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Master's in Psychology (MAPsyc) Research Report:
**Investigating the viability of a digital neurocognitive
measuring tool in older adults using the Asenze
population-based cohort**

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Abstract

Cognitive health disparities in low-resource settings remain a critical concern. Traditional neuropsychological assessments are often inaccessible due to resource constraints, necessitating scalable alternatives. This study examined the feasibility of NeuroScreen, a digital neuropsychological screening tool, for use among older adults residing in a peri-urban area of KwaZulu-Natal, South Africa. Using secondary data from the Asenze population-based cohort, the neurocognitive performance of 239 caregivers living without HIV, black, and aged 40-79 was examined across six cognitive domains. Descriptive statistics were analysed first, followed by inferential statistics. Age, education and SES significantly influenced cognitive outcomes. Older participants demonstrated slower processing speed and reduced motor speed, while lower education was associated with poorer executive function and visual discrimination. Compared to international norms, the cohort exhibited significantly slower processing speed and weaker motor function as expected, but better delayed recall. Verbal learning and delayed recall were comparable across age groups and international low-resource cohorts. Overall, the basic feasibility of NeuroScreen was demonstrated in this study. It has strong potential as a cost-effective, scalable neuropsychological screening tool for resource-limited environments. However, localised validation, normative data, longitudinal follow-up and compensatory strategies for digital literacy disparities are essential to enhance its cultural relevance and ensure equitable and contextually appropriate cognitive screening in diverse populations.

Keywords: neurocognitive screening; digital technologies; low-to-middle income country; aging; neuroscreen.

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Table of Contents

Abstract	1
Declaration of Independent Work	2
Table of Contents	3
Table of Tables.....	7
Table of Figures	8
Acknowledgements.....	9
Abbreviations	10
Chapter 1: Introduction.....	11
1.1 Introduction	11
1.2 Rationale	12
1.3 Research Aims	13
Chapter 2: Literature review	14
2.1 Evolution of the neuropsychological assessment	15
2.2 Challenges in Norming Neuropsychological Assessments	18
2.3 Cultural and Educational Influences on Neuropsychological Assessment in South Africa	20
2.3.1 Cultural and Linguistic Diversity	20
2.3.2 Educational Disparities.....	21
2.4 Methodological Considerations	22
2.5 Empirical Biases.....	23
2.6 Impact of Test-Wiseness and Cultural Biases.....	23
2.7 Comparing Digital Versus Pencil-and-Paper Approaches to Neuropsychological Assessments.....	25
2.8 Advantages of Digital Neuropsychological Assessments	26
2.9 Strengths, limitations and additional considerations for Digital Tools	27

2.10 NeuroScreen neuropsychological screening tool.....	30
2.11 Applying Luria's Functional Systems Theory to Digital Cognitive Assessments in Older Adults in Semi-Rural South Africa	32
2.12 Integration of Psychometrics into Neuropsychological Assessments.....	35
2.13 Demographic Influence on Performance	36
2.14 The South African Context	37
2.15 Focus of Research and Research Question	38
Chapter 3: Methods	40
3.1 Research design	40
3.2 Sampling.....	41
3.3 Instruments	42
3.3.1 Demographic Questionnaire	42
3.3.2 NeuroScreen	42
3.3.2.1 Verbal learning and memory: verbal list learning and verbal list delayed recall	43
3.3.2.2 Motor speed: finger tapping with dominant and non-dominant hand.....	44
3.3.2.3 Attention: trail making task 1.....	45
3.3.2.4 Working memory: number span forwards and backwards	45
3.3.2.5 Executive Function: trail making 2 and number speed.....	45
3.3.2.6 Processing speed: visual discrimination and trail making 3	46
3.4 Procedure	47
3.5 Ethical Considerations.....	48
3.6 Data analysis	49
Chapter 4: Results	52
4.1 Participant Characteristics and Demographic Profile	52
4.2 NeuroScreen Cognitive Performance.....	55

4.3 Comparative Analysis of NeuroScreen Performance Across Age Categories	56
4.4 Educational Stratification in NeuroScreen Performance: A Comprehensive Analysis ...	57
4.5 Socioeconomic Stratification in NeuroScreen Performance: A Detailed Analysis	58
4.6 Correlational analysis between performance on NeuroScreen and demographic characteristics	60
4.7 Regression analysis of the influence of demographic characteristics on the NeuroScreen Screening tool	62
4.8 Comparative performance against Manhattan HIV Brain Bank (MHBB; New York cohort).....	66
4.9 Comparative Performance Against the Cape Town Cohort (Masivukeni Study)	67
4.10 Comparative performance against the 2021 New York cohort (CASA cohort)	70
4.11 Comparative Performance Against the PREDICT Cohort (Thai Sample)	72
4.12 Summary	74
Chapter 5: DISCUSSION	76
5.1 Summary of main aims and results.....	76
5.2 Influence of Age on Cognitive Performance	77
5.3 Educational Attainment as a Critical Determinant.....	79
5.4 Socioeconomic Status and Environmental Factors	80
5.5 Digital Assessment in LMIC Settings: Strengths and Challenges.....	81
5.6 Comparisons with International Norms and Their Interpretations	83
5.7 Processing speed as an outcome measure	84
5.8 Theoretical Perspectives: Cognitive Reserve & Luria's Framework	86
5.9 Implications for Clinical Practice	88
5.10 Strengths and Limitations of the Present Research	89
5.11 Future directions for research and conclusion	90
5.11 Conclusion.....	90

Reference List	92
Appendices.....	109
Appendix A. Ethics approval	109
Appendix B. Normality checks	110
Appendix C-I. Linearity checks (For the regression and correlational analysis)	110
Appendix J. Permission letter to use Asenze data	115

Table of Tables

Table 1: Summary of NeuroScreen assessment

Table 2: Sociodemographic profile of participants

Table 3: Performance Metrics Across NeuroScreen Cognitive Domains

Table 4: Performance on NeuroScreen Tasks by Age Category

Table 5: Performance on NeuroScreen Tasks by Education Level

Table 6: Performance on NeuroScreen Tasks by Socioeconomic Status Index

Table 7: Correlation of NeuroScreen Tasks with Demographic Factors

Table 8: Regression Analysis of NeuroScreen Task Performance by Demographic Factors

Table 9: Comparison of NeuroScreen Task Performance Between Robbins et al. (2014) and Asenze

Table 10: Comparison of NeuroScreen Task Performance Between Robbins et al. (2018) and Asenze

Table 11: Comparison of NeuroScreen Task Performance Between Robbins et al. (2021) and Asenze

Table 12: Comparison of NeuroScreen Task Performance Between Robbins et al. (2022) and Asenze

Table of Figures

Figure 1: Sample refinement process

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Abbreviations

Abbreviation	Meaning
LMIC	Low-to-middle income country
SES	Socio-economic status
HIV	Human Immunodeficiency Virus
MHBB	Manhattan HIV Brain Bank
PHIV	Perinatally HIV-infected
PHEU	Perinatal HIV-exposed uninfected
CASAH	Child and Adolescent Self-Awareness and Health
WAIS-III	Wechsler Adult Intelligence Scale-III
RAVLT	Rey Auditory Verbal Learning Test
SACNA	South African Clinical Neuropsychological Society
WEIRD	Western, Educated, Industrialised, Rich, Democratic

Chapter 1: Introduction

1.1 Introduction

As populations age globally and healthcare disparities widen, access to neuropsychological assessments becomes increasingly essential (de Jager et al., 2017; Douthit et al., 2015; GBD 2015 Risk Factors Collaborators, 2016; McMaughan et al., 2020; Parra et al., 2019). Yet millions, particularly in low-resource settings, face systematic barriers to accessing these valuable tools (Douthit et al., 2015; McMaughan et al., 2020). Traditional neuropsychological assessments, though invaluable in diagnosing cognitive impairment, are resource-intensive, requiring specialised personnel and equipment that are often unavailable in rural and low-income communities (Chapman et al., 2020; Mattar et al., 2015; Robbins et al., 2021). Such barriers are especially prevalent in regions like rural South Africa, where underserved communities encounter systemic healthcare inequities (de Jager et al., 2024; Humphreys et al., 2016).

Digital neuropsychological screening tools like NeuroScreen (Robbins et al., 2014, 2018, 2021, 2022) offer a promising alternative by prioritising accessibility, portability, and scalability. Previous studies have validated its cultural adaptability and accuracy across diverse populations (Katzef et al., 2019; Robbins et al., 2014, 2018, 2021, 2022). However, research on its effectiveness in assessing older adults in rural settings remains limited, particularly in the South African context where cognitive decline is both significant and under-researched (Katzef et al., 2019; Robbins et al., 2021).

This study rigorously investigated the feasibility of applying NeuroScreen among older, healthy adults in rural Kwa-Zulu Natal, South Africa; with the use of secondary data from this cohort (Desmond et al., 2022). Participants were categorised as ‘older adults’ from age 40 onward, a demarcation supported by prior validations of the tool in younger populations and pragmatic considerations for evaluating cognitive performance in aging cohorts. Notably, while Robbins et al. (2018) reported a mean age of 33.31, and Robbins et al. (2021) and Robbins et al. (2022) reported mean ages of 17.7 and 24 years respectively, Robbins et al. (2014) included a sample with a mean age of 53.5 years, further supporting this age classification. By assessing performance, cultural sensitivity, and the ability to produce viable

cognitive profiles, the research aims to provide insights critical to the broader applicability of digital neurocognitive assessments and to impact cognitive health disparities (Katzef et al., 2019; Robbins et al., 2021, 2022).

1.2 Rationale

The Asenze population-based cohort offered an invaluable opportunity to assess the feasibility and performance of NeuroScreen among healthy older adults from a peri-urban community in South Africa (Desmond et al., 2022). Understanding the unique cognitive profile of this population provides critical insights into the neurocognitive demands and trajectories of aging in low-resource settings (Robbins et al., 2014; Katzef et al., 2019). Although NeuroScreen is validated among people living with HIV and in culturally diverse populations, there is limited research on its effectiveness in peri-urban, healthy, older South African adults (Robbins et al., 2014, 2021, 2022). By comparing overall NeuroScreen performance with both South African and international norms, this paper examines the tool's viability and its ability to accurately detect potential cognitive cutoffs (Robbins et al., 2018). Further, understanding the influence of demographic factors enhances the precision of NeuroScreen interpretations (Neumann, 2000; Reagan et al., 2023).

This study had two key objectives. First, it explored the cognitive profile of older adults in a peri-urban context, examining how demographic factors like age and education influence performance on this digital assessment (Nadler et al., 1994; Lam et al., 2013), ensuring a nuanced interpretation of individual outcomes (Messick, 1998). Second, it assessed whether performance on NeuroScreen aligns with established international and local norms, such as the processing speed norms from a study in Cape Town (Robbins et al., 2018). This comparative analysis is vital for standardising cognitive assessments across cultural contexts and for ensuring equitable cognitive health (Katzef et al., 2019).

The successful achievement of these objectives will highlight critical factors for the viability of NeuroScreen in LMICs like South Africa, thereby advancing the understanding of digital neuropsychological screening methods in under-researched populations. Ultimately, these findings will support the implementation of technology-assisted cognitive assessments in resource-constrained settings worldwide, addressing key issues of healthcare access and quality (Robbins et al., 2021).

1.3 Research Aims

This study sought to assess the practicality of employing a digital neuropsychological screening instrument for evaluating neuropsychological function in healthy elderly individuals within a LMIC context. Additionally, it aimed to delineate the cognitive characteristics of this demographic and to determine whether the results correspond with established international benchmarks or region-specific criteria. An additional objective was to explore the potential impact of sociodemographic variables on cognitive test performance. The findings were anticipated to provide valuable guidance on the optimal implementation and further refinement of mobile-based cognitive assessment tools for similar global public health initiatives.

Chapter 2: Literature review

A principal objective of cognitive neuroscience is to clarify the relationship between brain structure and function (Poldrack, 2010). By combining insights from neuropsychology, cognitive psychology, and allied fields, the discipline aims to identify the neural mechanisms supporting cognition and behaviour, spanning molecular and systemic levels of analysis (Chapman et al., 2020; Mattar et al., 2015). Progress in comprehending and defining the biological foundations of cognitive processes hold important consequences for detecting, mitigating, and managing cognitive impairments (Snyder et al., 2015). The methodological synergy between neuropsychology and cognitive neuroscience highlights the essential role of both fields in furthering research on cognition and its underlying neural architecture. Translating these interdisciplinary discoveries into reliable clinical tools hinges on rigorous neuropsychological evaluation.

A fundamental aspect of clarifying this relationship involves neuropsychological evaluation. These assessment tools offer researchers and clinicians critical insights into an individual's cognitive, affective, and behavioural capacities (Cipolotti & Warrington, 1995; Laher & Cockcroft, 2019; Lucas, 2013). The effectiveness of such evaluations nevertheless depends on multiple factors, including their precision, discriminative ability, and diagnostic specificity, alongside their appropriateness for varied socioeconomic backgrounds, cultural environments, and age groups (Arentoft et al., 2015; Bilder & Reise, 2019; Jaeger, 2018; Olson & Jacobson, 2014; Schatz & Browndyke, 2002). Consequently, establishing the psychometric robustness of these measures across diverse populations remains crucial.

A critical analysis of the historical and methodological evolution of neuropsychological assessment establishes essential context for evaluating contemporary tools, including digital platforms such as NeuroScreen. It evaluated the transition from traditional pencil-and-paper to digital methods, highlighting advantages and challenges inherent to each. Emphasis was placed on NeuroScreen's viability as a digital tool, with detailed analysis of its validity, reliability, sensitivity, specificity, and usability. Building on that overview, the review then turns to how demographic and cultural factors shape test performance.

The literature review also explored complexities in neuropsychological testing across diverse populations, addressing how demographic variables such as age, education, and

socioeconomic status influence test performance. Given South Africa's historical and cultural contexts, which shape neuropsychological assessment practices, focus was given to issues of bias, normative data, and test adaptation. By synthesising these themes, the review established a framework for evaluating NeuroScreen's feasibility in cognitively and socioeconomically diverse groups, informing its potential real-world clinical and research applications.

