Step 3. The Learner Profiler Reading scores were added to the model which explained an additional 27% of the variance in Reading scores. This model was significant; therefore, age, attention and Learner Profiler Reading scores significantly predict Reading Scores, F (3,36) = 5.79, p <.001.

An ANOVA indicated that there was a significant difference between step 2 and step 3, F (1,36) = 14.19, p <.001. The assumptions of linearity and homoscedasticity were met, however, the assumption of normality was violated.

Reading Composite.

Step 1. A model with the control variable age was created which explained 2% of the variance in Reading Composite scores. However, this model was not significant, and age does not predict Reading Composite scores, F (1,38) = 0.88, p = .36.

Step 2. The addition of the Digit Span Forwards scored accounted for 3% of the variance in Reading Composite scores. This model was not significant, and attention does not significantly predict Reading Composite scores, F (2,37) = 0.9, p = .41.

Step 2. The Learner Profiler Reading scores were added to the model which explained an additional 23% of the variance in Reading Composite scores. This model was significant; therefore, age, attention and Learner Profiler Reading scores significantly predict Reading Composite scores, F (3,36) = 4.61, p <.01.

An ANOVA indicated that there was a significant difference between step 2 and step 3 through the addition of the Learner Profiler Reading scores, F (1,36) = 11.51, p <.01. The assumptions of linearity, normality and homoscedasticity were all met.

Table 15

Multiple Regression Analyses Predicting Letter and Word Recognition, Reading and Reading Composite Scores from Learner Profiler Reading Scores Including Outliers (N = 40)

	Reading					
	LWR		Reading		RC	
Predictors	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1		0.00		0.06		0.02
Age	-0.09		-3.7		-1.94	
Step 2		0.06		0.00		0.03
Attention	0.67		-0.67		-0.01	
Step 3		0.12		0.27^{***}		0.23^{**}
LPREAD	5.6^{*}		6.41^{***}		6.38^{***}	
	$R^2 = 0.18$		$R^2 = 0.33$		$R^2 = 0.28$	
	Adj.$R^2 = 0.11$		Adj.$R^2 = 0.27$		Adj.$R^2 = 0.22$	

Note. LWR = Letter and Word Recognition scores, Reading = Reading scores, RC = Reading Composite scores, LPREAD = Learner Profiler Reading Score.
*$p < .05$. **$p < .01$. ***$p < .001$.

Analyses (Excluding Outliers). To assess if there were outliers in the dependent variables, boxplots were created (figures 10, 11 and 12 in Appendix F). There was 1 significant outlier. Similar to the previous sections, I reran the analyses without the outliers. The original Letter and Word Recognition model explained a further 7% of the variance in Letter and Word Recognition scores (original: $R^2 = 0.18$, F (3,36) = 2.6, $p = .07$) compared to the model with the outlier excluded ($R^2 = 0.11$, F (3,35) = 1.5, $p = .23$). The original Reading model explained a further 7% of the variance in Reading scores (original: $R^2 = 0.33$, F (3,36) = 5.79, $p < .001$) compared to the model with the outlier excluded ($R^2 = 0.27$, F (3,35) = 4.26, $p < .05$). For Reading Composite scores, the model created with the outlier excluded was no longer significant, thus, age, attention and Learner Profiler Reading scores did not significantly predict Reading Composite scores in this model, F (3,35) = 2.83, $p = .05$. The results from the hierarchical multiple regression with the outlier excluded is presented in table 16.

Table 16

Multiple Regression Analyses Predicting Letter and Word Recognition, Reading and Reading Composite scores from Learner Profiler Reading Scores Excluding Outliers (N = 39)

	Reading					
	LWR		Reading		RC	
Predictors	β	ΔR^2	β	ΔR^2	β	ΔR^2
Step 1		0.01		0.09		0.04
Age	-0.39		-3.94		-2.26	
Step 2		0.04		0.00		0.01
Attention	0.67		-0.67		-0.02	
Step 3		0.06		0.22^{**}		0.15
LPREAD	4.18		5.29^{**}		4.9^{*}	
	$R^2 = 0.11$		$R^2 = 0.27$		$R^2 = 0.2$	
	Adj.$R^2 = 0.04$		Adj.$R^2 = 0.2$		Adj.$R^2 = 0.13$	

Note. LWR = Letter and Word Recognition scores, , Reading = Reading scores, RC = Reading Composite scores, LPREAD = Learner Profiler Reading Score.
**p* < .05. ***p* < .01. ****p* < .001.

Discussion

The aim of the current study was to investigate if the Learner Profiler could successfully predict WM, numeracy, and literacy outcomes from traditional pen and paper neuropsychological tests typically used to assess and diagnose LDDs in a sample of high school learners.

The focus on LDDs is important, because LDDs can have long-lasting detrimental consequences on learners' academic achievement and future outcomes through association with school dropout, emotional problems, and increased risk for risk-taking behaviours (Francis et al., 2019; Gubbels et al., 2019; McNamara & Willoughby, 2010; Nakajima et al., 2018; Sainio, 2019). Thus, screening for LDDs is incredibly important to ensure learners at risk receive the support needed. In SA, defining LDDs is complex due to external barriers within the learner's environment, such as socio-economic factors, that impact learning (Mazibuko et al., 2019). The screening for LDDs in SA is informed by a policy that places most of the responsibility of screening and identification of LDDs on strained teachers who lack time, resources, and training in LDDs (Matolo & Rambuda, 2022; Mkhuma et al., 2014; Ntseto et al., 2021). Teachers are considered a fundamental part of the identification of learners at risk for LDDs, however, current policy is difficult for teachers to implement and there is a need for more efficient screening tools to assist teachers in identifying and supporting learners with LDDs. Formal neuropsychological pen and paper tests, typically used for the identification and diagnosis of LDDs, while clinically useful, are time-consuming, costly, require expertise in administration and lack language diversity and locally relevant norms (Cole et al., 2018; Howieson, 2019). Computerized assessments, such as the Learner Profiler, on the other hand, have been put forward as a useful supportive tool to aid the screening for and identification of LDDs.

No studies have investigated the Learner Profiler's ability to predict outcomes from formal neuropsychological pen and paper tests typically used to diagnose LDDs. To add to the literature on the assessment of LDDs and the use of computerized screening tools in SA, the current study implemented the Learner Profiler with a sample of learners in Cape Town high schools. Additionally, the current study assessed the predictive validity of the Learner Profiler by comparing the results from the modules of the Learner Profiler to results from formal neuropsychological pen and paper tests typically used to assess working memory, literacy, and numeracy, and to diagnose LDDs. A tool that has such predictive validity and is cost and time efficient and easy to use would be significantly helpful in tackling the issues regarding LDD screening and identification in SA and possibly contribute to reducing the current strain on SA teachers.

It was hypothesized that the outcomes from the WM, numeracy and literacy domains of the Learner Profiler could significantly predict outcomes from related measures on formal pen and paper neuropsychological tests. To test this hypothesis, participants took part in 2 stages of the current study. In the first stage, they completed the Learner Profiler and in the second stage, those who chose to, completed the neuropsychological pen and paper tests which included the KTEA3 and the WM section of the WISC-IV.

I will present and discuss the results for the WM, numeracy and literacy sections of the current study in the context of previous research on these constructs and the comparability of computer-based and paper-based tests, below. Age, and attention, measured by Digit Span Forwards scores, were the control variables in all the analyses discussed below. The sample included adolescents who scored in the average range for Digit Span Forwards suggesting that, overall, the sample had no difficulties with attention. However, age and attention shared a significant negative moderate correlation indicating that older participants had poorer attention scores than younger participants.

Working Memory

It was hypothesized that the WM outcomes from the Learner Profiler could significantly predict the WM outcomes from traditional neuropsychological pen and paper tests. The average score for the Learner Profiler WM module was *many challenges reported* indicating participants may have a number of WM difficulties. This was mirrored in the Digit Span Backwards, Letter-Number Sequencing and WMI scores, on the neuropsychological measures, where participants scored on average in the low average range. The low average performance in the sample could be due to the small sample size and poorer scores significantly affecting the average. Attentional difficulties are highly prevalent within the general population with research showing an estimate of 2-16% of the school-age population being affected by these difficulties (Schoeman & Liebenberg, 2017). Additionally, due to the nature of the study, students with poorer school performance may have been more interested in the study than higher performing students. These factors may have resulted in the poorer scores and lower overall average within the sample group.

Although the Learner Profiler WM test is a computerized version of the Digit Span Backwards test and both tests indicated WM difficulties in the sample, surprisingly, there was no statistically significant correlation between the Learner Profiler WM scores and Digit Span Backwards scores. Additionally, there were no statistically significant correlations between the Learner Profiler WM scores and the Letter-Number Sequencing or WMI scores. As expected, there were significant relationships between the WM neuropsychological subtest scores.

Regarding the control variables, Digit Span Backwards and the WMI both shared a significant negative moderate correlation with age. Additionally, Letter-Number Sequencing and Learner Profiler WM scores shared a non-significant weak negative correlation with age indicating that, overall, older participant's had poorer WM compared to younger participants. However, results from the Chi-square tests of independence only indicated a significant relationship between age and Letter-Number Sequencing scores. The difference in results between the correlations and the Chi-square analyses is likely due to correlation analyses investigating the overall association between age and the WM variables whilst Chi-square analyses analyze the variation between the age groups.

For the hierarchical multivariate analyses, the control variables and the Learner Profiler WM scores were added in a stepwise process to determine if the Learner Profiler WM scores could predict the scores from the Digit Span Backwards, Letter-Number Sequencing and WMI from the WISC-IV. Although the hypothesis was not confirmed for Digit Span Backwards and Letter-Number Sequencing, it was confirmed for the WMI scores as Learner Profiler WM outcomes could significantly predict WMI scores from the WISC-

IV. Age, attention, and Learner Profiler WM scores were all significant predictors for WMI scores with attention being the most significant. These results remained consistent after outliers were removed from the data. Although both models were significant, the model excluding outliers explained 61% of the variance in WMI scores whilst the original model explained 45%.