2.1 Evolution of the neuropsychological assessment

Neuropsychological assessments have long been instrumental in cognitive neuroscience, serving as critical tools for diagnosing, treating, and researching cognitive impairments (Casaletto & Heaton, 2017; Cipolotti & Warrington, 1995; Lezak, 2004; Wilson et al., 2015). These assessments emerged from early clinical and descriptive methods aimed at identifying cognitive deficits and distinguishing between various neurological conditions (Lezak, 2004). Initially, their application was largely subjective, reliant on the interpretative judgment of clinicians rather than standardised methodologies (Casaletto & Heaton, 2017; Carson, 1999; Cipolotti & Warrington, 1995; Suen & French, 2003). To overcome this limitation, structured neuropsychological assessments were developed to offer consistent and accurate cognitive function measurements, improving their diagnostic and research applications (Cipolotti & Warrington, 1995). These assessments primarily serve three core purposes: diagnosing neurological conditions, informing treatment interventions, and contributing to cognitive neuroscience research (Schroeder et al., 2019; Watt & Crowe, 2018).

In the domain of diagnosis, neuropsychological assessments facilitate the identification of neural correlates of cognitive impairments, enabling differentiation between organic and functional disorders (Cipolotti & Warrington, 1995; Watson et al., 2019; Watt & Crowe, 2018). Furthermore, they establish cognitive baselines, allowing clinicians to monitor disease progression and tailor treatment plans accordingly (Casaletto & Heaton, 2017; Donders, 2020; Prince & Bruhns, 2017; Stefan & Hopfengärtner, 2009). Beyond clinical applications, these assessments play a pivotal role in forensic and medicolegal contexts, where cognitive impairments can impact compensation claims and legal proceedings (Cipolotti & Warrington, 1995; Cunningham, 2016; Morel, 2009; Schutte et al., 2015). Neuropsychological assessments play a crucial role in research by validating cognitive models, enabling

investigation of brain-behavior relationships, and strengthening cognitive neuroscience theories; their foundational principles, however, trace back centuries to early clinical observations (Bilder & Reise, 2019; Casaletto & Heaton, 2017; Shallice et al., 1991).

Neuropsychological assessment emerged in the 17th-18th centuries as physicians systematically recorded cognitive impairments associated with neurological damage and pathology (Bellone & Van Patten, 2021; Eling, 2019). These observations highlighted the dissociation between different cognitive faculties, wherein some individuals exhibited selective impairments while others remained unaffected (Casaletto & Heaton, 2017). Such findings laid the groundwork for the fundamental principles of localisation and modularity in neuropsychology (Bellone & Van Pattern, 2021; Eling, 2019). By the 19th century, pioneers such as Wernicke developed systematic methods for assessing specific cognitive functions in neurologically impaired individuals (Eling, 2019). Simultaneously, figures like Conrad Reiger and Theodor Ziehen introduced comprehensive neuropsychological test batteries, assessing multiple cognitive domains concurrently (Bajaj, 2020; Eling, 2019; Eling & Whitaker, 2022). This transition from clinical observation to structured assessment methodologies marked a significant milestone in the field, establishing the foundation for modern neuropsychological testing (Barr, 2008; Bajaj, 2020; Eling, 2019).

The early 20th century saw the integration of psychometric principles into neuropsychology, profoundly shaping the standardisation and quantification of cognitive assessments (Bilder & Reise, 2019). Intelligence testing, spearheaded by figures such as Binet, Stern, Yerkes, Wechsler, and Franz, introduced normed data and statistical methodologies, transforming neuropsychological assessment into an empirical science (Casaletto & Heaton, 2017; Eling, 2019; Lezak, 2004). The progression resulted in psychometrics becoming an established discipline focused on quantifying cognitive and psychological phenomena using standardised assessment tools (Bilder & Reise, 2019; Casaletto & Heaton, 2017; Eling, 2019; Kiselica et al., 2024). As neuropsychological testing evolved, scholars such as Goldstein and Luria advocated for process-oriented and flexible assessment batteries that incorporated qualitative observations alongside quantitative measures (Lezak, 2004; Morgan & Ricker, 2008). This paradigm shift emphasised the importance of ecological validity, the degree to which test findings predict real-world functioning (Eling, 2019; Kessels, 2018), acknowledging compensatory mechanisms and individual differences in cognitive processing (Eling, 2019).

Contemporary neuropsychological assessment continues to integrate these principles, ensuring a holistic approach that accounts for both standardised measurement and nuanced clinical interpretation. Yet these advancements have not been immune to the distortions of political ideology and systemic inequity.

The development of neuropsychological assessment in South Africa reflects the nation's complex socio-political history, particularly the lasting impacts of apartheid-era racial policies. Under apartheid, psychological assessments were weaponised to enforce racial hierarchies, with tests normed exclusively on white populations and subsequently misapplied to Black South Africans, who had been systematically denied access to quality education (Watts & Shuttleworth-Edwards, 2016). This practice not only reinforced educational and occupational disparities but also entrenched widespread mistrust in psychometric testing among marginalised communities (Foxcroft, 1997; Laher & Cockroft, 2019). Furthermore, scientific research that contradicted apartheid-era racial ideologies, such as EEG studies that refuted claims of inherent cognitive inferiority, was actively suppressed by the government, stifling advancements in neuroscience (Watts, 2008; Besharati & Akinyemi, 2023).

Following the dismantling of apartheid, substantial efforts have been made to decolonise neuropsychology and address historical injustices in cognitive assessment. One such initiative is the South African Clinical Neuropsychological Society's (SACNA) peer credentialing system, which seeks to establish culturally informed standards for neuropsychological practice (Watts & Shuttleworth-Edwards, 2016). However, significant challenges remain due to the country's cultural and linguistic diversity, with 11 official languages and substantial educational disparities complicating test standardisation. Western-developed cognitive assessments often lack construct validity within local populations, as evidenced by verbal fluency tasks that disadvantage non-native English speakers (Pillay & Kathard, 2015). Moreover, persistent educational disparities stemming from apartheid continue to affect neuropsychological testing outcomes. Shuttleworth-Edwards et al. (2004) found that South Africans from educationally disadvantaged backgrounds scored 20-30 IQ points below American standardisation samples, highlighting significant diagnostic validity concerns.

To mitigate these disparities, researchers advocate for the implementation of demographically stratified normative data that consider educational quality rather than race (Ferreira-Correia & Cockcroft, 2023). For instance, Crawford and Howell's (1998) single-case methodology, which compares individuals to demographically matched control groups, has been successfully applied to reduce bias in cognitive assessments for Huntington's disease (Ferreira-Correia & Cockcroft, 2023). Contemporary digital adaptations like smartphone-administered neuropsychological tools (e.g., NeuroScreen) now enable detection of HIV-associated neurocognitive disorders in resource-limited environments (Cockcroft, 2024).

Ongoing efforts to balance global assessment standards with local relevance reflect progress in the field. SACNA's recent workshops on culturally responsive test adaptation and the push for a dedicated neuropsychology professional register exemplify the strides being made in fostering equitable cognitive assessments (Watts & Shuttleworth-Edwards, 2016). Moreover, South Africa's genetic diversity and multilingual population present unique opportunities for cognitive research, including studies on bilingualism's effects on cognitive functioning and the application of artificial intelligence to minimise test bias (Besharati & Akinyemi, 2023; Cockcroft, 2024). Despite these advancements, challenges persist, including limited access to neuroimaging infrastructure and continued reliance on foreign-developed normative data (Besharati & Akinyemi, 2023). Collaborative initiatives such as the African Stroke Organisation and open-science frameworks are essential to fostering equitable and locally relevant neuropsychological practices while contributing to the global knowledge base (Besharati & Akinyemi, 2023), though achieving true equity in cognitive assessment demands confronting deeper complexities in norming practices.

2.2 Challenges in Norming Neuropsychological Assessments

Creating population-specific normative standards for neuropsychological tests is critical for valid and fair cognitive assessment across different demographic groups (Watts & Shuttleworth-Edwards, 2016). This standardisation process presents particular challenges in ethnically diverse societies like the United States and South Africa, where controversial practices such as race-based norming have generated significant academic discourse (Laher & Cockcroft, 2019). Race-norming, which involves adjusting test norms based on racial categories, was originally introduced to reduce false positives among historically

disadvantaged groups who tended to score lower on standardised assessments, thereby reducing misdiagnoses (Gasquoine, 2022; Laher & Cockroft, 2019; Watts & Shuttleworth-Edwards, 2016). Despite its initial intent to promote fairness, critics argue that race-based norms risk reinforcing systemic inequities by failing to account for broader influences on test performance, such as acculturation, socioeconomic disparities, and educational quality (Gasquoine, 2022; Miao, 2022; Mindt et al., 2019; Tan et al., 2021).

The historical and socio-political context of South Africa further complicates neuropsychological norming procedures (Watts & Shuttleworth-Edwards, 2016; Laher & Cockroft, 2019). Under apartheid, psychological tests were standardised predominantly on white populations and misapplied to Black South Africans, reinforcing discriminatory narratives of intellectual inferiority and contributing to structural inequalities (Watts & Shuttleworth-Edwards, 2016). The misuse of such assessments has left a lasting legacy of mistrust towards psychometric testing among historically marginalised communities (Foxcroft, 1997; Laher & Cockroft, 2019). In response to these injustices, South African legislation, such as the Employment Equity Act No. 55 of 1998, mandates that psychological tests must be scientifically validated, reliable, and free from cultural bias before they can be legally administered (Huysamen, 2002; Laher & Cockroft, 2019). However, the continued reliance on Western-developed tests that fail to account for South Africa's linguistic and cultural diversity underscores the need for localised normative data and culturally sensitive assessment tools (Hong et al., 2022; Laher & Cockroft, 2019).

Cross-cultural neuropsychological testing demonstrates several forms of measurement bias, notably in test construction, administration procedures, and individual item performance (Fernández & Abe, 2018; Wong et al., 2024). Construct bias arises when a test measures a cognitive ability that is conceptualised differently across cultural groups, thereby limiting the universal applicability of the assessment (Fernández & Abe, 2018). Method bias occurs when differences in sampling, test administration, or familiarity with test materials influence results, leading to skewed interpretations of cognitive ability (Fernández & Abe, 2018). Differential item functioning (DIF) occurs when test items produce systematically different scores for individuals of equal cognitive ability from distinct cultural backgrounds, indicating cultural rather than cognitive differences (Fernández & Abe, 2018). The existence of these measurement biases underscores the necessity for ongoing

assessment tool refinement to maintain validity in culturally and linguistically heterogeneous populations (Vetter & Cubbin, 2019; Wong et al., 2024).

To overcome these limitations, researchers have proposed alternative normative approaches that move beyond race-based corrections in cognitive testing (Gasquoine, 2022; Malik & Norman, 2023). One approach is the individual comparison standard, which estimates a person's premorbid cognitive ability based on their unique background and history, rather than using broad racial classifications (Crawford et al., 2007). An alternative approach employs integrated normative datasets, applying universal benchmarks whilst accounting for key demographic variables including educational attainment, socioeconomic status, and language proficiency (Crawford et al., 2007; Gasquoine, 2022). These approaches are particularly pertinent in South Africa, where significant variability in educational access, literacy levels, and economic conditions exists even within racially or culturally similar groups (Crawford et al., 2007). By adopting more equitable normative frameworks, researchers and clinicians can minimise bias in neuropsychological assessments, reduce the risk of diagnostic inaccuracies, and ensure that cognitive evaluations more accurately reflect an individual's true cognitive abilities rather than extraneous sociocultural influences (Gasquoine, 2022; Laher & Cockcroft, 2019; Malik & Norman, 2023), highlighting the need to further examine how cultural and educational factors shape cognitive test performance in diverse settings.

2.3 Cultural and Educational Influences on Neuropsychological Assessment in South Africa

Building upon the normative challenges outlined earlier, this section examines how South Africa's sociocultural and educational heterogeneity directly shapes cognitive test performance and interpretation.

2.3.1 Cultural and Linguistic Diversity

The aforementioned complexities of norming in ethnically diverse contexts are acutely evident in South Africa, where 12 official languages and numerous cultural groups amplify the risk of measurement biases (e.g., construct, method, and DIF). Cognitive tests developed in singular linguistic and cultural contexts often lack validity when applied across this diversity (Jinabhai et al., 2003; Skuy et al., 2001; Laher & Cockcroft, 2017). Specifically, acculturation, the process of psychological adaptation during cross-cultural contact (Van de Vijver & Phalet,

2004; Besharati & Akinyemi, 2023), critically mediates test outcomes. In South Africa's complex cultural landscape, individuals experience varying exposure to Western and indigenous influences, necessitating nuanced test adaptation to distinguish true cognitive impairment from differential cognitive socialisation (Manly et al., 2004; Shuttleworth-Edwards et al., 2004; Ferreira-Correia & Cockcroft, 2023).

Compounding this, language proficiency presents distinct challenges. As noted earlier, the reliance on Western-developed tests administered predominantly in English, a secondary language for many, risks method bias, impairing comprehension of instructions/items and depressing scores irrespective of actual cognition (Ferrett et al., 2010a, 2010b; Jinabhai et al., 2003; Cockcroft, 2024). Furthermore, culturally specific stimuli in Western tests (e.g., norms, numerical systems, or problem-solving paradigms unfamiliar in traditional African contexts) may introduce construct bias or differential item functioning (DIF), disadvantaging under-exposed individuals (Ardila, 1996; Harris & Llorente, 2005; Pillay & Kathard, 2015).

To mitigate these issues, culturally adapted tools and stratified norms, aligning with the alternative normative approaches proposed earlier, are essential. Ferreira-Correia and Cockcroft (2023), for instance, demonstrated that Crawford and Howell's (1998) single-case methodology reduces over-pathologising in South African populations by individualising interpretation. Innovations like the digitally adapted NeuroScreen further enable culturally responsive assessments in low-resource settings (Cockcroft, 2024), underscoring the imperative for practices attuned to South Africa's diversity (Besharati & Akinyemi, 2023; Laher & Cockcroft, 2017).

2.3.2 Educational Disparities

Closely intertwined with cultural and normative challenges, educational inequities, rooted in South Africa's apartheid legacy, significantly confound cognitive assessment. Historically segregated education created profound disparities in resource allocation, teacher quality, and higher education access for Black and Coloured communities (Claassen et al., 2001). Despite policy reforms, underfunded schools in marginalised areas still lack infrastructure, materials, and trained educators, perpetuating systemic disadvantage

(Amnesty International, 2020; Fleisch, 2007; Matomela, 2008a, 2008b; van der Berg & Gustafsson, 2019).