The results from the hierarchical multivariate analyses and the ANOVAs indicated that the control variable attention had a significant influence on the WM outcomes. This finding can be explained by literature which has shown a significant and important relationship between attention and WM (Awh et al., 2006; Kiyonaga & Egner, 2013; Oberauer, 2019). In Baddeley's (1992) model of working memory, the central executive is a critical subcomponent of WM and is considered an attentional-controlling system.

The Learner Profiler WM module is comprised of an online version of the Digit Span Backwards assessment whereas the neuropsychological test is administered in person. Hence, participants completed the Learner Profiler independently without observation which differs from the WISC-IV subtest which was administered and overseen by a researcher. Further, for the neuropsychological test, an administrator reads aloud each sequence of numbers while in the Learner Profiler a recording of each sequence of numbers of varying lengths is played. A study investigating the effects of test administrator's attention or inattention to participants' computerized test performance found that the unobserved group had more errors on a computerized version of a memory test than the observed group (Yantz & McCaffrey, 2007). Furthermore, the lack of personal interaction or observation in the computerized Learner Profiler may reduce motivation to do well or remain attentive during the WM online assessment (Howieson, 2019). Therefore, the differences in administration between the WISC-IV WM tests and the Learner Profiler WM module could explain the result that the Learner Profiler WM scores did not significantly predict the Digit Span Backwards scores.

Overall, as the WMI is the overall measure of WM for the WISC-IV it can be said the hypothesis was confirmed and the WM outcomes from the Learner Profiler predicted the WMI outcomes from the neuropsychological pen and paper tests.

Numeracy

It was hypothesized that numeracy outcomes from the Learner Profiler could significantly predict the numeracy outcomes from traditional neuropsychological pen and paper tests. The average scores for Math Concepts and Applications, Math Computation and Math Composite were in the below-average range whilst for the Learner Profiler Math module, the average indicated *significant challenges* in this module for this sample. There was a non-significant moderate positive correlation between Learner Profiler Math scores and

Math Computation scores and a significant moderate positive correlation between Learner Profiler Math scores and Math Concepts and Application scores. Similar to the WM findings, there were negative correlations between age and the numeracy variables with a non-significant weak negative correlation between age and Math Concepts and Applications scores and a significant negative correlation between age and Learner Profiler Math scores. These results suggested that as age increased the participants' performance decreased. However, Chi-Square Tests of Independence conducted between age and the numeracy variables indicated no significant relationship between age and Math Computation, Math Concepts and Applications or Math Composite scores.

The hierarchical multivariate analyses for Math Composite scores indicated that the Learner Profiler Math scores did not significantly predict Math Concepts and Applications, Math Computation, or Math Composite scores. Therefore, the hypothesis was not confirmed, and the Learner Profiler could not significantly predict the numeracy outcomes from traditional neuropsychological pen and paper tests. Results from previous research on computer-based screeners for Dyscalculia vary.

Research using a self-administered computer program Dyscalculia Screener developed by Butterworth (2003) to provide a fast and reliable method of identifying Dyscalculia found that the screener misidentified students with both false positives and negatives (Gifford & Rockliffe, 2012; Lewis et al., 2021). This was attributed to the screener using speed of response to numerical questions as its measure although the screener was adjusted for slower reaction times (Voutsina & Ismail, 2007). The Learner Profiler also records response time as part of its measure of numeracy abilities.

A previous study found that a Dyscalculia web-based screener could be used as a first-pass screening tool for arithmetic learning difficulties (Zygouris et al, 2017). The aforementioned study included students who were previously diagnosed as dyscalculic through pen and paper tests as well as a control group. It was found that the Dyscalculia web-based assessment could not diagnose Dyscalculia but could act as a screening and referral tool (Zygouris et al, 2017). Considering the results of previous research, the Learner Profiler Math module's inability to predict numeracy scores may lie in the structure of its items.

The Learner Profiler Math's module is multiple choice which differs from the KTEA3 where the participant has to provide their calculated answer either verbally for the Math Concepts and Applications test or by writing it down for Math Computation. Research has shown that constructive-response test formats, which involve the student formulating their calculated answers, are more representative of student learning than multiple-choice tests for math education (Stankous, 2016). This has been attributed to the opportunity for students to guess the correct answer in multiple-choice questions and that teachers cannot where a student went wrong in their incorrect responses (Stankous, 2016). However, constructive-response tests like traditional neuropsychological pen and paper tests are time-consuming to score as each response differs slightly and can lead to inconsistencies in scoring (Cole et al., 2018; Howieson, 2019; Stankous, 2016).

Literacy

In this study, literacy was divided into written language and reading which were assessed separately. For written language, it was hypothesized that outcomes from the Learner Profiler Spelling, Non-Word Spelling and Missing Word modules could significantly predict the outcomes from the KTEA3 Spelling, Written Expression and Written Language Composite pen and paper tests. For reading, it was hypothesized that the outcomes from the Learner Profiler Reading module could significantly predict the outcomes from the KTEA3 Letter and Word Recognition, Reading and Reading Composite pen and paper tests.

Written Language

Written Language was measured through Spelling, Written Expression and the Written Language Composite of the KTEA3. The Learner Profiler has 3 written language modules: Spelling, Non-Word Spelling and Missing Word. For the Learner Profiler Spelling module, the average score for participants indicated *many challenges reported*, however, the most common score for this module was 4 which indicates *good skills*. For the Learner Profiler Non-Word Spelling composite participants scored in the *significant challenges reported* range whilst in the Missing Word module participants' scores were in the *reasonable skills* range. For the Spelling, Written Expression and Written Language Composite KTEA3, participants' scores were in the average range indicating no difficulties with this neuropsychological test section.

Spelling and Written Language composite scores from the KTEA3 both shared significant strong positive correlations with Learner Profiler Spelling scores. The Spelling, Written Expression and Written Language Composite scores all shared a significant moderate positive correlation with Learner Profiler Non-Word Spelling composite scores. Additionally, Spelling and Written Expression scores shared a significant moderate positive correlation with Learner Profiler Missing Word scores while Written Language Composite scores shared a significant strong positive correlation with Learner Profiler Missing Word scores.

Although Chi-Square Tests of Independence between the literacy variables and age showed no significant relationship between age and Spelling or Written Expression scores, they did show a significant relationship between age and Written Language Composite scores.

The hierarchical multivariate regression analyses revealed that the Learner Profiler Spelling, Non-Word Spelling and Missing word scores all significantly predicted the KTEA3 Spelling, Written Expression and Written Language composite scores. However, the ANOVAs revealed that there was only a significant difference in the models through the addition of the Learner Profiler Spelling scores. Additionally, the ANOVAs after the outliers were removed indicated a significant difference in the written expression and written language composite models through the addition of the Learner Profiler Non-Word Spelling scores. Overall, the hypothesis was confirmed, and the Learner Profiler Spelling scores significantly predicted the Spelling, Written Expression and Written Language Composite outcomes from the KTEA3.

These results were consistent with research on a computerized adaptable test battery which assessed children's academic skills and cognitive functions in the domains of written language, oral language, mathematics cognition, attention, and executive function (Billard et al., 2021a, Billard et al., 2021b). Billard et al (2021a; 2021b) compared a computerized adaptable test battery to similar pencil and paper test batteries and found that the results from the computerized test battery were highly predictive of the results from the reference tests and the tests were moderate to strongly correlated depending on the domain. Thus, they concluded that their computerized test battery for children aged 3-14 was a valuable first-line screening tool for LDDs. However, although the current study produced similar results, the computerized test battery investigated by Billard et al (2021a; 2021b) differed from the Learner Profiler as it required administration by a trained professional rather than independent test completion.

Reading

Reading was measured with Letter and Word Recognition, Reading and Reading Composite tests from the KTEA3. The average reading score for the Learner Profiler Reading module indicated participants had *significant challenges* and the average scores for the Reading and Reading Composite indicated participants scored in the below average range. Interestingly, Letter and Word Recognition scores were on average in the average range. Letter and Word Recognition scores, in addition to Reading and Reading Composite scores, shared a significant moderate correlation with Learner Profiler Reading scores. Similar to the working memory, numeracy and written language sections, there was a weak negative correlation between the Reading variables and age suggesting that as participants' age increased, their performance in the reading neuropsychological tests was poorer. However, this trend was not significant. Further, the Chi-Square Tests of Independence conducted between age and the Reading variables indicated no significant relationships between age and Letter and Word Recognition, Reading or Reading Composite scores. The difference in results between the correlations and the Chi-square analyses is likely due to correlation analyses investigating the overall association between age and the literacy variables whilst Chi-squared analyses are analyzing the variation between the age groups.

The hierarchical multiple regression analyses for the Reading variables were also done in a stepwise procedure with the control variable age as the predictor in the first model, then attention was added followed by the Learner Profiler Reading scores. It was revealed that Learner Profiler Reading scores significantly predicted Reading and Reading Composite scores but not Letter and Word Recognition scores. However, ANOVAs indicated that there was a significant difference between step 2 and step 3 through the addition of the Learner Profiler Reading scores in all models. The Learner Profiler's inability to significantly predict Letter and Word Recognition scores may be due to the differences in test items. For Letter and Word Recognition, the student is expected to recognize and read aloud grade-appropriate words. However, the Learner Profiler Reading module is more similar to the pen and paper Reading test with passages that must be read for meaning with corresponding questions as opposed to single word reading. Considering these differences in test items and as the Learner Profiler could significantly predict the Reading and Reading Composite scores, the hypothesis was confirmed and the reading outcomes from the Learner Profiler significantly predicted the reading outcomes from the KTEA3.

The results for the literacy modules of the Learner Profiler are promising as Dyslexia, a learning disorder characterized by poor spelling, issues with fluent and accurate word recognition and poor decoding (APA, 2013), is the most common LDD globally accounting for 80% of all specific learning disorders (Scaria et al., 2022; Yang et al., 2022) and having an estimated worldwide presence of 7.10% in primary school children (Yang et al., 2022). As the Learner Profiler modules with the most promising results were the literacy modules, which included Spelling, Non-Word Spelling, Missing Word and Reading, the Learner Profiler may be better suited to screen for dyslexia as opposed to other LDDs such as Dyscalculia and WM-related difficulties.