Critically, educational quality directly impacts test performance on skills like problem-solving, memory, and executive functioning (van der Berg & Gustafsson, 2019). As highlighted earlier, individuals from educationally disadvantaged backgrounds score lower on cognitive tests, including those deemed "culturally fair", due to limited exposure to critical thinking, unfamiliarity with test formats, and rote-learning pedagogies (Laher & Cockcroft, 2019; Manly, 2005; Shuttleworth-Edwards et al., 2004; Eduah, 2024; Grieve & Viljoen, 2000; Nell, 1999). These disparities are exacerbated by curricular variations: Western-style education (emphasising abstract reasoning) versus resource-constrained environments (reliant on memorisation) create divergent cognitive profiles (Gallo, 2020; van der Berg & Gustafsson, 2019). Consequently, neuropsychological assessments must account for these educational gradients to avoid conflating systemic disadvantage with cognitive deficit, reinforcing the need for demographically stratified norms.

2.4 Methodological Considerations

Building on the normative and sociocultural challenges outlined in Sections 2.2 and 2.3, the reliance on normative data that does not adequately represent the target population remains a fundamental methodological challenge in neuropsychological assessment. Tests developed and normed in Western contexts often fail to capture the cognitive profiles of individuals from non-Western backgrounds, leading to the underestimation of cognitive abilities in African populations (Casaletto & Heaton, 2017; Eling, 2019; Jinabhai et al., 2003; Pillay & Kathard, 2015; Skuy et al., 2001). For instance, using North American or European norms to interpret cognitive test results in South African populations can yield misleading conclusions, as these norms fail to account for linguistic diversity, educational disparities, and culturally specific cognitive strategies.

Furthermore, standardised test administration procedures may not be universally appropriate across cultural and educational groups. Timed assessments, for example, may disadvantage individuals who are unfamiliar with time-constrained testing environments or who have limited prior exposure to formal standardised assessments (Ardila, 1996; Harris & Llorente, 2005). These issues necessitate the development of locally normed cognitive

assessments that consider the specific educational and cultural realities of South African test-takers.

2.5 Empirical Biases

Research evidence indicates consistent performance disparities on standardised cognitive tests among South African population groups, with White participants typically achieving higher scores than Black and Coloured participants on conventional neuropsychological measures (Claassen et al., 2001; Shuttleworth-Edwards et al., 2004; van der Berg & Gustafsson, 2019; Watts & Shuttleworth-Edwards, 2016). However, as established earlier (Sections 2.2, 2.3) these discrepancies cannot be attributed to racial or ethnic factors alone; rather, they are shaped by a confluence of educational, linguistic, as well as SES influences (Jinabhai et al., 2003; Skuy et al., 2001; Watts & Shuttleworth-Edwards, 2016). Crucially, ensuring that neuropsychological tests are appropriately adjusted for demographic factors such as educational background, and linguistic proficiency is crucial for minimising bias.

2.6 Impact of Test-Wiseness and Cultural Biases

Neuropsychological assessments remain essential tools for evaluating cognitive functioning; however, their validity and reliability can be significantly influenced by test-wiseness and cultural biases, particularly in diverse and under-researched contexts (Cipolotti & Warrington, 1995; Daugherty et al., 2017; Fernández, 2019, 2022; Fernández & Abe, 2018; Olson & Jacobson, 2014). These factors, influence an individual's acquired proficiency in navigating assessment procedures, strategic approaches, and evaluative expectations, a skillset frequently presumed as inherent among western-educated populations. (Fernández, 2019, 2022; Fernández & Abe, 2018). In contrast, individuals from non-Western and educationally disadvantaged backgrounds may have limited exposure to formal testing environments or the implicit behavioural expectations of structured assessments, such as sustaining concentration, managing time constraints, or interpreting test instructions efficiently. Consequently, suboptimal test performance may reflect unfamiliarity with testing procedures rather than genuine cognitive impairment (Fernández, 2019, 2022; Fernández &

Abe, 2018). This challenge proves particularly acute in South Africa, where marked educational and socioeconomic inequalities result in limited test literacy acquisition among older adults and under-resourced communities, contrasting sharply with the assessment competencies routinely developed in more privileged contexts (Aghvinian et al., 2021; Cockcroft & Laher, 2022).

The challenges associated with test-wiseness become even more pronounced in the context of digital neuropsychological assessments. Fernández (2019) highlights that individuals in low-income settings may have limited access to computers or tablets, resulting in elevated error rates that stem from technological unfamiliarity rather than cognitive dysfunction. This concern holds particular significance in the South African context, where intersecting educational and digital literacy disparities amplify the potential for misinterpretation in neuropsychological assessments (van der Berg & Gustafsson, 2019; Watts & Shuttleworth-Edwards, 2016). Individuals who have received inconsistent or substandard schooling frequently lack essential foundational skills, including reading comprehension, test-taking strategies, and time-management, resulting in poorer cognitive test performance that does not necessarily reflect their true cognitive abilities (Gallo, 2020; Watts & Shuttleworth-Edwards, 2016).

Cultural biases in test design further exacerbate these challenges. Many neuropsychological assessments incorporate culturally specific stimuli, language structures, or problem-solving approaches that do not translate seamlessly across diverse linguistic and socio-cultural groups (Aghvinian et al., 2021; Cockcroft & Laher, 2022; Daugherty et al., 2017; Fernández, 2019). The failure to account for cultural relevance in test items diminishes ecological validity, as cognitive assessments may measure cultural familiarity rather than cognitive capacity (Aghvinian et al., 2021; Fernández & Abe, 2018; Velu & Leathem, 2017; Wong et al., 2024). Manly et al. (2004) demonstrated that when participants were matched on years of formal education, racial differences in test performance persisted. However, when reading level was introduced as a proxy for educational quality, these differences were significantly reduced. This finding underscores the importance of considering educational quality rather than merely years of schooling in neuropsychological assessments, ensuring that differences in test outcomes are not misattributed to innate cognitive deficits (Manly et al., 2004).

The persistent legacy of apartheid-era educational and socioeconomic inequalities continues to influence neuropsychological assessment outcomes in South Africa (van der Berg & Gustafsson, 2019; Watts & Shuttleworth-Edwards, 2016). Individuals from historically marginalised communities frequently demonstrate limited familiarity with standardised assessment procedures, creating significant disadvantages relative to their more educationally advantaged peers (Aghvinian et al., 2021; Fernández, 2019; Watts & Shuttleworth-Edwards, 2016). Consequently, test-wiseness, the ability to leverage the structure and design of a test to improve performance, remains deeply intertwined with these systemic inequities (Daugherty et al., 2017; Fernández, 2019, 2022; Fernández & Abe, 2018). Without appropriate cultural and educational adjustments, neuropsychological tests risk measuring test-taking proficiency rather than actual cognitive ability.

Addressing these issues requires culturally and contextually informed test adaptation to ensure that cognitive assessments accurately reflect underlying neurocognitive functioning rather than socio-economic and educational disadvantage. To enhance the validity and equity of cognitive assessments in South Africa, implementation of the following evidence-based strategies is essential: (1) demographic stratification of normative data, (2) linguistic and cultural adaptation of test instruments, and (3) incorporation of educational quality and acculturation metrics into scoring methodologies (Daugherty et al., 2017; Fernández, 2019, 2022; Fernández & Abe, 2018; Olson & Jacobson, 2014). Through careful test development and refinement, researchers and clinicians can work towards more equitable and ecologically valid neuropsychological assessments in South Africa's complex and diverse cultural landscape.

2.7 Comparing Digital Versus Pencil-and-Paper Approaches to Neuropsychological Assessments

Conventional neuropsychological assessments, traditionally administered through paper-and-pencil formats, have been widely established as the benchmark methodology for cognitive evaluation (Ye et al., 2020). Their reliability stems from well-established normative data, high levels of standardisation, and the capacity to generate comprehensive cognitive profiles (Schmand, 2019). When administered by an experienced clinician, these methods allow for detailed and nuanced assessments, facilitating differential diagnoses, treatment

planning, forensic evaluations, and the monitoring of cognitive changes over time (Schmand, 2019; Sahoo & Grover, 2022). However, despite their diagnostic strengths, traditional assessments can be time-intensive and resource-demanding, often requiring in-person administration and specialised training for both administration and scoring (Sahoo & Grover, 2022). Additional limitations include practice effects, whereby repeated exposure to the same test leads to improved scores independent of true cognitive change, as well as variability in test administration across different settings and examiners, which may impact reliability (Sahoo & Grover, 2022), though it is important to note that this occurs in both traditional as well as digital assessments, the one help digital assessments is that there is possible variability and changes that can be made to prevent this. For individuals with chronic conditions requiring long-term monitoring, traditional methods can also pose logistical and financial challenges, making them impractical for widespread and repeated use (Sahoo & Grover, 2022).

To address these constraints, digital neuropsychological assessments have developed as promising alternatives, utilising tablet, smartphone and web-based platforms (Kush et al., 2011; Parsey & Schmitter-Edgecombe, 2013; Stanley & Osgood, 2011). These computerised approaches employ automated administration and scoring systems, minimising examiner bias while improving procedural efficiency (Parsey & Schmitter-Edgecombe, 2013). Their capacity to incorporate multimedia components enhances participant engagement and enables immediate data capture, yielding more comprehensive cognitive profiles (Kush et al., 2011; Parsey & Schmitter-Edgecombe, 2013; Stanley & Osgood, 2011). Crucially, studies demonstrate strong acceptability and usability across diverse demographics, including older populations, indicating wider applicability than originally anticipated (Sahoo & Grover, 2022; Staffaroni et al., 2020).

2.8 Advantages of Digital Neuropsychological Assessments

A primary advantage of digital assessments is their enhanced precision and standardisation (Germine et al., 2019). Unlike traditional methods, which may introduce variability due to examiner differences, digital tools ensure consistent stimulus presentation and automated response recording, minimising environmental and human-related inconsistencies (Germine et al., 2019; Parsey & Schmitter-Edgecombe, 2013). The digital

approach holds particular value in resource-constrained healthcare systems like South Africa's, where digital neuropsychological tools may: (1) enhance assessment efficiency, (2) maximise specialist resources, and (3) enable standardised data acquisition across heterogeneous populations. (Germine et al., 2019). Furthermore, digital assessments reduce reliance on highly trained personnel, potentially lowering costs and improving accessibility for individuals in rural or under-resourced areas. Many platforms also support remote administration, allowing individuals to complete assessments from home and mitigating geographic and socioeconomic barriers to care (Wright, 2020).

Beyond accessibility, digital assessments provide greater sensitivity in capturing cognitive fluctuations over time. Unlike static paper-based measures, computerised tools can record moment-to-moment variations in response times, error patterns, and other behavioural markers, offering a more detailed and dynamic assessment regarding mental processes (Kush et al., 2011; Parsey & Schmitter-Edgecombe, 2013; Stanley & Osgood, 2011). This feature enhances ecological validity, as it allows for assessments that better reflect real-world cognitive functioning. Additionally, some digital assessments can be seamlessly integrated into individuals' daily routines or administered with minimal clinician involvement, reducing the logistical burden associated with frequent in-person visits (Kush et al., 2011; Parsey & Schmitter-Edgecombe, 2013; Stanley & Osgood, 2011).

2.9 Strengths, limitations and additional considerations for Digital Tools

Despite the significant advantages of digital neuropsychological assessments, their implementation is not without challenges. One major limitation is the variability in hardware and software, which can introduce measurement bias, particularly when assessments are conducted on different devices with varying screen sizes, processor speeds, or operating systems (Germine et al., 2019). This challenge proves especially acute in South Africa, where marked urban-rural divides exist in both technological infrastructure and digital competency levels (Germine et al., 2019; Spreji et al., 2020). For instance, people from low-resource communities may underperform due to unfamiliarity with smartphones or tablets, rather than genuine cognitive impairment (Germine et al., 2019; Lunardini et al., 2020; Spreji et al., 2020).

Additionally, digital technologies and their fast-paced evolution necessitates frequent updates to both assessment software and normative data, posing logistical and financial

challenges (Parsey & Schmitter-Edgecombe, 2013; Sahoo & Grover, 2022). The need for ongoing recalibration is particularly problematic in healthcare systems already operating under significant strain, where financial and human resources are limited (Joosub et al., 2024; Parsons et al., 2018). Furthermore, construct-irrelevant variance, where digital proficiency rather than cognitive ability influences test outcomes, can compromise validity, leading to inflated scores for frequent technology users and disproportionately lower scores for those less familiar with digital interfaces (Germine et al., 2019; Spreji et al., 2020).

Data protection and confidentiality present significant ethical considerations, given that digital cognitive assessments routinely handle sensitive neuropsychological records and personal health information (Jiang & Shi, 2021; Sahoo & Grover, 2022). Ensuring robust cybersecurity measures is essential, particularly in self-administered digital assessments where the lack of controlled environments may introduce additional risks (Parsey & Schmitter-Edgecombe, 2013). Without direct oversight, external distractions, fatigue, or even third-party assistance may interfere with results, further complicating data reliability and test interpretation (Parsey & Schmitter-Edgecombe, 2013).

Furthermore, certain cognitive domains may be less effectively assessed through digital platforms. Tasks requiring fine motor skills, tactile precision, or direct interaction with physical objects may not translate seamlessly into digital formats, potentially reducing test sensitivity for conditions such as Parkinson's disease or stroke-related impairments (Parsey & Schmitter-Edgecombe, 2013). Although some digital tools incorporate stylus-based or touchscreen alternatives, these do not always replicate the motor demands of traditional pencil-and-paper assessments, raising concerns about their ecological validity.

While traditional neuropsychological assessments, guided by clinician expertise, remain invaluable for differential diagnosis and longitudinal cognitive tracking, digital tools offer automation, portability, and real-time data collection that can significantly enhance accessibility, particularly in resource-limited environments like South Africa (Kush et al., 2011; Parsey & Schmitter-Edgecombe, 2013; Sahoo & Grover, 2022; Stanley & Osgood, 2011). Successfully leveraging both approaches requires rigorous validation of digital assessments, investment in technical infrastructure, and culturally sensitive adaptations to ensure accuracy and fairness across diverse populations (Parsey & Schmitter-Edgecombe, 2013; Sahoo & Grover, 2022).

One of the most pressing concerns is tech-driven construct-irrelevant variance, where frequent users of digital devices may achieve higher scores due to their familiarity with touchscreen or keyboard-based interactions rather than actual cognitive ability (Germine et al., 2019; Spreji et al., 2020). Exacerbated by the digital divide, familiarity bias, risks distorting test outcomes and further entrenching disparities. Ensuring equitable assessments demands a combination of technological solutions, user training, adaptive test formats, and culturally relevant content that mitigate such biases (Germine et al., 2019; Spreji et al., 2020).

Moreover, both digital and traditional contemporary cognitive screening tools were originally designed for highly controlled experimental settings rather than real-world clinical use (Kessels, 2018). Many widely used assessments remain overly lengthy, impractical, or narrowly focused, making them cumbersome in applied settings, especially within low-resource healthcare environments where test administration time is limited (Kessels, 2018). Computerised assessments may further exacerbate these challenges by requiring specialised hardware and software, restricting their widespread implementation in underfunded healthcare systems (Germine et al., 2019). In an LMIC, where technological infrastructure, healthcare disparities, and human resource constraints persist, such barriers present significant obstacles to the adoption of sophisticated neuropsychological tools (Laher & Cockcroft, 2019; Ye et al., 2020).

Another critical limitation is the psychometric validity of existing digital tools, particularly for populations with minimal formal education or older adults with age-related declines in processing speed (Carone, 2007; Kessels, 2018; Van der Elst et al., 2008). Many digital paradigms rely heavily on reaction-time-based measures, which may be inappropriate for individuals unfamiliar with time-constrained tasks, leading to potential misclassification of cognitive impairment (Kessels, 2018). Furthermore, ecological validity remains a major concern, as assessments conducted in highly standardised digital environments may not accurately reflect individuals' everyday cognitive performance (Eling, 2019; Kessels, 2018).

Historically, widely used neuropsychological assessments were developed within WEIRD (Western, Educated, Industrialised, Rich, Democratic) populations and may fail to accommodate the cultural, linguistic, and educational diversity present in low-income regions (Henrich et al., 2010; Marcopulos & Łojek, 2019). In South Africa, where educational disparities and the enduring legacy of apartheid continue to shape cognitive test performance,

the application of Western-derived test norms may lead to misdiagnoses and inappropriate interventions (Laher & Cockcroft, 2019; Lucas, 2013). These discrepancies highlight the urgent need for culturally adapted neuropsychological tools that account for sociocultural context, language diversity, and differential educational exposure (Cockcroft, 2024; Laher & Cockcroft, 2019).

Addressing these limitations requires continuous refinement of neuropsychological assessments to ensure they reflect real-world cognitive functioning across diverse populations. Greater emphasis must be placed on culturally relevant content, adaptive testing methods, and robust psychometric validation within under-researched communities (Kessels, 2018). The integration of machine learning and artificial intelligence into digital assessments holds promise for improving diagnostic precision, but these technologies must be rigorously tested to prevent biases that disproportionately impact marginalised groups (Eling, 2019; Kessels, 2018).

Ultimately, the evolution of neuropsychological assessment methods should prioritise equity, accessibility, and ecological validity, ensuring that both traditional and digital tools meet the needs of diverse populations rather than inadvertently perpetuating healthcare disparities (Kessels, 2018).

2.10 NeuroScreen neuropsychological screening tool

NeuroScreen, the focal digital assessment tool in this investigation, is a tablet-administered neuropsychological battery comprising 10 brief tests evaluating six cognitive domains particularly vulnerable to HIV-associated impairment (Katzef et al., 2019; Robbins et al., 2014, 2018, 2021, 2022). This section details its validation studies across diverse cohorts, providing essential demographic context for interpreting later comparisons with the Asenze cohort. The tool was originally validated against the Modified HIV-Battery (MHBB), a criterion-standard pencil-and-paper assessment evaluating seven domains: processing speed, learning, memory, executive function, verbal fluency, working memory, and motor skills (Robbins et al., 2014). While distinct from the MHBB, NeuroScreen was designed to approximate its sensitivity in a digital format optimised for resource-constrained settings.

The foundational validation by Robbins et al. (2014) in the PREDICT cohort (New York City; N = 44; 61% male; mean age 53.4 years; mean education 11.8 years; 100% HIV-positive)

demonstrated high acceptability: 93% of participants reported comfort with tablet administration, while 73% rated usability as straightforward. Crucially, NeuroScreen exhibited strong criterion validity, with its composite z-scores correlating significantly with MHBB global T-scores ($r = 0.72$, $p < 0.001$). Sensitivity for detecting neurocognitive impairment (NCI) reached 93.9% (specificity 63.6%) using a Global Deficit Score threshold of ≥ 0.5 . This established NeuroScreen's feasibility for clinical screening despite the cohort's older age profile and high NCI prevalence (75%).

Subsequent validation by Robbins et al. (2018) in the CASA-H cohort (later referred to as the Masivukeni study) (Cape Town, South Africa; $N = 121$; 38% male; mean age 35.4 years; mean education 9.1 years; 100% HIV-positive) evaluated three scoring composites against a criterion battery. Composite 1 (all tests) achieved 74.7% sensitivity and 81.5% specificity, while Composite 2 (incorporating error scores) improved sensitivity to 81.3% (specificity 81.5%). Composite 3 (abbreviated battery) prioritised specificity (92.6%) at the cost of sensitivity (70.7%). When administered by lay health workers, NeuroScreen showed strong construct validity ($r = 0.86$ against criterion measures), though variability across composites highlighted the need for context-specific optimisation. This underscored the tool's adaptability to low-resource settings but also identified demographic considerations, notably younger age and lower education, relative to the PREDICT cohort.

Katzef et al. (2019) focused on processing speed (PS) within a South African normative cohort ($N = 150$; 40% male; mean age 30.6 years; mean education 11.8 years; 33% HIV-positive). Factor analysis confirmed PS measures loaded onto a single factor (56.2% variance), with age identified as the strongest performance predictor ($\beta = -0.52$). HIV-positive participants performed significantly worse on PS tasks than neuropsychologically healthy controls ($\eta^2 = 0.18$, $p < 0.001$), aligning with established HIV-associated cognitive slowing. This dual-normative approach provided critical benchmarks for LMIC populations while verifying NeuroScreen's clinical sensitivity to HIV-related deficits.

Most recently, Robbins et al. (2021) assessed executive function in a New York AYA cohort ($N = 62$; 64% male; median age 24 years; 90% ethnic minorities; 53% PHIV). NeuroScreen tasks showed moderate-to-strong correlations with gold-standard measures: Trail Making/Number Speed tests correlated at $r = 0.32$ – 0.59 with analogous pencil-and-paper tests, while Number Span (working memory) achieved $r = 0.50$ – 0.70 . The study

confirmed NeuroScreen's capacity to detect domain-specific impairments in PHIV youth, extending its validation to ethnically diverse adolescent populations with distinct cognitive risk profiles.

Robbins et al. (2022) validated NeuroScreen in a Thai adolescent cohort (N = 120; 53% female; mean age 18.5 years; mean education 9.2 years; 50% with perinatal HIV [PHIV]). The tool demonstrated strong convergent validity with traditional batteries ($r = 0.82$ globally), with domain-specific correlations ranging from $r = 0.32$ (executive function) to $r = 0.61$ (processing speed). The PHIV group showed significantly poorer performance ($d = 0.91$, $p < 0.001$), supporting NeuroScreen's utility in detecting youth-specific HIV-associated deficits. The cohort's distinct demographic profile, younger, higher female representation, and mixed HIV status highlighted the tool's versatility across developmental stages.

NeuroScreen demonstrates robust psychometric properties across geographically and demographically heterogeneous cohorts. Key consistencies include high usability (>70% "straightforward" ratings), significant sensitivity to HIV-associated deficits (70.7–93.9% across studies), and predictive utility of core demographic variables (age, education, sex). Variability in sensitivity/specificity balances—e.g., the trade-off between Composite 2's sensitivity (81.3%) and Composite 3's specificity (92.6%) in the CASAH cohort—underscores the importance of cohort-specific optimisation. Critically, this section provides a consolidated demographic reference for later comparisons with the Asenze cohort, enabling nuanced interpretation of performance differences attributable to age, HIV status, education level, and cultural context.

2.11 Applying Luria's Functional Systems Theory to Digital Cognitive Assessments in Older Adults in Semi-Rural South Africa

Luria's Functional Systems Theory (Luria, 1966) provides a comprehensive framework for understanding cognitive processes as dynamic interactions between multiple neural systems, shaped by socio-cultural, educational, and environmental factors (Ardila, 1992; Glozman, 2020). This theoretical model is particularly relevant for interpreting digital cognitive assessments in older adults living in semi-rural South Africa, a population that faces significant educational disparities, limited access to healthcare, and varying levels of familiarity with technology (Desmond et al., 2022; Robbins et al., 2014, 2018). Applying Luria's theory to

NeuroScreen, a mobile-based neuropsychological assessment, offers a holistic perspective on executive function, working memory, and processing speed in this underrepresented group, ensuring that cognitive deficits are not conflated with technological inexperience or socio-environmental factors.

An important factor to consider alongside Luria's model is cognitive reserve. Cognitive reserve theory posits that individual differences in cognitive processing capacity enable some people to better withstand brain pathology or functional challenges, thereby explaining the frequent dissociation between neural degeneration and clinical symptoms (Stern, 2002). This latent construct is typically operationalised via proxies such as educational attainment, occupational complexity and engagement in cognitively stimulating activities, all of which have been linked to delayed cognitive decline and preserved functional performance across diverse groups (Pettigrew & Soldan, 2019). Such an approach not only refines interpretative precision but also fosters more equitable diagnostic standards by contextualising individual scores against the backdrop of each person's unique cognitive reserve profile (Stern, 2002; Pettigrew & Soldan, 2019)[full reference in notes app]

The first component of Luria's model, Unit I, is responsible for regulating tone, arousal, and sustained attention (Luria, 1973). This function is particularly vulnerable in populations facing chronic health burdens such as undiagnosed hypertension, malnutrition, and metabolic disorders, which are prevalent among older adults in low-resource settings (Yulia & Luis, 2018). Reduced arousal may contribute to fluctuating attentional engagement, making it difficult to distinguish between true cognitive impairment and performance decrements caused by fatigue or disengagement (Hopstaken et al., 2015).

To mitigate these challenges, NeuroScreen must incorporate culturally appropriate instructions, flexible pacing, and task adjustments that accommodate varying levels of cognitive endurance (Fernández & Abe, 2018; Watts & Shuttleworth-Edwards, 2016; Wong et al., 2024). Allowing breaks or adaptive timing mechanisms may improve test validity, ensuring that poor performance is not simply a consequence of fatigue or low familiarity with structured assessments. These considerations align with Luria's emphasis on integrating physiological, cognitive, and environmental factors into neuropsychological evaluations, particularly in populations where health and cognitive status are intertwined (Luria, 1973).

Luria's Unit II governs the reception, processing, and storage of sensory information, functions that can be significantly influenced by literacy levels and prior exposure to abstract reasoning tasks (Mikadze et al., 2019). Many older adults in peri-rural South Africa have limited formal education and may lack familiarity with digital interfaces, potentially affecting performance on visual attention and memory tasks (Korkman, 1999). These individuals may struggle not due to intrinsic cognitive decline, but rather because of unfamiliarity with touchscreen navigation, abstract symbols, or the test's structure.

To ensure that NeuroScreen's assessments accurately measure sensory processing and memory, tasks should be ecologically valid, incorporating familiar stimuli and culturally relevant problem-solving paradigms. For example, rather than relying on Western-centric visual or numerical patterns, assessments could integrate locally meaningful images or auditory cues that reflect daily experiences. Such modifications reduce the likelihood that low scores stem from test novelty rather than actual neurocognitive deficits (Korkman, 1999; Mikadze et al., 2019).

Unit III of Luria's framework encompasses higher-order executive functions, including planning, self-monitoring, and error detection (Jørgensen & Christensen, 1995). In semi-rural populations, socioeconomic and cultural factors can intersect with executive function performance, influencing both task completion time and accuracy (Golden & Thomas, 2000). For instance, language barriers, minimal exposure to formal education, and economic constraints may extend response times on cognitively demanding tasks, not due to intrinsic deficits, but rather due to anxiety about unfamiliar digital platforms or test-taking hesitation (de Vito et al., 2019).

Luria's holistic approach underscores the importance of interpreting digital assessment scores in relation to the individual's sociocultural background, rather than solely through neurobiological explanations (Eilam, 2003). By supplementing quantitative test results with qualitative observations, such as noting visible anxiety, hesitation, or uncertainty during testing, clinicians and researchers can differentiate between genuine impairments and external influences like digital unfamiliarity (Eilam, 2003). Providing clear, step-by-step instructions or offering a practice phase may help reduce test-related stress, improving engagement and test validity in populations with limited technological experience.

Grounding NeuroScreen's implementation in Luria's Functional Systems Theory provides a more nuanced and context-sensitive approach to cognitive assessment in semi-rural South African older adults. Instead of treating deficits as isolated reflections of brain pathology, Luria's framework emphasises the complex interplay between arousal, sensory processing, and executive function, acknowledging cultural and socioeconomic influences on test performance. This perspective is particularly valuable in ensuring that digital cognitive assessments remain both accurate and equitable, addressing key challenges such as health disparities, digital anxiety, and linguistic diversity.

By adapting task complexity, providing culturally relevant stimuli, and incorporating flexible administration techniques, NeuroScreen can better differentiate between true neurocognitive deficits and performance variations driven by unfamiliarity with assessment methods. Such theoretically informed modifications enhance both diagnostic accuracy and clinical utility, allowing digital cognitive assessments to function as culturally attuned, accessible, and effective tools in low-resource environments.

2.12 Integration of Psychometrics into Neuropsychological Assessments

Psychometrics, which focuses on the measurement of psychological attributes, is critical for ensuring that digital neuropsychological tools such as NeuroScreen are both reliable and valid in diverse settings (Vetter & Cubbin, 2019). In a resource-limited context such as South Africa, where healthcare disparities and varied educational backgrounds are pronounced, rigorous psychometric evaluation is indispensable for adapting assessments to local needs (Gasquoine, 2022; Laher & Cockcroft, 2019; Watts & Shuttleworth-Edwards, 2016). The Asenze cohort, comprising older adults from semi-rural communities, underscores these challenges. Participants often present with heterogeneous socio-cultural and educational experiences, necessitating the careful application of psychometric principles to ensure that instruments like NeuroScreen remain culturally sensitive and clinically relevant (Vetter & Cubbin, 2019).