Research on the validity of a computerized screener for dyslexia for adults produced similar findings to the current study, in terms of the possible sensitivity of the Learner Profiler reading modules in identifying those with possible reading challenges. Singleton and Horne (2009) investigated the validity of a computerized screener for dyslexia in adults through comparing the performance of dyslexic and non-dyslexic groups on the computer screener. Although the screener differed from conventional tests of literacy, as it contained three tests that measured phonological processing, lexical access and working memory, it was found that the dyslexic group's performance on the screener substantially differed from the non-dyslexic group (Singleton & Horne, 2009). Additionally, the dyslexia screener showed high rates of sensitivity and specificity and it was concluded that the computerized tool was a valid and practical approach to dyslexia screening in adults (Singleton & Horne, 2009). They also reported the tool as beneficial as they, similar to the Learner Profiler, did not need trained administration or expert interpretation, were quick to administer and could assess large numbers (Singleton & Horne, 2009).

Some studies have shown a significant difference in reading performance between reading from paper and reading from screens with reading from screens having a negative effect on reading performance when compared to paper (Clinton, 2019). This result was limited to expository texts and did not apply to narrative texts (Clinton, 2019), and the Learner Profiler reading module has both narrative and expository texts as test items Contrastingly, other research on the interchangeability between computer-based tests and pen and paper tests of reading comprehension found no significant differences between the scores from the computer-based tests when compared to the scores from paper-based tests (Khoshsima & Toroujeni, 2017; Toroujeni, 2022). Additionally, the mode of test administration did not influence the results, however, it was found that attitudes about the use of computers was a moderator variable (Toroujeni, 2022). Similar to the results from the literacy section of the current study, computer-based tests, such as the Learner Profiler, show potential for use as a dyslexia or language-specific LDD screening tool due to their comparability and predictability with pen and paper tests (Khoshsima & Toroujeni, 2017; Singleton & Horne, 2009; Toroujeni, 2022).

Limitations

Although most of the Chi-square analyses showed no significant interactions between age and the dependent variables, almost all the dependent variables shared a negative relationship with age. These results could be due to the small sample size and the unequal number of participants in each age group. Additionally, the outlier analyses showed participants with higher than the group average scores were in the youngest group and that those with lower than the group average scores were in the older groups. Future research of this nature should include a much larger sample size which can allow for greater variation in the sample and mitigate against such within sample trends.

As noted, G*Power (Version 3.1.9.4) was used to conduct an a priori power analysis that indicated a minimum sample size of 104 participants; therefore, the study was limited by a small sample size (N=51). Future studies with larger sample sizes and equal numbers in age groups may yield more significant results for the Learner Profiler. Additionally, as many analyses were run, a small sample size could have affected results as it increases the risk of type II errors (Miot, 2018). Therefore, future studies with larger sample sizes should conduct further analyses to verify the results of the current study and determine if similar results will be obtained.

Although participants were able to successfully complete the Learner Profiler independently, the current study did not measure or account for familiarity with computers or attitudes towards the use of computers. It has been found that those with less familiarity with computers tend to perform worse in computerized neurocognitive tests than those with self-reported frequent computer use (Iverson et al., 2009) and that, attitudes about the use of computers can have an influence on testing performance (Toroujeni, 2022). Therefore, future studies should account for attitudes towards computers and the impact they may have on performance in computer-based tests.

The KTEA3 includes a section for the examiner to note behavioural observations of the participant after their test which can be useful in thoroughly evaluating their performance. A list of descriptions is provided for the examiner to choose to describe the participant's behaviour during the assessment that may have been disruptive or enhancing to their performance. Some computerized testing, like the Learner Profiler, lacks this capability as the participant completes the test independently. Future studies could compare observed and unobserved test performance in the Learner Profiler to determine if this has a significant effect on performance in the Learner Profiler as research has shown differences in participant performance based on administrator attention or inattention (Yantz & McCaffrey, 2007) and a lack of observation may reduce motivation to do well (Howieson, 2019)

Further, as the Learner Profiler can be translated into other SA languages, future studies may also assess its ability to assess learning abilities in other SA languages.

Conclusion

Overall, participants were able to complete the Learner Profiler independently and the study showed positive results for the use of this computerized screening tool. The Learner Profiler did not predict any numeracy outcomes and only significantly predicted outcomes from the overall WMI outcomes and not outcomes from the individual neuropsychological tests. Most notably, the Learner Profiler literacy outcomes did significantly predict the literacy outcomes from traditional neuropsychological tests. This was a promising result as the language related LDD, Dyslexia is the most common LDD globally (Scaria et al., 2022; Schelbe et al., 2021; Yang et al., 2022). Computerized tests cannot replace expert diagnoses through traditional neuropsychological tests, but they can help to indicate within the large group of students who may be at-risk and therefore require further assessment. The results of the study showed that the Learner Profiler may be beneficial in being used as a screening tool to identify students with language-related LDDs as it was shown to produce similar results to traditional neuropsychological tests of literacy. Although, the Learner Profiler did not significantly predict the results from the individual tests for WM it did significantly predict the composite scores indicating its potential for screening for WM related LDDs too.

There are challenges with the screening for LDDs in SA. The SIAS policy, which was intended to assist with the screening, identification, assessment, and support of learners who face barriers to learning, places excessive responsibility on strained teachers who do not have the time, resources, or training in LDDs to identify learners at-risk (Matolo & Rambuda, 2022; Mkhuma et al., 2014; Ntseto et al., 2021). This means that learners at risk for LDDs may go unidentified and not receive the support needed which can have detrimental consequences on their academic achievement (Nelson & Powell, 2018) and psychosocial well-being (Francis et al., 2019; Sainio, 2019). Therefore, the results of this study are significant as they have shown the capabilities and potential of the Learner Profiler as a tool to help alleviate the strain on teachers and be a supportive tool to aid the screening, identification, and possible diagnosis of language related LDDs in SA.

This study, through using the Learner Profiler to screen for working memory, numeracy, and literacy difficulties in high school students in SA and comparing its outcomes to results from neuropsychological pen and paper tests, adds to the literature on the assessment of LDDs in SA, the use of computerized assessment and screening tools and the use of the Learner Profiler in SA.

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Appendix A

YOUR CHILD IS INVITED TO PARTICIPATE IN A RESEARCH STUDY

I am a UCT psychology researcher looking for 13-16-year-old high school students to participate in my research study.

I would like to learn more about computers and their ability to detect strengths and needs in learning areas such as reading. In order to do this, I am asking high school learners to complete 2 sets of activities to compare computer-based activities to pen and paper activities.

This study will involve 2 Stages.

In the first stage your child will be asked to complete a set of computer-based activities. These activities include reading, basic math problems and memory activities. This will take approximately 30 minutes to complete.

In the second stage your child will be asked to complete a set of pen and paper activities in person at school. This will take approximately 1 hour and 30 minutes and will require your child to miss 2-3 school periods.

If your child chooses to take part, they will receive a R50 Checkers/Pick 'n Pay voucher for each stage completed and a 250MB data bundle to allow for internet access for the study. Your child will also be provided with a summary of their learning strengths and needs from the activities.

Any information provided by your child in the sessions will be kept confidential. Their name will be removed, and they will instead be given a code that is only recognisable by the researchers involved. Any information provided will only be used for research purposes such as a research report.

If you are interested in participating in this research or if you have any questions, please contact Khayreyah: antkha001@myuct.ac.za

Appendix B

UCT Department of Psychology

Participant Information Sheet

Your child is being invited to participate in my research. I would like to learn more about computers and their ability to detect strengths and needs in learning areas such as reading and math. In order to do this, I am asking 13-16-year-old high school learners to complete 2 sets of activities to compare computer-based activities to pen and paper activities.

If you agree to participate in this study, your child will be asked to participate in two stages/sessions. During the first session, your child will be asked to complete a set of computer-based activities. These activities include reading, basic math problems and memory activities. This will take approximately 30 minutes to complete. During the second session, your child will be asked to complete a set of pen and paper activities that are similar to previous session. This session will take approximately 1 hour and 30 minutes and will be conducted in person at school during the school day.

Taking part in this study will not cause any harm to your child, however, participation during the session may make them feel tired. Should your child wish to take a break, they may do so at any time. Should your child wish to stop participating in this study, they may do so at any point in the study without any changes to their schooling. There are no known benefits to your child by taking part in this study. However, as part of taking part in this study, they will receive a R50 Checkers/Pick 'n Pay voucher at the end of each session as compensation. Your child will also receive a 250MB bundle to allow for internet access for the computer-based activities.

Any information provided by your child in the sessions will be kept confidential. Your names will be removed and will instead be given a code that is only recognisable by the researchers involved. Any information provided will only be used for research purposes such as a research report.

Should you wish to participate in this research or if you have any questions, please contact the following email for more information: antkha001@myuct.ac.za (Khayreyah)

Appendix C

UCT Department of Psychology

Parent Consent Form

Informed consent for your child to participate in research

Your child is being invited to participate in a research study. This form provides you with the information about the study and requests your permission for your child to take part. Your child's participation will be voluntary. To better inform your decision, please read the information below and should you have any questions, feel free to contact the primary researcher. Your child will not be disadvantaged in any way by choosing to participate in the research or not.

1. **Title of research study**

   Does the Learner Profiler successfully detect strengths and needs in learning areas in high school learners?

2. **Principal researchers and contact details**

   Khayreyah Antvorskov
   Masters in Clinical Psychology student
   Department of Psychology
   University of Cape Town
   antkha001@myuct.ac.za
   Dr. Leigh Schrieff
   Supervisor
   Department of Psychology
   University of Cape Town
   leigh.schrieff-elson@uct.ac.za

3. **Source of funding**

   South Africa's National Research Foundation

4. **Purpose of the study**

   The purpose of the study is to compare outcomes of a computerised-screening measure to outcomes of traditional pen and paper measures, and so to see whether both measures can successfully produce similar results.

5. **Participation in this study**

   Your child will be asked to complete a set of activities during two stages/sessions. In Stage 1, your child will be asked to complete a set of activities on a computer. Stage 2 your child will be asked to complete a set of activities with pen and paper in person at school. Both stages will assess your child's reading fluency and comprehension, spelling and arithmetic ability, and their attention and working memory.

6. **Duration of participation**

   Completion of Stage 1 will take approximately 30 minutes and completion of Stage 2 will take approximately 1 hour and 30 minutes. This will take place during the school day, and your child will miss lessons while I am working with them. If at any time, your child wishes to stop their participation, they may do so without any consequences for their schooling.

7. **Number of participants**

   For Stage 1 of the study, we seek to recruit at least 104 participants. All learners will be invited to participate in Stage 2, should they have completed Stage 1 and have parental consent, and give their own assent to participation for Stage 2.

8. **Possible risks and/or discomforts**

   There are very few risks involved in participating in this study. For example, your child may feel tired during completion of the activities. However, your child will be allowed to take a break should they wish to do so. If there are any discomforts your child may experience by participating in this study, you may contact the principal researcher. Moreover, there is the potential that the activities completed in the study could indicate that your child may have a potential learning difficulty. However, should this be the case, you will be informed, and we will work with you to refer your child for further testing. Referrals will go to the district educational psychologist and/or to the Groote Schuur Neuropsychology clinic, for further assessment.

9. **Possible benefits**

   Your child may not personally benefit from participating in this study. However, any information gathered from their participation may help in assessing the feasibility of computerised-screening techniques. There is the potential that we could find indications that your child may have problems in learning. However, should this be the case, you will be informed, and we will work with you to refer your child for further testing. Referrals will go to the district educational psychologist and/or to the Groote Schuur Neuropsychology clinic, for further assessment.

10. Compensation

Your child will be compensated with a R50 Checkers/Pick ‘n Pay voucher for each stage that they participate in. We will also provide a bundle of 250MB of data to allow for internet connectivity to participate in the study.

11. Voluntary participation and withdrawal

Participating in this study is entirely voluntary (it is your and your child’s choice). Your child may stop participating at any point during the study. Should your child wish to withdraw, there will be no penalties or repercussions. If your child withdraws, we will ask you and your child for permission to use the information already provided.

If you or your child has any questions regarding their rights in participating in this research, you may contact the Psychology Department office on 021 650 3417 or email Rosalind Adams (rosalind.adams@uct.ac.za). Alternatively, you can contact the primary researchers should you have any questions about the study (contact information provided on Page 1).

12. Confidentiality of information and privacy

Any information provided by your child will be kept confidential and will only be accessed by researchers of this study. All the information provided will be coded for anonymity and will be kept anonymous when included in reports. Your child’s information will not be released without your permission unless required by law.

13. Requirements

A working computer with access to the internet is required to access the computerised tasks. Alternatively, the computer-based tasks can be accessed using a smartphone with internet access.

14. Signatures

Signature of person obtaining consent:

As a primary researcher of this study, I have explained the purpose, procedures, possible risks and benefits as well as voluntary participation and confidentiality to the participants’ parent or legal guardian. Furthermore, I have explained how the data will be collected and used:

____ ____________

Signature of primary researcher Date

<u>Signature of person providing consent:</u>

I (the parent/legal guardian) have been informed about purpose of the study, the risks and benefits involved, procedure of collecting data and how it will be used. I have received a copy of this form with the details of the primary researchers should I wish to ask any questions.

I voluntarily agree that my child may be invited to participate in this study and hereby provide permission for the collection and use of the data based on my child's performance. By signing this form, you are not giving away any of your legal rights.

Initials and surname of person providing consent

____

Date

____

Signature (add electronic signature or print, sign and scan form)

____

By signing this form, I agree that my child may be invited to participate in Stage 1 (computerised tasks) of the study.

Date

____

Initial and surname of child

____

Grade

____

I also agree that my child may be invited to participate in Stage 2 (neuropsychological pen and paper tasks) of the study.

Signature (add electronic signature or print, sign and scan form)

____

Appendix D

UCT Department of Psychology

Participant Assent Form

PERMISSION TO PARTICIPATE IN RESEARCH

You are being invited to participate in my research. I would like to learn more about computers and their ability to detect strengths and needs in learning areas such as reading and arithmetic. In order to do this, I am asking high school learners to complete 2 sets of activities to compare computer-based activities to pen and paper activities.

If you agree to participate in this study, you will be asked to participate in two stages/sessions. During the first session, you will be asked to complete a set of computer-based activities. These activities include reading, basic math problems and memory activities. This will take approximately 30 minutes to complete. During the second session, you will be asked to complete a set of pen and paper activities that are similar to previous session. This session will take approximately 1 hour and 30 minutes and will take place during the school day. To participate in this study, you will need a working computer with access to the internet for access to the computerised tasks. Alternatively, the platform that will be used for the first task can be accessed using a smartphone with internet access.

Taking part in this study will not cause any harm to you, however, participation during the session may make you feel tired. Should you wish to take a break, you may do so at any time. Participating in this study is entirely voluntary (it is your choice). Should you wish to stop participating in this study, you may do so at any point in the study without any consequences to your schooling. If you choose to stop participating we will ask you for permission to use the information already provided. There are no known benefits to you by taking part in this study. However, as part of taking part in this study, you will receive a R50 Checkers/Pick 'n Pay voucher at the end of each session as compensation. You will also receive a summary of your learning strengths and needs from the activities.

Any information provided by you in the sessions will be kept confidential. Your name will be removed, and you will instead be given a code that is only recognisable by the researchers involved. Any information provided will only be used for research purposes such as a research report.

By signing this, it means that you would like to participate in this study. Should you wish to not take part, you do not have to sign this form. Before, signing this form, I will answer any questions you may have about the study. If you cannot think of any questions now, you may ask them the next time we meet.

If you have any questions regarding your rights in this study, you may contact the Psychology Department office on 021 650 3417 or email Rosalind Adams (rosalind.adams@uct.ac.za). Alternatively, you may also contact the primary researchers involved in this study:

Dr. Leigh Schrieff (supervisor) – leigh.schrieff-elson@uct.ac.za

Khayreyah Antvorskov (researcher) – antkha001@myuct.ac.za

I would like to take part in this study:

By signing, I agree that I have been informed of the purpose of the study, the benefits and risks of this study and of my rights in this study:

Initials and surname

____

Date

____

Signature (add electronic signature or print, sign and scan form)

____

By signing this form, I agree to my participation in Stage 1 (computerised tasks) of the study.

I also agree to my participation in Stage 2 (neuropsychological pen and paper tasks) of the study.

Signature (add electronic signature or print, sign and scan form)

Date

Signature of Researcher Date

Appendix E

UCT Department of Psychology

Participant Debriefing Letter

Thank you for your participation in this study titled: Does the Learner Profiler successfully detect strengths and needs in learning areas in high school learners?

Your participation in this study is appreciated. The current study is being conducted by a Psychology Masters student. The purpose of the study is to assess how well a computerised-screening measure can tell us about the outcomes on pen and paper assessments of attention, mathematics and language skills. Thus, the information gathered from this study will help us to see whether using computer-based assessments like these will be helpful in a South African context.

Should you have any questions or concerns related to your participation in this study or participating in this study made you feel anxious, please feel free to contact the researcher or the supervisor:

Dr. Leigh Schrieff (supervisor) – leigh.schrieff-elson@uct.ac.za

Khayreyah Antvorskov (researcher) – antkha001@myuct.ac.za

Appendix F

UNIVERSITY OF CAPE TOWN
Faculty of Health Sciences
Human Research Ethics Committee

Room 45 E-52-E-Floor- Old Main Building
Groote Schuur Hospital
Observatory 7925
Telephone [021] 406 6492
Email: hrec-submissions@uct.ac.za
Website: www.health.uct.ac.za/fhs/research/humanethics/forms

10 May 2022

HREC REF: 354/2021

A/Prof L Schrieff-Elson
Department of Psychology
UCT
Email: leigh.schrieff-elson@uct.ac.za
Student: ANTKHA001@myuct.ac.za

Dear A/Prof Schrieff-Elson

PROJECT TITLE : USING THE LEARNER PROFILER TO SCREEN FOR LEARNING DIFFICULTIES AND DISABILITIES AND IN PREDICTING NEUROPSYCHOLOGICAL OUTCOMES IN A SAMPLE OF HIGH SCHOOL LEARNERS-
(MASTERS CANDIDATE-MS KHAYREYAH ANTVORSKOV)

Thank you for your letter and study staff amendment to the Faculty of Health Sciences Human Research Ethics Committee (HREC).

It is a pleasure to inform you that the HREC has **formally approved** the above-mentioned study.

This approval is subject to strict adherence to the HREC recommendations regarding research involving human participants during COVID -19. Please refer to guidance letter dated 02 February 2022 on our website:
http://www.health.uct.ac.za/fhs/research/humanethics/forms

Approval is granted for one year until the 30 May 2023.

Please submit a progress form, using the standardised Annual Report Form if the study continues beyond the approval period. Please submit a Standard Closure form if the study is completed within the approval period.
(Forms can be found on our website: www.health.uct.ac.za/fhs/research/humanethics/forms)

The HREC acknowledge that the student: Khayreyah Antvorskov will also be involved in this study

Please quote the HREC REF 354/2021 in all your correspondence.

Please note that the ongoing ethical conduct of the study remains the responsibility of the principal investigator.

Please note that for all studies approved by the HREC, the principal investigator **must** obtain appropriate institutional approval, where necessary, before the research may occur.