Reliability refers to the consistency of a tool's results across different populations and settings (Vetter & Cubbin, 2019). Given that many semi-rural areas in South Africa have limited access to specialised healthcare professionals, NeuroScreen's effectiveness hinges on its capacity to produce stable and reproducible findings in such contexts. Equally important is

validity, which determines whether the tool measures its intended cognitive constructs. Establishing the validity of NeuroScreen in the Asenze cohort is vital for enabling accurate identification and tracking of cognitive functioning among underserved populations, an important step towards informed diagnosis and targeted interventions (Vetter & Cubbin, 2019).

Psychometric approaches also embody core values, including objectivity, fairness, quantification, and utility (Wijsen et al., 2021). These values are particularly salient for instruments like NeuroScreen, which strive to offer standardised and unbiased measures of cognitive performance in populations characterised by substantial variability in language, literacy, and life experience. Measurement invariance, ensuring that a test assesses the same construct across different groups, is especially relevant. Adhering to this principle can help minimise the risk of perpetuating existing inequalities, thereby enabling more equitable assessments. By incorporating such psychometric safeguards, NeuroScreen can provide robust and unbiased data on cognitive abilities, offering a valuable framework for clinical and research applications alike (Wijsen et al., 2021).

2.13 Demographic Influence on Performance

A substantial body of research underscores the significant role played by demographic characteristics in shaping cognitive performance. Variables such as age, education, and sex frequently emerge as influential. For instance, older adults tend to experience slower processing speed and diminished fluid cognition, likely linked to the decline of prefrontal brain regions implicated in executive control (Salthouse, 1996; West, 1996). Verbal fluency is also notably sensitive to the effects of ageing (Elgamal et al., 2011). Flynn effects in assessment are further relevant, with cohort studies indicating rising visuospatial short-term memory in modern environments (Wongupparaj et al., 2017), though recent evidence suggests these gains may persist into older age alongside slower rates of cognitive decline (Zhang et al., 2024). In older adults, however, cohort advantages may be counter-balanced by earlier natural declines in right-hemisphere-mediated visuospatial skills relative to left-hemisphere verbally based abilities (Zhang et al., 2024). Conversely, higher levels of education can buffer against such decline by fostering cognitive reserve, thereby protecting individuals from the full impact of age-related neurodegeneration (Stern, 2006). In contrast, those with fewer years of

schooling may find tasks requiring abstract problem-solving or executive functions more challenging due to less sustained exposure to cognitively demanding activities.

Research into sex differences in cognition underscores the nuanced and often overstated nature of demographic influences, with neuropsychological research identifying gender-based performance variations alongside racial and educational disparities in cognitive testing. While males tend to show a moderate advantage in tasks involving mental rotation, often linked to limited spatial training in curricula, and females demonstrate small but consistent strengths in verbal domains, particularly in writing, these differences are typically modest, context-dependent, and demonstrate small effect sizes (Hyde, 2016; Petersen, 2018). Contemporary meta-analytical evidence indicates that males and females perform similarly across most cognitive domains, with only modest differences observed in specific areas, lending support to the Gender Similarities Hypothesis, which posits that males and females are more alike than different across most cognitive domains and largely alike in psychological functioning (Hyde, 2016). Nevertheless, considering sex as a demographic variable remains important when interpreting cognitive test outcomes across diverse populations, underscoring the necessity of accounting for gender as a moderating factor in neuropsychological evaluation protocols. Consequently, ensuring that neuropsychological tests are appropriately adjusted for demographic factors such as gender, educational background, and linguistic proficiency is crucial for minimising bias and enhancing the validity of cognitive assessments across diverse populations (Fernández & Abe, 2018; Lucas, 2013).

Beyond these well-studied domains, broader demographic variables, including race, ethnicity, socioeconomic status, native language, and acculturation, further shape neuropsychological test results (O'Bryant et al., 2004). These factors may be especially salient in multicultural contexts such as South Africa, where stark linguistic and cultural diversity can amplify differences in cognitive performance. Unfortunately, underreporting of demographic data in research hinders the generalisability of findings, particularly when test norms fail to reflect the considerable variability across ethnic or socioeconomic subgroups.

2.14 The South African Context

As discussed above, historical challenges within South Africa offer a clear illustration of why culturally sensitive norms and adaptations are indispensable. Landmark tests such as

the Wechsler Adult Intelligence Scale (WAIS) and the Wechsler Intelligence Scale for Children (WISC) were historically adapted and standardised on predominantly white South African populations, systemically biasing test interpretations for other racial and ethnic groups (Cockcroft, 2024; Cilliers, 2020; Nyamayaro et al., 2019). This legacy highlights the continuing need for rigorous psychometric evaluation, along with localised norms that more accurately represent the country's diverse population. Establishing culture-specific norms and implementing suitable score-adjustment procedures remain vital steps to mitigate potential discrimination and enhance validity in cognitive assessments (Gouse et al., 2024; Ebeogu et al., 2023; Robbins et al., 2022).

By recognising and systematically accounting for these demographic variables, researchers and clinicians can more effectively distinguish genuine cognitive impairment from expected variability (Cysique et al., 2022; Katzev et al., 2019; Mwesiga, 2021). Detailed demographic reporting, encompassing not only age, sex, and education but also socioeconomic background, language proficiency, and acculturation, is therefore critical. Such reporting fosters a deeper and more equitable understanding of cognitive functioning, particularly in underrepresented or historically disadvantaged groups (Cockcroft, 2024; Witten, 2015; Cilliers, 2020). Ultimately, this demographic awareness fortifies the interpretative power of neuropsychological assessments, reducing misdiagnoses and enabling more targeted interventions (Nyamayaro et al., 2019; Gouse et al., 2024; Katzev et al., 2019).

2.15 Focus of Research and Research Question

Cognitive neuroscience, through its interdisciplinary framework, has played a critical role in advancing understanding of the complex interplay between neurological structures, cognitive processes, and behavioural outcomes (Cockcroft, 2024; Cilliers, 2020; Nyamayaro et al., 2019). By synthesising neuropsychological and neuroscientific methodologies, the field has sought to clarify the biological foundations of cognition, providing critical insights for diagnosing and managing cognitive disorders (Gouse et al., 2024; Katzev et al., 2019; Ebeogu et al., 2023). Neuropsychological evaluations have emerged as essential methodologies for clinical diagnosis, intervention design, and empirical investigation (Cysique et al., 2022; Witten, 2015; Robbins et al., 2022). The historical progression of these assessments, from

observational case studies to standardised protocols, underscores their enduring value in elucidating brain-behaviour relationships.

The advent of digital assessment tools, exemplified by NeuroScreen, represents a significant methodological innovation, offering advantages such as automated administration, enhanced portability, and immediate data acquisition (Robbins et al., 2022; Katzef et al., 2019; Nyamayaro et al., 2019). While challenges persist, including hardware variability and data security considerations, these tools have demonstrated significant potential for improving cognitive evaluation in resource-constrained environments (Gouse et al., 2024; Cilliers, 2020; Ebeogu et al., 2023). Validation studies have substantiated NeuroScreen's psychometric robustness and clinical applicability, positioning it as a viable solution for large-scale neurocognitive screening (Mwesiga, 2021; Cockcroft, 2024; Cysique et al., 2022). Nevertheless, the integration of digital and traditional assessment paradigms remains crucial for ensuring ecologically valid cognitive profiling across diverse populations.

Against this backdrop, this study addressed the following primary research question, what is the viability of NeuroScreen as a digital neurocognitive assessment tool for evaluating neuropsychological function in healthy older adults within the Asenze population-based cohort? A secondary question further guided the investigation, what characterises the neuropsychological functioning profile of healthy older adults in peri-rural South Africa, and how is this associated with sociodemographic factors?

Chapter 3: Methods

3.1 Research design

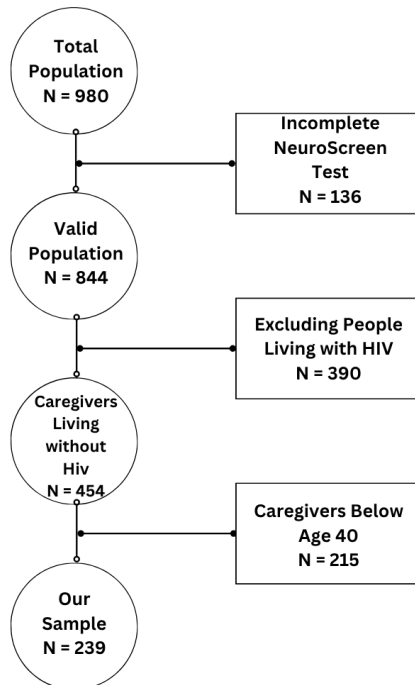
The research philosophy of this study was grounded in the positivism paradigm, emphasising empiricism and objective measures of cognitive performance. Neurocognitive assessments, which sought to elucidate universal principles of brain-behaviour relationships, aligned with the ontological assumptions of positivism. Crucially, positivism's reductionist approach is exemplified by how neurocognitive assessments deconstruct complex phenomena into discrete, quantifiable units for focused investigation (Newman, 2000; Reagan et al., 2023; Tengil, 2020). However, it is acknowledged that this approach may overlook holistic interactions within cognitive processes, a limitation inherent to positivist frameworks (Smith et al., 2023).

A deductive approach was employed in this study to address the research objectives systematically. This methodology allowed the integration of existing theory and knowledge of cognition and neurocognitive assessment, accounting for contextual variables across populations. By adopting this approach, the study formulated hypotheses with operational precision, permitting granular analysis of specific facets of the tool's viability. Methodological rigor was ensured through the application of a structured research design and established theoretical models, thereby enhancing the reliability and generalisability of the study. Furthermore, the deductive approach enabled transparent evaluation of the tool's viability while contributing to theoretical refinement within the field of neurocognitive screening (Newman, 2000; Bryman, 2016).

This investigation employed a quantitative, non-experimental, correlational research design. Secondary data were derived from the Asenze population-based cohort, a pre-existing epidemiological dataset. The cross-sectional nature of the necessitated careful consideration of temporal causality limitations, though this design aligned with the study's viability aims (Rothman, 2021).

3.2 Sampling

Figure 1: Sample refinement process



This investigation employed data from the Asenze cohort, a population-based longitudinal study conducted in the Valley of a Thousand Hills, a peri-urban region of KwaZulu-Natal, South Africa (Desmond et al., 2022). Study participants consisted of primary caregivers whose children were enrolled in the Asenze cohort study. For Wave 3, which was administered between October 2019 and January 2022, the final caregiver sample included $n = 980$ participants (representing 1027 households). To investigate the viability of NeuroScreen in healthy older adults, inclusion criteria were defined as: (1) participants aged 40 years or older. Exclusion criteria were: (1) diagnosed HIV-positive status; and (2) a history of neurological or psychiatric conditions. HIV status was ascertained through rapid diagnostic testing (RDT) and/or participant self-report. Similarly, histories of neurological and psychiatric conditions were self-reported. The exclusion of HIV-positive individuals was methodologically justified to evaluate the tool's efficacy in detecting neurocognitive impairments within an HIV-seronegative population, ensuring its validity as a screening device independent of HIV-related confounders.

3.3 Instruments

The following standardised assessment tools were employed to facilitate the collection of demographic data and the evaluation of cognitive performance across specified domains, as derived from the broader cohort study.

3.3.1 Demographic Questionnaire

A demographic questionnaire was administered to gather essential socio-demographic data, including participants' age, date of birth, sex, highest level of educational attainment, history of neurological or psychiatric conditions, and HIV status. Additionally, socio-economic status was assessed using a standardised asset index adapted from prior South African cohort studies (Nazareth et al., 2022). This tool, administered as part of the broader demographic data collection, captured household characteristics (e.g., building materials, water sources, energy use), ownership of durable assets (e.g., appliances, vehicles), and landownership.

3.3.2 NeuroScreen

Table 1:

Summary of NeuroScreen assessment

Neuropsychological Tests and Outcome Measures				
Test Name	Domain Measured	Outcome Measure	Max Score/Time	Direction (Higher/Lower)
1) Verbal list learning slope	Verbal learning & Memory	1) Trial 2 – Trial 1	1) [-5; 5]	Higher = Better
2) Verbal list learning delayed recall		2) Total recalled words	2) [0; 5]	
Finger Tapping Task	Fine Motor Speed	Total taps (dominant/non-dominant hands)	5 10-second trials per hand	Higher = Better
Trail Making Task 1	Attention/ Processing Speed	Completion time (seconds)	120 seconds (auto-stop)	Lower = Better
Number Span	Working Memory	Calculated score (forward & backward spans)	Variable (3–8 digits)	Higher = Better

Trail Making Task 2	Executive Function/ Processing Speed	Completion time (seconds)	120 seconds (auto-stop)	Lower = Better
Number Speed Task	Executive Function	Total time across trials (seconds)	75 sec/trial (450 total)	Lower = Better
Visual Discrimination (1 & 2)	Processing Speed/ Working Memory	Correct items ((1) figure match + (2) number & figure match)	61 (Task 1); 150 (Task 2)	Higher = Better
Trail Making Task 3	Processing Speed/ Working Memory	Completion time (seconds)	120 seconds (auto-stop)	Lower = Better

NeuroScreen is a digital neuropsychological assessment tool designed to evaluate neurocognitive impairment, with a particular focus on cognitive domains commonly affected by HIV (Robbins et al., 2014). It assessed six key domains of cognition, namely verbal learning and memory, motor speed, attention, working memory, executive functioning, and processing speed (Katzef et al., 2019; Robbins et al., 2014, 2021). The tests were embedded within a graphical user interface and were accompanied by standardised test instructions or audio-visual guidance to facilitate administration (Robbins et al., 2022). NeuroScreen had been linguistically and culturally adapted into multiple languages, including Afrikaans, isiXhosa, and isiZulu, to enhance accessibility in diverse South African populations. The screening battery required approximately 25 minutes to complete (Robbins et al., 2018, 2021, 2022).