Appendix G

UNIVERSITY OF CAPE TOWN

Department of Psychology

University of Cape Town Rondebosch 7701 South Africa
Telephone (021) 650 3417
Fax No. (021) 650 4104

17 May 2022

Khayreyah Antvorskov
Department of Psychology
University of Cape Town
Rondebosch 7701

Dear Khayreyah

I am pleased to inform you that ethical clearance has been given by an Ethics Review Committee of the Faculty of Humanities for your study, *Does the learner profiler successfully screen for neurodiversity and predict neuropsychological outcomes in high school learners.* The reference number is PSY2022-009.

I wish you all the best for your study.

Yours sincerely

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

Appendix H

Directorate: Research

meshack.kanzi@westerncape.gov.za
Tel: +27 021 467 2350
Fax: 086 590 2282
Private Bag x9114, Cape Town, 8000
wced.wcape.gov.za

REFERENCE: 20220527-2555
ENQUIRIES: Mr M Kanzi

Ms Khayreyah Antvorskov
56 Elgin Road
Sybrandpark
Rondebosch
7700

Dear Khayreyah Antvorskov,

RESEARCH PROPOSAL: USING THE LEARNER PROFILER TO SCREEN FOR LEARNING DIFFICULTIES AND DISABILITIES AND IN PREDICTING NEUROPSYCHOLOGICAL OUTCOMES IN A SAMPLE OF HIGH SCHOOL LEARNERS.

Your application to conduct the above-mentioned research in schools in the Western Cape has been approved subject to the following conditions:

1. Principals, educators and learners are under no obligation to assist you in your investigation.
2. Principals, educators, learners and schools should not be identifiable in any way from the results of the investigation.
3. You make all the arrangements concerning your investigation.
4. Educators' programmes are not to be interrupted.
5. The Study is to be conducted from **27 May 2022 till 30 September 2022.**
6. No research can be conducted during the fourth term as schools are preparing and finalizing syllabi for examinations (October to December).
7. Should you wish to extend the period of your survey, please contact Mr M Kanzi at the contact numbers above quoting the reference number.
8. A photocopy of this letter is submitted to the principal where the intended research is to be conducted.
9. Your research will be limited to the list of schools as forwarded to the Western Cape Education Department.
10. A brief summary of the content, findings and recommendations is provided to the Director: Research Services.
11. The Department receives a copy of the completed report/dissertation/thesis addressed to:

    The Director: Research Services
    Western Cape Education Department
    Private Bag X9114
    CAPE TOWN
    8000

We wish you success in your research.

Kind regards,
Meshack Kanzi
Directorate: Research
DATE: 27 May 2022

1 North Wharf Square, 2 Lower Loop Street,
Foreshore, Cape Town 8001
tel: +27 21 467 2531

Private Bag X 9114, Cape Town, 8000
Safe Schools: 0800 45 46 47
wcedonline.westerncape.gov.za

Appendix I

Attention and Age

Cross tabulations and Chi-squared analyses

A cross tabulation between Digit Span Forwards scaled scores and age categories showed that for the 13-years-old, 14-years-old and 15-years-old age groups majority of the participants scored in the average range whilst for the 16-years-old age group most participants scored in the low average and average ranges. A summary of the cross tabulation between Digit Span Forwards and age is presented in Table 17.

A Chi-Squared Test of Independence was performed to assess the relationship between age and Digit Span Forwards which showed no significant relationship between Digit Span Forwards scaled scores and age, $X^2(12, N{=}40) = 12.98$, $p = .26$.

Table 17

Cross Tabulation DSF And Age

	Borderline		Low Average		Average		High Average		Superior		Very Superior		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	1	20	2	40	1	20	1	20	0	0	5	100
14	0	0	1	9.1	9	81.8	0	0	1	9.1	0	0	11	100
15	4	22.2	4	22.2	8	44.4	2	11.1	0	0	0	0	18	100
16	1	16.7	2	33.3	2	33.3	1	16.7	0	0	0	0	6	100
Total	5	12.5	8	20	21	52.5	4	10	2	5	0	0	40	100

Note. DSF = Digit Span Forwards Scaled Scores (<5 =borderline; 6-7 = low average; 8-11 = average, 12 – 13 = high average; 14-15 = superior; >16 = very superior).

Working Memory

Cross tabulations and Chi-squared analyses

The cross tabulation between Digit Span Backwards scaled scores and Age categories showed that majority of the participants in the 13-years-old, 14-years-old and 15-years-old age groups scored in the low average range whilst majority of the 16-years-old participants scored in the average range. A summary of the cross tabulation between Digit Span Backwards and age is presented in Table 18. Chi-Square Tests of Independence indicated there was no significant relationship between age and Digit Span Backwards, $X^2(12, N=40) = 20.4$, p = .06.

A cross tabulation of the Letter Number Sequencing scaled scores and Age categories showed that majority of the 13-years-old, 14-years-old and 16-years-old age groups scored in the average range. For the 15-years-old age group participants scored in equal majorities in the average and low average ranges. A summary of the cross tabulation between Letter Number Sequencing and age is presented in Table 19. Chi-Square Tests of Independence indicated there was a significant relationship between age and Letter Number Sequencing, $X^2(9, N=40) = 19.04$, $p = .02$.

A cross tabulation of the WMI scores and Age categories showed that majority of participants in the 13-years-old and 14-years old age groups scored in the average range whilst majority of the participants in the 15-years-old and 16-years-old age groups scored in the low average range. Table 20 shows the cross tabulation between WMI Scores and Age. Although, Cramer's V indicated that there is a moderate association between age and WMI scores, $V = 0.42$, the Chi-Square results indicated there was no significant relationship between age and WMI scores., $X^2(12, N=40) = 21.59$, $p = .05$.

Table 18

Cross Tabulation DSB And Age

	Borderline		Low Average		Average		High Average		Superior		Very Superior		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	2	40	1	20	1	20	0	0	1	20	5	100
14	1	9.1	4	36.4	4	36.4	2	18.2	0	0	0	0	11	100
15	6	33.3	8	44.4	4	22.2	0	0	0	0	0	0	18	100
16	2	33.3	0	0	4	66.7	0	0	0	0	0	0	6	100
Total	9	22.5	14	35	13	32.5	3	7.5	0	0	1	2.5	40	100

Note. DSB = Digit Span Backwards Scaled Scores (<5 =borderline; 6-7 = low average; 8-11 = average, 12 – 13 = high average; 14-15 = superior; >16 = very superior).

Table 19

Cross Tabulation LNS And Age

	Borderline		Low Average		Average		High Average		Superior		Very Superior		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	1	20	0	0	3	60	0	0	0	0	1	20	5	100
14	0	0	2	18.2	9	81.8	0	0	0	0	0	0	11	100
15	4	22.2	7	38.9	7	38.9	0	0	0	0	0	0	18	100
16	0	0	0	0	6	100	0	0	0	0	0	0	6	100
Total	5	12.5	9	22.5	25	62.5	0	0	0	0	1	2.5	40	100

Note. LNS = Letter-Number Sequencing Scaled Scores (<5 =borderline; 6-7 = low average; 8-11 = average, 12 – 13 = high average; 14-15 = superior; >16 = very superior).

Table 20

Cross Tabulation WMI And Age

	Extremely Low		Borderline		Low Average		Average		High Average		Superior		Very Superior		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	1	20	1	20	2	40	0	0	0	0	1	20	5	100
14	0	0	0	0	3	27.3	8	72.7	0	0	0	0	0	0	11	100
15	3	16.7	2	11.1	10	55.6	3	16.7	0	0	0	0	0	0	18	100
16	0	0	0	0	4	66.7	2	33.3	0	0	0	0	0	0	6	100
Total	3	7.5	3	7.5	18	45	15	37.5	0	0	0	0	1	2.5	40	100%

Note. WMI = Working Memory Index Scores (<70 = extremely low; 70-79 = borderline; 80-89 = low average; 9-109 = average; 110-119 = high average; 120-129 = superior, > 130 = very superior).

Outliers

Figures 1, 2 and 3 show the boxplots and outliers for Digit Span Backwards, Letter Number Sequencing and Working memory Index scores, respectively.

Figure 1

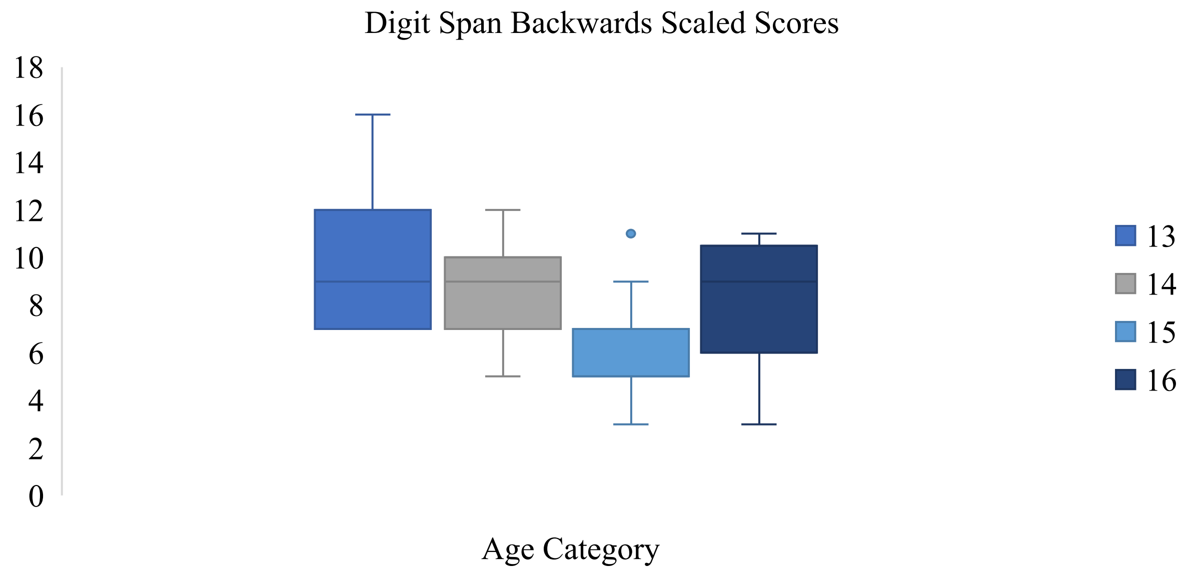


Figure 2

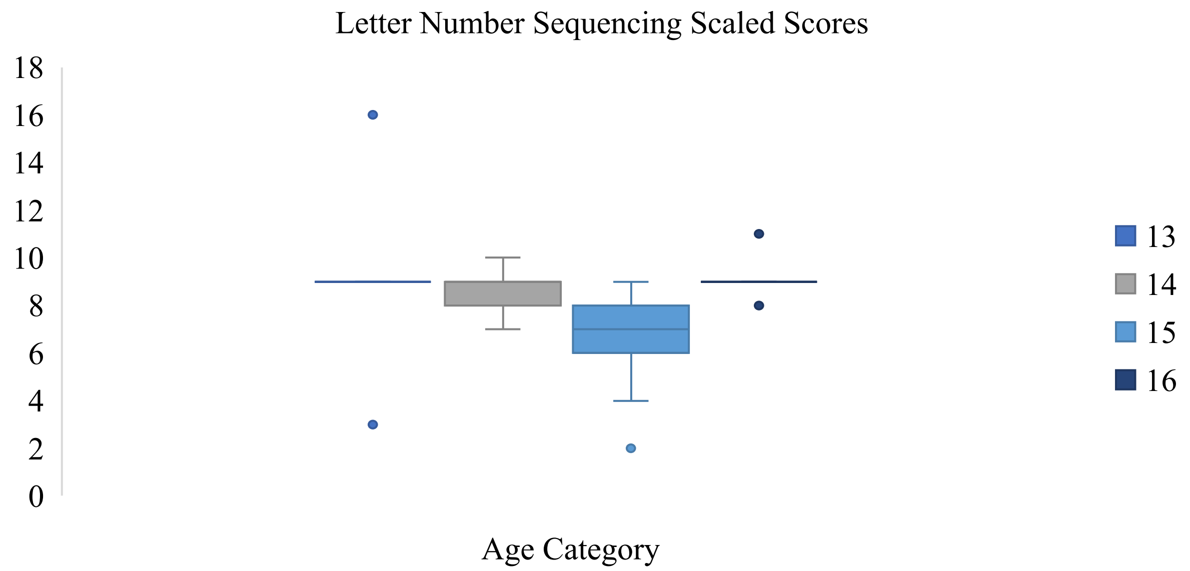


Figure 3

Numeracy

Cross tabulations and Chi-squared analyses

A cross tabulation between Math Computation and age revealed that for all age groups majority of the participants scored in the below average range. Additionally, for the 15-years-old age group 16.7% ($N = 3$) scored in the low range and 16.7% ($N = 3$) scored in the average range. Similar results were found for Math Concepts and Applications with the cross tabulation showing that for all age groups majority of the participants scored in the below average range with all participants in the 16-years-old age group (100%, $N = 6$) scoring in the below average range.

The cross tabulation between Math composite scores and age showed majority of the participants in the 13-years-old, 14-years-old and 15-years-old age groups scoring in the below average range with all participants in the 13-years-old age group scoring in the below average range (100%, $N = 5$). Only 2 participants scored in the average range for Math composite scores and both were in the 15-years-old age group. For the 16-years-old age group participants scored indicated they were split evenly between the low (50%, $N = 3$) and below average ranges (50%, $N = 3$). Tables 21-23 show a summary of the results of the cross tabulations.

Chi-Square Tests of Independence were conducted between age and Math Computation, Math Concepts and Applications and Math composite scaled scores, respectively and all 3 produced similar results. The Chi-square results showed that Age had no significant relationship with Math Computation ($X^2(6, N=40) = 2.68, p = .97$), Math Concepts and Applications ($X^2(6, N=40) = 8.58, p = .33$) or Math Composite scores $X^2(6, N=40) = 8.62, p = .26$).

Table 21

Cross Tabulation MC And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	1	20	4	80	0	0	0	0	0	0	0	0	5	100
14	0	0	2	18.2	8	72.7	1	9.1	0	0	0	0	0	0	11	100
15	0	0	3	16.7	12	66.7	3	16.7	0	0	0	0	0	0	18	100
16	0	0	2	33.3	4	66.7	0	0	0	0	0	0	0	0	6	100
Total	0	0	8	20	28	70	4	10	0	0	0	0	0	0	40	100%

Note. MC = Math Computation (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Table 22

Cross Tabulation MCA And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	0	0	3	60	2	40	0	0	0	0	0	0	5	100
14	0	0	0	0	9	81.8	2	18.2	0	0	0	0	0	0	11	100
15	0	0	4	22.2	11	61.1	3	16.7	0	0	0	0	0	0	18	100
16	0	0	0	0	6	100	0	0	0	0	0	0	0	0	6	100
Total	0	0	4	10	29	72.5	7	17.5	0	0	0	0	0	0	40	100%

Note. MCA = Math Concepts and Applications scaled score (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Table 23

Cross Tabulation Math And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	0	0	5	100	0	0	0	0	0	0	0	0	5	100
14	0	0	1	9.1	10	90.9	0	0	0	0	0	0	0	0	11	100
15	0	0	3	16.7	13	72.2	2	11.1	0	0	0	0	0	0	18	100
16	0	0	3	50	3	50	0	0	0	0	0	0	0	0	6	100
Total	0	0	7	12.5	31	77.5	2	5	0	0	0	0	0	0	40	100%

Note. Math = Math Composite scores (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Outliers

Figures 4, 5 and 6 show the boxplots and outliers for Math Computation, Math Concepts and Application and Math Composite scores, respectively.

Figure 4

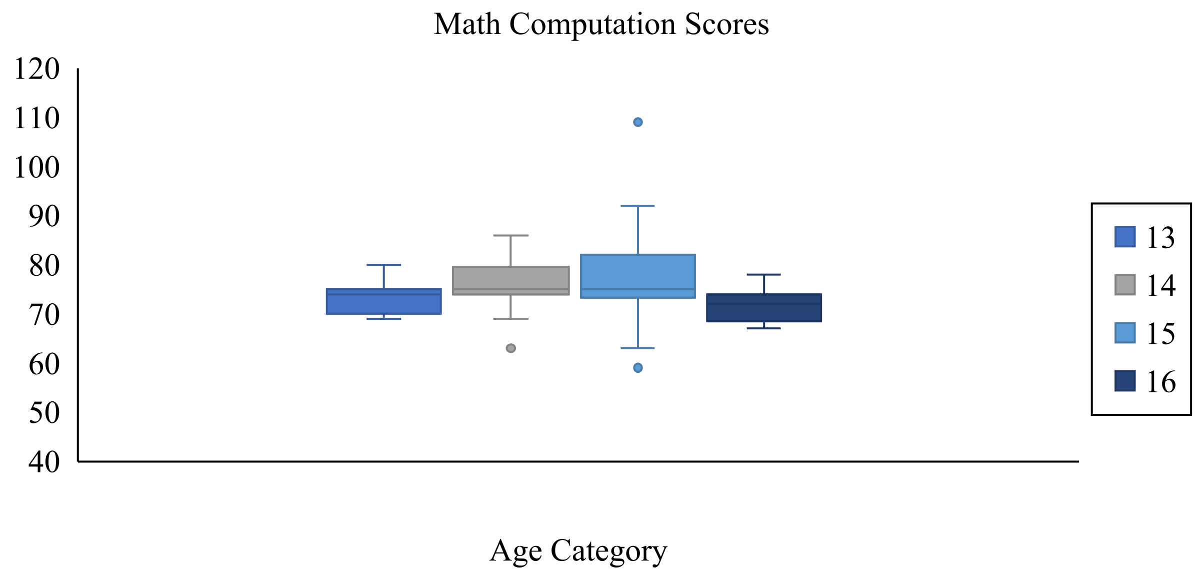


Figure 5

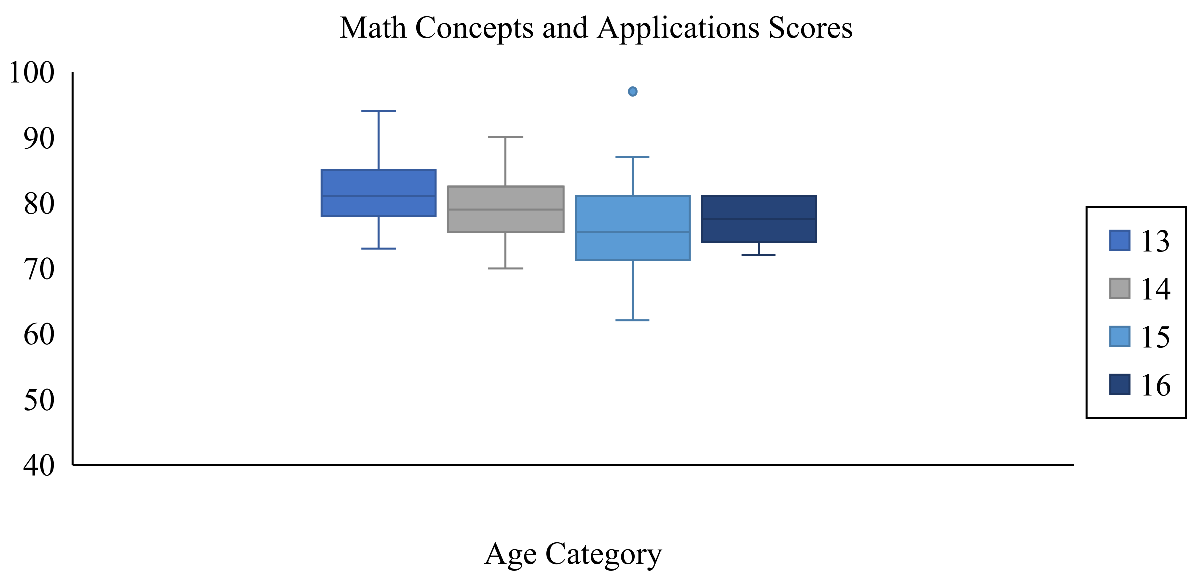
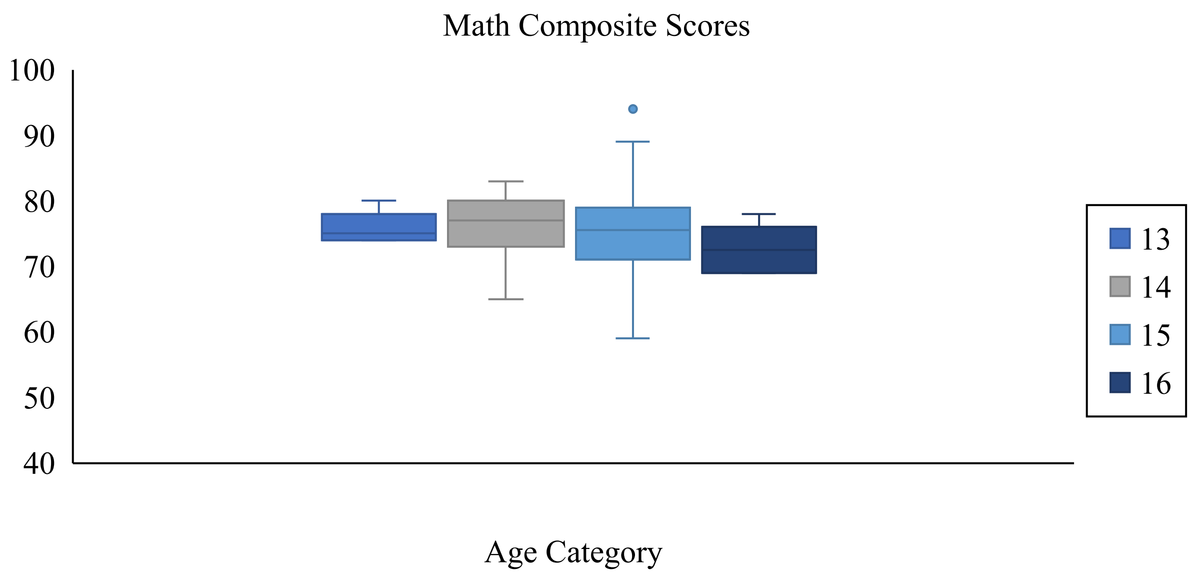