This study specifically examined the following domains utilising the following subtests:

3.3.2.1 Verbal learning and memory: verbal list learning and verbal list delayed recall

The verbal learning and memory assessment consisted of two phases: list learning and delayed recall. During list learning, participants were presented with a 5-word list in English or isiZulu, delivered via standardised audio recordings at 2-second intervals using a neutral pre-recorded voice to ensure consistency. After each presentation, participants were asked to recall as many words as possible immediately, in any order and without time limits, over two consecutive trials. Responses were digitally recorded to capture the number of correctly recalled words in Trial 1, repetitions, intrusions, and completion time, followed by the same

measures for Trial 2. The Verbal List Learning Learning Slope, reflecting improvement across trials, was calculated as Trial 2 correct words minus Trial 1 correct words, with scores ranging from -5 to 5; higher values indicated greater learning capacity. This task adapted the Rey Auditory Verbal Learning Test (RAVLT) format but used a shorter word list to improve multilingual and cross-cultural applicability (Robbins et al., 2014, 2021).

The delayed recall phase commenced approximately five minutes after the final learning trial. This timing was approximate, as NeuroScreen's protocol prioritised uninterrupted completion of any ongoing assessments; if the five-minute interval elapsed during another test, the delayed recall trial was initiated only after the current task concluded. Participants were instructed to verbally recall as many words as possible from the original list. The administrator recorded responses by selecting corresponding on-screen buttons for correctly recalled words, with an "other" button tapped for intrusions (non-list items). No semantic cues or recognition prompts were provided during this phase. The delayed recall score was calculated as the total number of correctly recalled words (range: 0–5), directly reflecting retention without compensatory scaffolding. This approach ensured a focused assessment of spontaneous retrieval ability, distinguishing pure recall performance from aided retrieval strategies (Robbins et al., 2014, 2021).

3.3.2.2 Motor speed: finger tapping with dominant and non-dominant hand

Motor speed was assessed using a finger-tapping task, in which participants tapped a virtual on-screen button as rapidly as possible. Each trial lasted 10 seconds, with participants completing three trials for the dominant hand, followed by three trials for the non-dominant hand, and then two additional trials for each hand (totalling five trials per hand). Handedness, pre-specified in the NeuroScreen patient profile, automatically determined the trial sequence. The task was scored by summing the total number of taps for each hand across all five trials, with higher scores indicating greater motor speed. NeuroScreen's digital interface standardised administration by eliminating manual scoring bias, while the fixed trial duration and structured progression ensured reliable within- and between-hand comparisons (Robbins et al., 2014, 2021).

3.3.2.3 Attention: trail making task 1

The attention domain was assessed using Trail Making Task 1. Participants used their finger to draw a line connecting numbered circles (1–8) in ascending order on a digital screen. The device automatically recorded completion time (in seconds) and systematically detected errors, such as skipped numbers or incorrect sequences. If an error occurred, a pop-up message instructed participants to return to the last correctly connected circle before resuming. The trial was automatically discontinued after 120 seconds if unfinished, with incomplete attempts scored at the maximum time limit. Performance was quantified by total completion time (capped at 120 seconds) and error frequency, with shorter times and fewer errors indicating stronger attentional control and processing speed (Robbins et al., 2021).

3.3.2.4 Working memory: number span forwards and backwards

The working memory domain was assessed using a number span test (forwards and backwards). Participants heard pre-recorded digit sequences, starting at 3 digits and progressing to a maximum of 8 digits. Each digit was spoken at 1-second intervals in a clear, enunciated voice. In the forwards span, participants repeated sequences in the presented order. If they provided two consecutive incorrect responses at a given span length, the task transitioned to the backwards span, where participants recalled sequences in reverse order (also starting at 3 digits). Two trials were administered per span length in both conditions; if both trials were incorrect, the respective condition terminated (Robbins et al., 2014, 2021).

The test recorded the longest correctly repeated span for forwards and backwards separately, with each condition ranging from 3 to 8 digits. For example, a participant achieving a forwards span of 6 and a backwards span of 4 would have their scores recorded as 6 (forwards) and 4 (backwards) respectively, rather than being summed. This design isolated short-term storage (forwards) and mental manipulation (backwards), with higher individual span lengths indicating stronger working memory capacity in each domain. Automated progression rules and standardised auditory delivery ensured reliable, bias-free administration (Robbins et al., 2014, 2021).

3.3.2.5 Executive Function: trail making 2 and number speed

Trail Making Task 2 (Alternating Numbers and Colours): Participants used their finger to draw a line connecting numbered circles (1–8) in ascending order, alternating between

blue- and yellow-coloured circles, as quickly as possible on a smartphone screen. The task included two key rules: (a) participants received audio warnings if they lifted their finger off the screen, requiring them to resume from the last correct circle; (b) sequencing errors (e.g., skipping a number, selecting the wrong colour) triggered an audio prompt instructing them to return to the last correctly connected circle, with progression blocked until the error was corrected. The smartphone automatically recorded total completion time (capped at 120 seconds), time between circles, finger lifts, sequencing errors, and wrong starts (incorrect initial selections). Shorter completion times indicated superior cognitive flexibility and task-switching ability (Robbins et al., 2014, 2021).

Number Speed Task: Participants inputted numerical sequences using an on-screen keypad, starting with a 3-digit number and progressing in one-digit increments up to a 9-digit number over six trials. Target numbers turned green as digits were entered correctly; incorrect entries turned red, requiring correction via a back button before proceeding. The smartphone recorded completion time (max 75 seconds per trial) and errors. A practice trial familiarised participants with the keypad. The final score was the sum of completion times (in seconds) across all six trials, with lower totals reflecting faster processing speed and attentional accuracy (Robbins et al., 2014, 2021).

3.3.2.6 Processing speed: visual discrimination and trail making 3

Visual Discrimination 1: This subtest measured processing speed by requiring examinees to determine whether one of two target figures (top of the screen) matched any of five figures in a row below. Responses were made via check (match) or X (no match) buttons. A practice trial with corrective feedback ensured comprehension, and examinees could not proceed until all practice items were answered correctly. The task discontinued after 45 seconds, with the primary score being the total correct responses. This subtest aligned conceptually with the Symbol Search (WAIS-III) but differed in its shorter duration (45 seconds vs. 2 minutes) and elimination of graphomotor demands (Robbins et al., 2014, 2021).

Visual Discrimination 2: Examinees matched symbols to corresponding numbers using an on-screen key. For each item, a central symbol was displayed, and responses were recorded via numbered buttons at the bottom. A practice trial with feedback and mandatory mastery preceded the test. The task discontinued after 45 seconds, scored by the total correct

responses. This subtest paralleled the Coding subtest (WAIS-III) but was shorter (45 seconds) and required no writing, isolating processing speed from motor skills. Both subtests were domain-similar to traditional processing speed measures (e.g., CTT-1) (Robbins et al., 2014, 2021).

Trail Making Task 3 (Dotted Line): Examinees traced a pre-dotted line connecting numbered circles (1–8) on a smartphone screen, mimicking the motor demands of Trail Making 1/2 but without cognitive switching. Rules included: (a) audio warnings for finger lifts, requiring resumption from the last correct circle; (b) sequencing errors triggered prompts to return to the prior circle, blocking progression until corrected. The smartphone recorded completion time (capped at 120 seconds), finger lifts, errors, and time between circles. Longer completion times indicated poorer visual-motor integration. This task prioritised pure motor execution over higher-order executive function (Robbins et al., 2014, 2021).

3.4 Procedure

This research study utilised secondary data derived from the Asenze population-based cohort study, as outlined in the preceding sections. The dataset was accessed following a formal data request submitted by the study supervisor, who also serves as a co-investigator in the current wave of the Asenze study. The request was reviewed and approved by the wider research team to ensure compliance with ethical and procedural guidelines. Ethical clearance for the primary Asenze study had already been obtained; however, an additional ethical waiver application was submitted and granted to permit the use of fully anonymised secondary data for this Master's project. This waiver ensured that the use of the data adhered to ethical standards while maintaining participant confidentiality. The ethics waiver, along with the formal permission letter granting access to the data, has been included in appendix J for reference.

The NeuroScreen assessment, a key component of the third wave of the Asenze study, was administered between 2019 and 2021. This wave focused on evaluating broader aspects of adolescent and caregiver functioning, including cognitive abilities and the impact of early childhood adversities on development. For the caregiver population, the NeuroScreen assessment was used to measure cognitive functions such as processing speed, working memory, and executive functioning, which are critical for understanding the cognitive health

of caregivers in this context. The assessments were carried out using a digital tablet-based interface, which allowed for standardised administration and precise data capture. Testing took place at a designated site within the participants' local community in KwaZulu-Natal, ensuring accessibility and convenience for the cohort. The assessments were conducted by experienced and trained fieldworkers who had undergone rigorous training to ensure consistency and accuracy in the administration of the NeuroScreen tasks. The use of digital technology facilitated real-time data collection and minimised errors, while the structured protocol ensured that all participants received the same instructions and testing conditions.

Prior to analysis, the dataset underwent a comprehensive cleaning process to address errors, inconsistencies, and missing values. Specific cleaning procedures were applied depending on the nature of the issues identified. For instance, in cases of minor data entry errors or implausible values, reasonable replacements or corrections were made where feasible. In situations where data points were irretrievably missing or deemed unreliable, listwise deletion was employed to preserve the integrity of the dataset. This approach ensured that the subsequent analysis was based on accurate and reliable data. Following the completion of the data cleaning process, the dataset was prepared for analysis, with appropriate statistical methods applied to address the research objectives. This methodological rigor ensured the validity and reliability of the findings derived from the secondary data analysis.

3.5 Ethical Considerations

This study utilised secondary data from the Asenze Cohort Study, a longitudinal population-based research project, necessitating careful attention to ethical considerations associated with the use of pre-existing data. Ethical clearance for this secondary analysis was granted by the University of the Witwatersrand Human research Ethics Committee (non-medical; see Appendix A), ensuring compliance with ethical standards for the use of anonymised data in this Master's project. This approval confirmed that the study adhered to the ethical protocols established by the original Asenze research team, including the safeguarding of participant confidentiality and anonymity.

The Asenze study obtained informed consent from all participants during its initial waves, ensuring that participants were fully aware of the study's objectives, procedures, and

their rights. For this secondary analysis, the data provided was fully anonymised, with all identifying information removed to minimise any potential risks to participants. This approach aligns with the ethical principles of beneficence and non-maleficence, ensuring that the research does not harm participants or compromise their privacy. Furthermore, the anonymisation process was rigorously monitored to ensure compliance with data protection laws, including South Africa's Protection of Personal Information Act (POPIA) and international standards for ethical research.

Data storage and future use were managed in accordance with stringent ethical and legal requirements. The anonymised dataset was stored securely on password-protected systems, accessible only to the research team, and was used exclusively for the purposes outlined in this study. Any restrictions on data sharing or future use, as stipulated by the original Asenze research team, were strictly respected. This included obtaining formal permission for data access and ensuring that the data would not be disseminated beyond the scope of this research without explicit approval.

By addressing these ethical considerations, this study demonstrates its commitment to upholding the highest standards of research integrity. The ethical framework guiding this research prioritises the rights and well-being of participants, ensuring that their trust as contributors to the Asenze study is honoured. This approach not only aligns with the ethical obligations of the academic institution but also reinforces the credibility and reliability of the research findings. Through this rigorous adherence to ethical principles, the study affirms its dedication to responsible and ethical research practices, safeguarding the integrity of the data and the dignity of the participants.

3.6 Data analysis

The analytical process began with a detailed examination of the cohort's demographic characteristics, including gender, age, educational attainment, socioeconomic status, handedness, and linguistic background. Normality assumptions were assessed using Shapiro-Wilk tests, which revealed significant deviations from normality across most NeuroScreen performance variables ($p < 0.001$) (see appendix B-I for skewness and linearity checks). As a result, non-parametric statistical methods were employed to ensure robustness against non-normal data distributions.

Given that factors like gender handedness and language are inherently non-normal within this cohort (the majority of caregivers will more often than not be women, most people are right handed and other than save a few took the test in IsiZulu), are what make up the majority of the demographic factors that are used to test and analyse the difference and relationship with performance on the NeuroScreen, the most robust manner to run statistical test was to do it with non-parametric measures, as elaborated above.

Descriptive statistics, including medians and interquartile ranges (IQRs), were calculated to summarise both demographic variables and cognitive performance metrics, providing a foundational profile of the cohort and contextualising its sociodemographic variability.

The asset index was derived using principal components analysis (PCA) based on household assets, structural characteristics, and utilities, following methods validated in similar LMIC contexts (Davidson et al., 2012; Nazareth et al., 2022). The index was standardised (mean = 0, SD = 1) and categorised into tertiles (low, middle, high) to reflect socio-economic stratification.

The analysis proceeded with normative benchmarking, where one-sample t-tests compared the cohort's NeuroScreen performance against established normative data from both local (Robbins et al., 2018) and international studies. Effect sizes (Cohen's *d*) were reported to quantify the magnitude of observed disparities. Following this, inferential analyses focused on identifying performance differences across categorical demographic strata. The Kruskal-Wallis H test was used to evaluate variations in cognitive performance across age groups, educational levels, and SES categories. Where significant omnibus results were observed ($p < 0.05$), post-hoc pairwise comparisons with Bonferroni correction were conducted to identify specific inter-group differences.

To further explore relationships between demographic variables and cognitive performance, Spearman's rank-order correlations examined associations between continuous variables (age, education, SES) and NeuroScreen outcomes. Linear regression analyses were then employed to assess the predictive capacity of these demographic variables on task performance, with collinearity diagnostics confirming predictor independence ($VIF < 5$) and model fit evaluated via adjusted R^2 . All analyses were conducted using IBM SPSS Statistics

(Version 30; IBM Corp., 2024), with results systematically synthesised to evaluate NeuroScreen's psychometric validity and clinical utility within this semi-rural South African population.