Figure 6



Literacy

Written Expression

Cross tabulations and Chi-squared analyses. Cross tabulations between age and Spelling scores showed that majority of participants in the 13-years-old age group scored in the below average range whilst majority of participants in the 14-years-old and 16-years-olf age groups scored in the average range. For the 15-years-old age group participants scores were split between the average (44.4%) and below average range (44.4%).

For Written Expression the cross tabulation with age showed that majority of the participants in all four age groups performed in the average range for Written Expression. For Written Language Composite scores, the cross tabulation with age showed majority of the participants in the 13-years-old age group scored in the below average range whilst majority of the participants in the 14-years-old and 15-years-old age groups scored in the average range. For the 16-years-old age group participants scores were split evenly between the average and below average ranges. Tables 24-26 show a summary of the results of the cross tabulations.

Chi-Square Tests of Independence were conducted between age and Spelling, Witten Expression and Written Language Composite scaled scores, respectively. The Chi-square results showed that age had no significant relationship with Spelling ($X^2(9, N=40) = 11.93$, $p = .19$) and Written Expression scores ($X^2(6, N=40) = 8.13$, $p = .43$). The Chi-square results for age and Written Language Composite showed that age had a significant relationship with Written Language Composite, $X^2(6, N=40) = 13.83$, $p = .03$).

Table 24

Cross Tabulation SP And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	0	0	4	80	1	20	0	0	0	0	0	0	5	100
14	0	0	1	9.1	3	18.2	8	72.7	0	0	0	0	0	0	11	100
15	0	0	1	5.6	8	44.4	8	44.4	1	5.6	0	0	0	0	18	100
16	0	0	2	33.3	1	16.7	3	50	0	0	0	0	0	0	6	100
Total	0	0	4	10	15	47.5	20	50	1	2.5	0	0	0	0	40	100%

Note. SP = Spelling (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Table 25

Cross Tabulation WE And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	0	0	1	20	3	60	1	20	0	0	0	0	5	100
14	0	0	0	0	1	9.1	10	90.9	0	0	0	0	0	0	11	100
15	0	0	0	0	4	22.2	14	77.8	0	0	0	0	0	0	18	100
16	0	0	0	0	1	16.7	5	83.3	0	0	0	0	0	0	6	100
Total	0	0	0	0	7	17.5	32	80	1	2.5	0	0	0	0	40	100%

Note. WE = Written Expression (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Table 26

Cross Tabulation WLC And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	0	0	3	60	1	20	1	20	0	0	0	0	5	100
14	0	0	0	0	1	9.1	10	90.9	0	0	0	0	0	0	11	100
15	0	0	0	0	5	27.8	13	72.2	0	0	0	0	0	0	18	100
16	0	0	0	0	3	50	3	50	0	0	0	0	0	0	6	100
Total	0	0	0	0	12	30	27	67.5	1	2.5	0	0	0	0	40	100%

Note. WC = Written Language Composite (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Outliers. Figures 7, 8 and 9 show the boxplots and outliers for Spelling, Written Expression and Written language Composite scores, respectively.

Figure 7

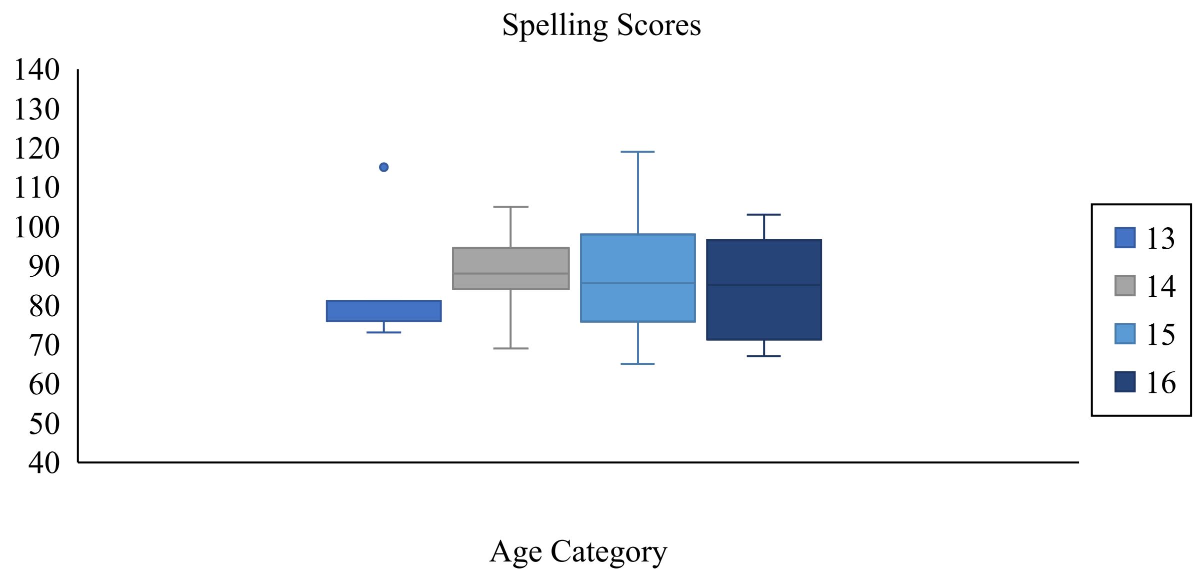

Spelling Scores
140
130
120
110
100
90
80
70
60
50
40
Age Category
13
14
15
16

Figure 8

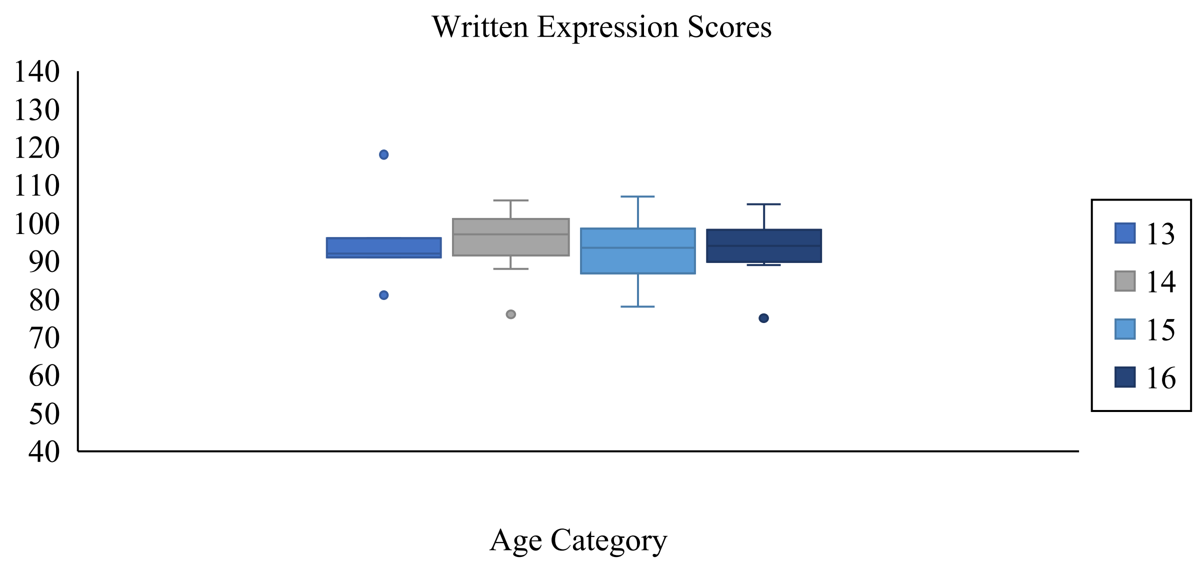
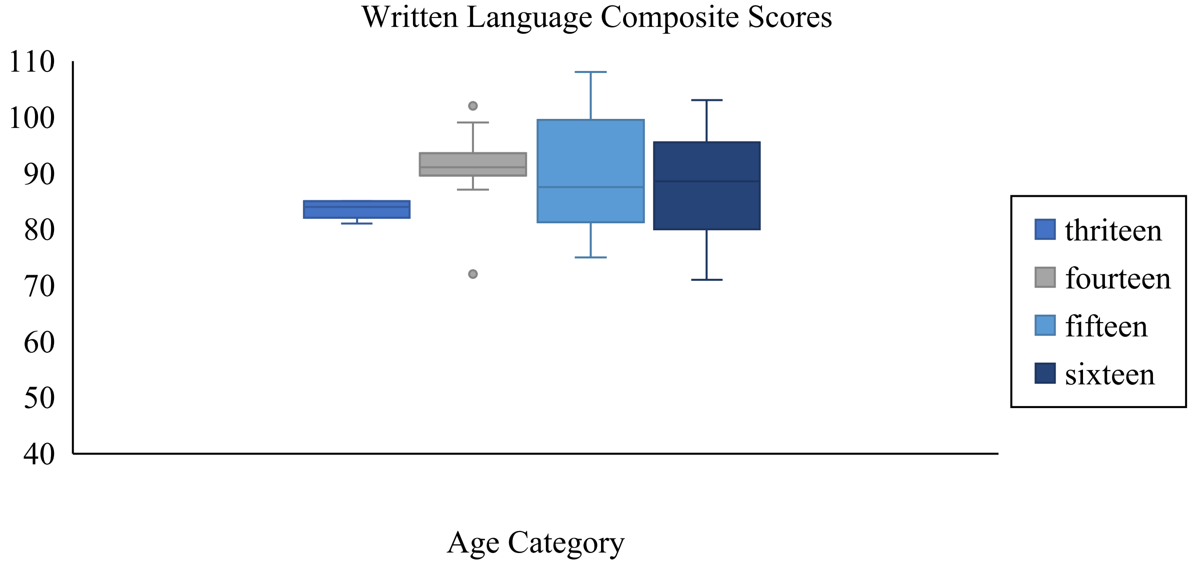

Written Expression Scores
140
130
120
110
100
90
80
70
60
50
40
Age Category
13
14
15
16

Figure 9



Reading

Cross tabulations and Chi-squared analyses. Cross tabulations between age and Letter and Word Recognition scores, see Table 27, showed that majority of participants in the 13-years-old and 16-years-old age groups scored in the below average range whilst majority of participants in the 14-years-old and 15-years-olf age groups scored in the average range.

For Reading the cross tabulation with age, see Table 28, showed that for the 14-years-old and 15-years-old age groups majority of the participants scored in the below average range whilst for the 16-years-old age group majority of the participants scored in the low range. For the 13-years-old age group 40% of the participants scored in the below average range and 40% of the participants scored in the average range.

For Reading Composite scores, the cross tabulation with age, see Table 29, showed that for the 13-years-old, 15-years-old and 16-years-old age groups majority of the participants scored in the below average range whilst majority of the participants in the 14-years-old age group scored in the average range.

Chi-Square Tests of Independence were conducted between age and Letter and Word Recognition, Reading and Reading Composite scores, respectively. The Chi-square results showed that Age had no significant relationship with Letter and Word Recognition (X^2(9, N=40) = 13.62, p = .06), Reading (X^2(6, N=40) = 7.85, p = .18) or Reading Composite scores (X^2(9, N=40) = 9.77, p = .2)

Table 27

Cross Tabulation LWR And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	0	0	3	60	1	20	1	20	0	0	0	0	5	100
14	0	0	1	9.1	1	9.1	9	81.8	0	0	0	0	0	0	11	100
15	0	0	0	0	7	38.9	8	44.4	3	16.7	0	0	0	0	18	100
16	0	0	0	0	4	66.7	2	33.3	0	0	0	0	0	0	6	100
Total	0	0	1	2.5	15	37.5	20	50	4	10	0	0	0	0	40	100%

Note. LWR = Letter and Word Recognition scores (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Table 28

Cross Tabulation Reading And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	1	20	2	40	2	40	0	0	0	0	0	0	5	100
14	0	0	0	0	6	54.5	5	45.5	0	0	0	0	0	0	11	100
15	0	0	6	33.3	9	50	3	16.7	0	0	0	0	0	0	18	100
16	0	0	3	50	2	33.3	1	16.7	0	0	0	0	0	0	6	100
Total	0	0	10	25	19	47.5	11	27.5	0	0	0	0	0	0	40	100%

Note. Reading = Reading scores (40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Table 29

Cross Tabulation RC And Age

	Very Low		Low		Below Average		Average		Above Average		High		Very High		Total	
	n	%	n	%	n	%	n	%	n	%	n	%	n	%	n	%
13	0	0	1	20	3	60	1	20	0	0	0	0	0	0	5	100
14	0	0	1	9.1	4	36.4	6	54.5	0	0	0	0	0	0	11	100
15	0	0	0	0	11	61.1	6	33.3	1	5.6	0	0	0	0	18	100
16	0	0	2	33.3	3	50	1	16.7	0	0	0	0	0	0	6	100
Total	0	0	4	10	21	51.5	14	35	1	2.5	0	0	0	0	40	100%

Note. RC = Reading Composite scores(40-54 = very low; 55-69 = low; 70-84= below average; 85-115 = average, 116-130= above average; 131-145 = high; 146-160 = very high).

Outliers. Figures 10, 11 and 12 show the boxplots and outliers for Letter and Word Recognition, Reading and Reading Composite scores, respectively.

Figure 10

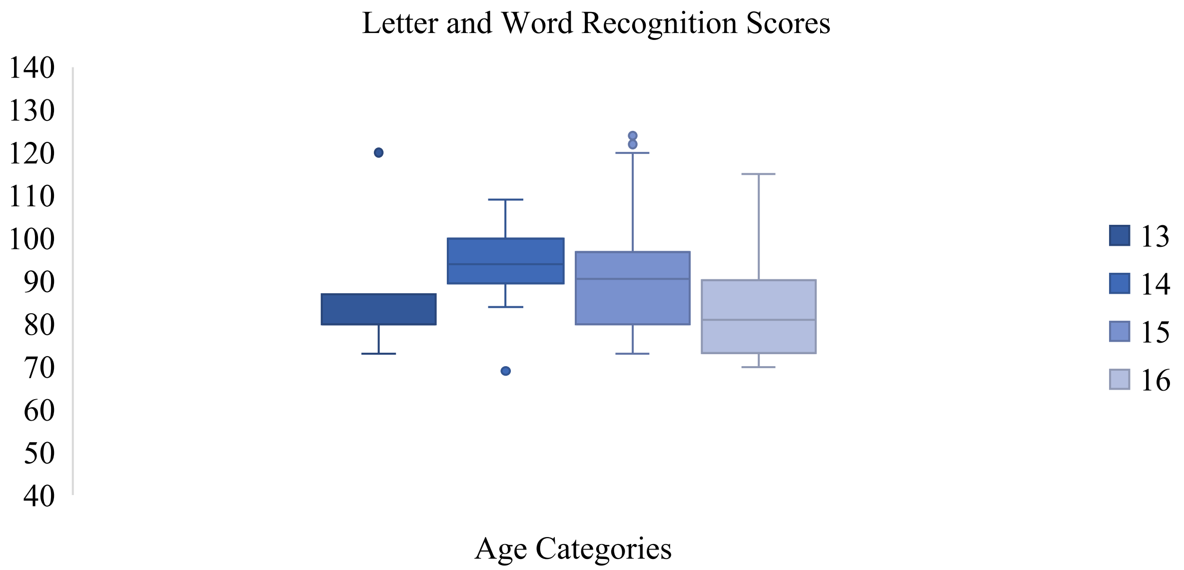


Figure 11

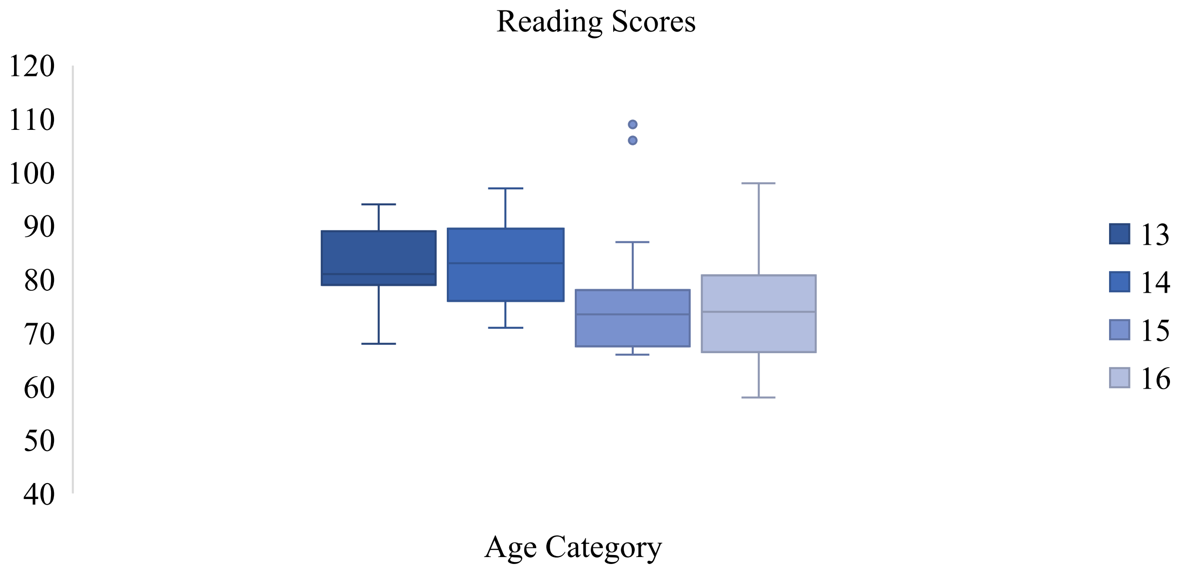


Figure 12