Chapter 4: Results

This study aimed to evaluate the efficacy of NeuroScreen within a cohort of healthy older adults residing in a semi-rural region of KwaZulu-Natal. Through comprehensive secondary data analyses, this cohort's participants' neurocognitive performance was examined across multiple domains in the NeuroScreen assessment, including trail making, number speed as well as the overall completion time, whilst accounting for important demographic variables such as age, education attainment and socioeconomic indices. The findings are presented systematically in distinct analytical components: demographic characteristics of the sample population, descriptive statistical analysis of cognitive performance, correlational investigations between demographic factors and NeuroScreen outcomes, stratified performance analyses utilising inferential statistics, and comparative assessments against established international and local normative data. This methodological analytical framework was used to ascertain NeuroScreen's psychometric properties and clinical utility within this specific population and contextual setting.

4.1 Participant Characteristics and Demographic Profile

The analysis of demographic and participant characteristics established the foundational context for examining associations between sociodemographic factors and cognitive test performance. A total of $n = 239$ participants were included in the study based on the predefined inclusion and exclusion criteria, drawn from a broader sample of caregivers ($N = 980$). As presented in Table 1, the sample was predominantly female, comprising 91.6% ($n = 219$) of participants. This gender distribution aligns with expectations given the caregiving nature of the wider cohort.

The sample exhibited a middle-aged predominance, with a median age of 52.00 years (IQR = 12) and a range spanning 40–79 years. Interquartile analysis revealed that 50% of participants clustered between approximately 46 and 58 years, reflecting a concentration in late middle age. This distribution was further substantiated by categorical analysis: 78.2% ($n = 187$) of participants were aged 40–59 years, comprising near-equal proportions in their 40s (39.3%, $n = 94$) and 50s (38.9%, $n = 93$). Older age groups were progressively underrepresented, with only 14.0% ($n = 35$) aged 60–69 years and 7.1% ($n = 17$) in the 70–79

year bracket. The skew toward younger cohorts suggests limited generalizability to older populations, a consideration critical for interpreting cognitive performance given established age-related neurocognitive decline.

The sample exhibited a bimodal distribution of educational attainment, reflective of socioeconomic disparities in semi-rural South African communities. The median educational level corresponded to incomplete secondary education (Median = 4.00, IQR = 2 on a 6-point scale), with half of participants clustered between grades 3 (some primary education) and 5 (matric completion). The largest subgroup comprised individuals with partial secondary education (40.1%, $n = 91$), while those with only primary-level exposure - whether incomplete (25.1%, $n = 57$) or complete (9.7%, $n = 22$) - collectively represented over a third of participants. Notably, the distribution's tails captured educational extremes: 4.4% ($n = 10$) reported no formal schooling, while a comparable proportion (4.0%, $n = 9$) had accessed higher education. This 10-fold disparity between the highest and lowest attainment levels underscores the sample's heterogeneity, with implications for cognitive test performance that must be accounted for in subsequent analyses.

The sample was racially homogeneous, consisting entirely of Black participants (100%, $n = 239$). Regarding language, 98.7% ($n = 236$) completed NeuroScreen in isiZulu and 1.3% ($n = 3$) in English, matching the language of administration to each participant's self-reported primary language. Handedness distribution showed 97.5% ($n = 233$) were right-handed and 2.5% ($n = 6$) were left-handed.

Socioeconomic status stratification revealed that nearly half of the participants were categorised as middle SES (47.8%, $n = 109$), while the remainder were relatively evenly distributed across the low SES (27.2%, $n = 62$) and high SES (24.0%, $n = 57$) groups. These SES distributions broadly reflect the socioeconomic landscape of semi-rural KwaZulu-Natal communities.

These demographic indicators provide essential context for the interpretation of neurocognitive assessment results, given the established influence of age and education on cognitive performance metrics.

Table 2*Sociodemographic profile of participants*

Characteristic	N	Percentage (%)		
N	239	-		
Age (years)				
40-49	94	39.3		
50-59	93	38.9		
60-69	35	14.0		
70-79	17	7.1		
Gender				
Female	219	91.6		
Male	20	8.4		
Highest level of education				
None (1)	10	4.4		
Some primary (2)	57	25.1		
Complete primary (3)	22	9.7		
Some secondary (4)	91	40.1		
Matric complete (5)	38	16.7		
Higher education (6)	9	4.0		
Language				
IsiZulu	236	98.7		
English	3	1.3		
Handedness				
Right-handed	233	97.5		
Left-handed	6	2.5		
Socioeconomic status group (SES)				
Low SES	62	27.2		
Middle SES	109	47.8		
High SES	57	24.0		
Characteristic	Median	IQR	Minimum	Maximum
Age	52.00	12.00	40.00	79.00
Level of education	4.00	2.00	1.00	6.00

Note: Percentages are based on valid responses. Median age and education levels are reported with interquartile range (IQR). Missing data were excluded from percentage calculations.

4.2 NeuroScreen Cognitive Performance

The cohort's overall performance profile provides a critical baseline for understanding normative performance ranges across cognitive domains. While these findings offer intrinsic value for characterizing population-level performance distributions, their primary analytical significance emerges when comparatively assessed against other demographic groups in subsequent analyses.

Analysis of NeuroScreen performance revealed substantial variability across cognitive domains (see Table 3). The total completion time had a median duration of 28.00 minutes (IQR = 7), with times ranging from 21 to 50 minutes. The seven-minute interquartile range reflected clustered completion times for most participants, while outliers extended to the upper limit of 50 minutes.

In the domain of learning and delayed recall/memory, the learning list slope (rate of improvement between trials 1 and 2) exhibited a median of 1.00 (IQR = 2; range = -3.00–2.00). Negative slopes indicated reduced recall accuracy in subsequent trials for some participants. The learning list delayed recall (post-distraction retention) ranged from 0 to 5 items (median = 4.00, IQR = 1), with 0 representing no retained items and 5 reflecting full immediate recall capacity.

For motor speed, the finger tapping task (dominant hand) measured taps per minute (median = 159.00, IQR = 118.75; range = 18–309), while the non-dominant hand showed a median of 177.00 taps (IQR = 103.00; range = 24–290). Dominant hand scores were numerically lower but exhibited greater variability.

Attention, measured via Trail Making Task 1 (sequential number connection), had a median completion time of 46.34 seconds (IQR = 38.85; range = 12.06–120.00). The shortest time was approximately one-fifth of the longest recorded duration.

Working memory, assessed using the number span test, demonstrated a median forward span (immediate repetition) of 3.00 digits (IQR = 2; range = 1–7) and a backward span (reverse repetition) of 1.00 digits (IQR = 1; range = 0–4). Backward spans were uniformly lower than forward spans across the sample.

Executive functioning, evaluated with Trail Making Task 2 (alternating number-colour sequencing) and the number speed task (rapid categorical matching), showed median completion times of 54.24 seconds (IQR = 44.26; range = 17.38–120.00) and 57.74 seconds (IQR = 50.81; range = 23.00–192.80), respectively. Both tasks exhibited comparable median times but differed in maximum durations.

Processing speed measures included Trail Making Task 3 (dotted line tracing), with a median completion time of 19.07 seconds (IQR = 12.72; range = 5.62–120.00), and the visual discrimination tasks: Task 1 (symbol matching) yielded a median of 7.00 correct responses (IQR = 5; range = 0–20), while Task 2 (symbol-number matching) showed a median of 12.50 correct responses (IQR = 13; range = 0–32). Task 2 scores were both higher and more variable than Task 1.

4.3 Comparative Analysis of NeuroScreen Performance Across Age Categories

The subsequent within-sample analyses—stratifying participants by age, educational attainment, and socioeconomic status—are designed to systematically demonstrate how demographic factors influence cognitive test performance. This stratified approach will elucidate the specific effects of each variable while controlling for potential confounding interactions between these covariates.

A Kruskal-Wallis H test examined NeuroScreen performance differences across age categories, revealing significant variations in multiple cognitive domains (Table 4). Effect sizes (η^2) ranged from negligible to large, indicating variable age-related impacts.

Participants aged 40–49 years demonstrated superior motor function, with higher median finger-tapping scores (dominant: 190; non-dominant: 202) compared to older groups ($H = 29.42, p < .001, \eta^2 = 0.12$; $H = 27.96, p < .001, \eta^2 = 0.12$). This group also completed assessments faster ($H = 44.08, p < .001, \eta^2 = 0.19$) and scored higher on visual discrimination task 1 ($H = 26.99, p < .001, \eta^2 = 0.11$).

The 50–59 age group showed stable performance overall but exhibited declines in verbal list learning delayed recall ($H = 7.78, p = .051, \eta^2 = 0.03$) and visual discrimination task 2 ($H = 57.08, p < .001, \eta^2 = 0.24$).

Pronounced declines emerged in the 60–69 group: prolonged trail making task times (Task 1: $H = 27.02$, $p < .001$, $\eta^2 = 0.11$; Task 2: $H = 40.02$, $p < .001$, $\eta^2 = 0.17$) and reduced motor speed ($H = 29.42$, $p < .001$, $\eta^2 = 0.12$). Paradoxically, number span backwards scores were higher ($H = 9.24$, $p = .026$, $\eta^2 = 0.04$).

The 70–79 group exhibited marked declines: slower number speed ($H = 72.96$, $p < .001$, $\eta^2 = 0.31$), prolonged trail making times (Task 1: $H = 27.02$, $p < .001$, $\eta^2 = 0.11$; Task 3: $H = 18.85$, $p < .001$, $\eta^2 = 0.08$), and reduced motor function ($H = 29.42$, $p < .001$, $\eta^2 = 0.12$). Number span forwards showed no age differences ($H = 1.08$, $p = .783$, $\eta^2 = 0.00$).

Post hoc analyses (Table 4) revealed progressive performance gradients: younger groups outperformed older peers in processing speed (e.g., 40–49 vs. 70–79: $H = -6.47$, $p < .001$) and motor function (e.g., 40–49 vs. 60–69: $H = 3.75$, $p < .001$). The largest effect sizes occurred in number speed ($\eta^2 = 0.31$) and visual discrimination task 2 ($\eta^2 = 0.24$), indicating age-sensitive domains.

4.4 Educational Stratification in NeuroScreen Performance: A Comprehensive Analysis

A Kruskal-Wallis H test revealed significant differences in cognitive performance across educational levels ($p < .001$), with effect sizes (η^2) ranging from small to large (Table 5). Participants with higher education (matric/higher) demonstrated superior performance across most domains compared to those with limited/no formal schooling.

Motor speed, assessed via finger tapping (dominant/non-dominant), showed pronounced educational gradients (dominant: $H = 24.60$, $p < .001$, $\eta^2 = 0.10$; non-dominant: $H = 20.22$, $p < .001$, $\eta^2 = 0.09$). The matric/higher group exhibited medians of 200.00 (dominant) and 212.00 (non-dominant), outperforming the no/some primary group (medians = 125.00/152.00; post hoc $H = -4.75/-4.34$, $p < .001$).

Processing speed differences were robust. Completion time ($H = 43.93$, $p < .001$, $\eta^2 = 0.18$) favoured higher-educated participants. As well as attention with Trail Making Task 1 showing significant differences (numbers only) ($H = 37.97$, $p < .001$, $\eta^2 = 0.16$).

Visual discrimination exhibited the largest effects: task 1 (symbol matching) ($H = 59.37$, $p < .001$, $\eta^2 = 0.25$) and task 2 (symbol-number matching) ($H = 68.19$, $p < .001$, $\eta^2 = 0.29$). The

matric group achieved medians of 11.00 (task 1) and 18.00 (task 2), contrasting with 5.00 and 5.00 in the lowest education group (post hoc $H = -7.40/-7.85$, $p < .001$).

Executive functioning, measured via Trail Making Task 2 (numbers with alternating colours), showed slower performance in less-educated groups ($H = 32.63$, $p < .001$, $\eta^2 = 0.14$; medians = 40.89 vs. 75.62; post hoc $H = 5.12$, $p < .001$). Number speed ($H = 52.99$, $p < .001$, $\eta^2 = 0.22$) also favoured higher-educated participants. For example, number speed medians were 43.51 (matric) vs. 94.86 (no education; post hoc $H = 6.63$, $p < .001$). Verbal learning differences emerged in learning slope ($H = 9.22$, $p = .010$, $\eta^2 = 0.04$), though delayed recall was stable ($H = 5.95$, $p = .311$, $\eta^2 = 0.03$).

Working memory showed limited educational effects: number span forwards was consistent ($H = 4.07$, $p = .539$, $\eta^2 = 0.02$), while backwards span trended higher in the matric group ($H = 10.41$, $p = .064$, $\eta^2 = 0.04$; post hoc $H = -2.75$, $p = .006$).

These results underscore strong educational gradients, particularly in processing speed, visual discrimination, and motor function, with higher attainment linked to enhanced performance. Non-significant findings in working memory and delayed recall suggest domain-specific resilience to educational influences.

4.5 Socioeconomic Stratification in NeuroScreen Performance: A Detailed Analysis

A Kruskal-Wallis H test revealed socioeconomic status SES-related differences in cognitive performance, though effect sizes (η^2) were predominantly small (Table 6). SES tertiles (low/middle/high), derived from a standardised asset index (Nazareth et al., 2022), showed domain-specific associations.

Processing speed exhibited SES-linked gradients: Trail Making Task 3 (dotted line) times were prolonged (median = 21.16s vs. 16.65s; $H = 6.49$, $p = .039$, $\eta^2 = 0.03$). Attention, measured via Trail Making Task 1 (numbers only), showed marginal SES effects ($H = 4.94$, $p = .085$, $\eta^2 = 0.02$).

For executive functioning number speed scores were slower in the low SES group (median = 79.48s; $H = 6.47$, $p = .039$, $\eta^2 = 0.03$).

Table 3*Performance Metrics Across NeuroScreen Cognitive Domains*

Domain	NeuroScreen task	Median	IQR	Minimum	Maximum
Global	Completion time (in minutes)	28.00	7.00	21.00	50.00
Verbal learning and memory	Verbal list learning slope (learned words from trial 2-trial 1)	1.00	2.00	-3.00	2.00
	Verbal list learning delayed recall (words recalled)	4.00	1.00	0.00	5.00
Motor Speed	Finger tapping: Dominant hand (total taps)	159.00	118.75	18.00	309.00
	Finger tapping: Nondominant hand (total taps)	177.00	103.00	24.00	290.00
Attention	Trail making task 1 (in seconds)	46.34	38.85	12.06	120.00
Working Memory	Number span: Forwards (calculated score)	3.00	2.00	1.00	7.00
	Number span: Backwards (calculated score)	1.00	1.00	0.00	4.00
Executive functioning	Trail making task 2 (in seconds)	54.24	44.26	17.38	120.00
	Number speed (total time seconds)	57.74	50.81	23.00	192.80
Processing speed	Trail making task 3 (in seconds)	19.07	12.72	5.62	120.00
	Visual discrimination 1 (total correct responses)	7.00	5.00	0.00	20.00
	Visual discrimination 2 (total correct responses)	12.50	13.00	0.00	32.00

Visual discrimination demonstrated the clearest SES disparity: task 1 (symbol matching) scores were significantly lower in the low SES group (median = 6 vs. 9; $H = 8.68$, $p = .013$, $\eta^2 = 0.04$), though task 2 (symbol-number matching) showed no differences ($H = 2.66$, $p = .265$, $\eta^2 = 0.01$).

Motor speed, assessed via finger tapping, showed no SES-related variation (dominant: $H = 0.53$, $p = .765$, $\eta^2 = 0.00$; non-dominant: $H = 0.71$, $p = .702$, $\eta^2 = 0.00$). Similarly, working memory (number span forwards: $H = 2.97$, $p = .290$, $\eta^2 = 0.01$) and verbal learning (delayed recall: $H = 0.19$, $p = .908$, $\eta^2 = 0.00$) were SES-resilient.

The high SES group showed non-significant trends toward faster completion times (median = 27.00 vs. 30.00; $H = 6.25$, $p = .044$, $\eta^2 = 0.03$) and enhanced visual discrimination, while the middle SES group mirrored overall sample medians. Post hoc analyses confirmed low vs. high SES differences in visual discrimination task 1 ($H = -2.81$, $p = .005$) and number speed ($H = 2.39$, $p = .017$).

These results suggest a multifactorial relationship between SES and cognition, with visual discrimination and processing speed most sensitive to socioeconomic gradients, while motor function and working memory remain comparatively insulated. The limited effect sizes ($\eta^2 \leq 0.04$) underscore the complex interplay of SES with neurocognitive performance beyond material resource access alone.

4.6 Correlational analysis between performance on NeuroScreen and demographic characteristics

Consistent with the established demographic influences on cognitive performance noted earlier, a correlational analysis framework was employed to systematically examine the relationship between key demographic variables (age, education level, and socioeconomic status) and test performance outcomes. This analytical approach allows for quantification of both the direction and magnitude of these associations while controlling for potential confounding factors.

Significant associations emerged between demographic factors and cognitive performance, with age and education showing the strongest relationships (Table 7).

Table 4

Performance on NeuroScreen Tasks by Age Category

NeuroScreen tasks	Kruskal-Wallis H test of difference			Age category				Post Hoc For Kruskal-Wallis H test of difference Significance of difference between groups											
	H	p-value	η²	Median values for each category				40-49		40-49		40-49		50-59		50-59		60-59	
				40-49	50-59	60-69	70-79	40-49 50-59	p-value	H-stat	p-value	H-stat	p-value	H-stat	p-value	H-stat	p-value	H-stat	p-value
Completion time	44.08	<.001	0.19	26.00	29.00	31.00	33.00	-3.36	.001	-5.28	.000	-4.98	.000	-2.87	.004	-3.17	.002	-0.90	.367
Verbal list learning slope	2.01	.570	0.01	1.00	1.00	1.00	1.00	4.19	.639	-0.62	.533	1.02	.307	-0.97	.333	0.76	.447	0.33	.184
Verbal list learning delayed	7.78	.051	0.03	4.00	3.00	3.00	3.00	4.76	.017	2.05	.041	1.45	.148	0.28	.782	0.12	.907	-0.08	.935
Finger tapping: Dominant	29.42	<.001	0.12	190.00	160.00	125.00	86.00	2.63	.009	3.75	.000	4.55	.000	1.81	.071	3.13	.002	1.62	.106
Finger tapping: Nondominant	27.96	<.001	0.12	202.00	169.00	140.00	104.00	2.84	.004	3.30	.000	4.61	.000	1.91	.232	3.07	.002	1.97	.049
Trail making task 1	27.02	<.001	0.11	41.48	44.37	57.04	75.98	-1.78	.075	-3.91	.000	-4.12	.000	-2.58	.010	-3.14	.002	-1.12	.263
Number span: Forwards	1.08	.783	0.00	3.00	3.00	3.00	3.00	-0.78	.438	-0.59	.556	0.33	.743	-0.02	.988	0.30	.438	0.69	.492
Number span: Backwards	9.24	.026	0.04	1.00	1.00	2.00	1.00	2.30	.022	-0.52	.605	1.76	.079	-2.22	.027	0.48	.632	1.91	.056
Trail making task 2	40.02	<.001	0.17	42.72	53.69	81.24	95.08	-2.88	.004	-4.93	.000	-4.86	.000	-2.78	.005	-3.29	.001	-1.12	.263
Number speed	72.96	<.001	0.31	46.29	61.04	96.37	118.24	-4.61	.000	-6.68	.000	-6.47	.000	-3.27	.000	-3.91	.000	-1.30	.195
Trail making task 3	18.85	<.001	0.08	16.54	19.34	22.01	28.16	-2.02	.043	-3.07	.002	-3.60	.000	-1.56	.116	-2.50	.013	-1.21	.225
Visual discrimination 1	26.99	<.001	0.11	10.00	6.00	6.00	6.00	0.47	.000	3.54	.000	3.49	.000	0.44	.659	1.16	.250	0.74	.460
Visual discrimination 2	57.08	<.001	0.24	17.00	12.00	6.00	5.00	2.40	.000	5.58	.000	5.72	.000	2.06	.040	3.14	.002	1.47	.142

Processing speed measures exhibited robust age-related declines, particularly number speed ($\rho = 0.57, p < .001$) and Trail Making Task 3 (dotted line) ($\rho = 0.28, p < .001$). Motor speed, assessed via finger tapping, correlated negatively with age (dominant: $\rho = -0.34, p < .001$; non-dominant: $\rho = -0.32, p < .001$), indicating reduced performance in older participants.

Visual discrimination showed education-linked enhancements: task 1 (symbol matching) ($\rho = 0.49, p < .001$) and task 2 (symbol-number matching) ($\rho = 0.53, p < .001$) correlated strongly with educational attainment. Processing speed also improved with education, evidenced by negative correlations for completion time ($\rho = -0.43, p < .001$) and Trail Making Task 1 (numbers only) ($\rho = -0.39, p < .001$).

Socioeconomic status demonstrated weaker associations. Visual discrimination task 1 showed a small positive correlation ($\rho = 0.18, p = .005$), while Trail Making Task 3 exhibited an unexpected positive relationship ($\rho = 0.16, p = .012$). Number speed correlated negatively with SES ($\rho = -0.16, p = .017$), suggesting modest socioeconomic influences on processing efficiency.

Working memory and verbal learning showed limited demographic associations. Only number span backwards correlated weakly with education ($\rho = 0.16, p = .018$), while verbal list delayed recall declined with age ($\rho = -0.16, p = .011$).

These results underscore age and education as primary demographic correlates of neurocognitive performance, with SES exerting domain-specific effects. The patterning of correlations aligns with theoretical models of cognitive reserve and environmental enrichment (Table 7).

4.7 Regression analysis of the influence of demographic characteristics on the NeuroScreen Screening tool

To further investigate these relationships, we conducted regression analyses to model the predictive effects of demographic variables on test performance. This approach provides a more nuanced understanding of these associations by: (1) quantifying the relative contribution of each demographic factor, (2) accounting for potential interactions between variables, and (3) enabling predictive modeling of performance outcomes. The resulting mathematical model offers a robust framework for understanding the complex interplay between demographic characteristics and cognitive test performance.

Table 5
Performance on NeuroScreen Tasks by Level of Education

NeuroScreen task	Kruskal-Wallis H test of difference			Level of Education			Post Hoc For Kruskal-Wallis H test of difference					
	H	p-value	η^2	Median values for each category			Significance of difference between groups					
				None Some Primary	Complete Primary Some Secondary	Complete Matric Higher Education	Complete matric & Post school		Complete matric & Post school		Complete Primary & Some secondary	
							Complete Primary & Some secondary	p-value	H-stat	p-value	H-stat	p-value
Completion time	43.93	<.001	0.18	32.00	28.00	25.00	3.39	.000	6.37	.000	4.05	.000
Verbal list learning slope	9.22	.010	0.04	1.00	1.00	1.00	-0.41	.684	0.35	.730	0.88	.377
Verbal list learning delayed	5.95	.311	0.03	3.00	4.00	4.00	1.72	.086	-1.10	.271	-0.88	.380
Finger tapping: Dominant	24.60	<.001	0.10	125.00	159.00	200.00	-2.84	.004	-4.75	.000	-2.67	.005
Finger tapping: Nondominant	20.22	<.001	0.09	152.00	171.00	212.00	-3.27	.001	-4.34	.000	-1.68	.092
Trail making task 1	37.97	<.001	0.16	63.21	45.37	34.47	2.90	.004	5.82	.000	3.93	.000
Number span: Forwards	4.07	.539	0.02	3.00	3.00	3.00	0.12	.905	0.31	.758	-0.20	.841
Number span: Backwards	10.41	.064	0.04	1.00	1.00	2.00	-2.91	.004	-2.75	.006	-0.11	.910
Trail making task 2	32.63	<.001	0.14	75.62	52.59	40.89	2.42	.016	5.12	.000	3.61	.000
Number speed	52.99	<.001	0.22	94.86	55.11	43.51	2.58	.010	6.63	.000	5.34	.000
Trail making task 3	18.82	.002	0.08	21.93	19.72	14.43	3.10	.002	4.07	.000	1.58	.115
Visual discrimination 1	59.37	<.001	0.25	5.00	8.00	11.00	-4.09	.000	-7.40	.000	-4.54	.000
Visual discrimination 2	68.19	<.001	0.29	5.00	14.00	18.00	-3.45	.000	-7.85	.000	-5.81	.000

Multiple linear regression models revealed demographic factors differentially predicted performance across cognitive domains, with processing speed and visual discrimination showing the strongest associations (Table 8).

Executive functioning measures were robustly predicted by age and education. Number speed exhibited the strongest model (adjusted $R^2 = 0.39$, $F(3, 221) = 49.48$, $p < .001$), with age ($\beta = 1.91$, $p < .001$) and education ($\beta = -8.02$, $p < .001$) as primary predictors. Attention (Trail Making Task 1) and executive functioning (Trail Making Task 2) models were significant (adjusted $R^2 = 0.19$ – 0.20 , $p < .001$), though Task 3 (dotted line) failed significance ($p = .056$).

Completion time (adjusted $R^2 = 0.21$, $F(3, 223) = 21.47$, $p < .001$) similarly highlighted age ($\beta = 0.16$, $p < .001$) and education ($\beta = -1.11$, $p < .001$) effects. Socioeconomic status

Table 7

Correlation of NeuroScreen Tasks with Demographic Factors

NeuroScreen Variables	Demographic variables		
	Age	Level of education	Socioeconomic status
	ρ	ρ	ρ
Completion time	.42**	-.43**	-.10*
Trail making task 1	.34**	-.39**	-.14*
Trail making task 2	.41**	-.36**	-.10
Trail making task 3	.28**	-.24**	.16
Finger tapping: Dominant hand	-.34**	.29**	.04
Finger tapping: Nondominant hand	-.32**	.26**	.02
Visual discrimination task 1	-.34**	.49**	.18**
Visual discrimination task 2	-.50**	.53**	.10
Number speed	.57**	-.47**	-.16*
Number span: Forwards	.07	.03	.10
Number span: Backwards	-.05	.16*	.07
Verbal list learning slope	-.01	-.08	-.09
Verbal list learning delayed recall	-.16*	.12	-.02

Note: (* $p < .05$. ** $p < .01$.)

contributed uniquely to number speed ($\beta = -7.41$, $p = .011$).

Table 6

Performance of NeuroScreen Tasks by Socioeconomic Status

NeuroScreen task	Kruskal-Wallis H test of difference			Socioeconomic Status			Post Hoc For Kruskal-Wallis H test of difference					
	H	p-value	η^2	Median values for each category			Significance of difference between groups					
				Low SES	Middle SES	High SES	High SES		High SES		Middle SES	
							Middle SES		Low SES		Low SES	
							H-stat	p-value	H-stat	p-value	H-stat	p-value
Completion time	6.25	.044	.03	30.00	28.00	27.00	1.07	.284	2.46	.014	1.78	.079
Verbal list learning slope	3.61	.164	.02	1.00	1.00	1.00	1.86	.063	1.39	.165	-0.25	.862
Verbal list learning delayed	0.19	.908	.00	4.00	4.00	3.00	0.42	.677	0.35	.725	-0.01	.993
Finger tapping: Dominant	0.53	.765	.00	160.00	155.00	164.00	0.00	1.000	-0.60	.549	-0.69	.490
Finger tapping: Nondominant	0.71	.702	.00	163.00	175.00	183.00	0.42	.678	-0.36	.719	-0.83	.408
Trail making task 1	4.94	.085	.02	46.97	48.35	41.95	1.60	.111	2.19	.029	0.94	.349
Number span: Forwards	2.97	.290	.01	3.00	3.00	3.00	-0.62	.537	-1.54	.124	-1.16	.245
Number span: Backwards	2.83	.243	.01	1.00	1.00	2.00	-1.68	.093	-1.04	.298	-0.46	.644
Trail making task 2	2.18	.337	.01	58.37	53.29	52.50	1.05	.292	1.45	.146	0.63	.530
Number speed	6.47	.039	.03	79.48	55.57	57.04	0.66	.508	2.39	.017	2.10	.036
Trail making task 3	6.49	.039	.03	21.16	18.67	16.65	1.12	.262	2.15	.012	1.79	.074
Visual discrimination 1	8.68	.013	.04	6.00	7.00	9.00	-0.87	.383	-2.81	.005	-2.37	.018
Visual discrimination 2	2.66	.265	.01	11.00	13.00	14.00	-0.67	.503	-1.60	.109	-1.18	.239

For processing speed, visual discrimination performance was strongly predicted by demographic factors. Task 2 (symbol-number matching) showed the highest explanatory power (adjusted $R^2 = 0.39$, $F(3, 222) = 48.00$, $p < .001$), driven by age ($\beta = -0.29$, $p < .001$) and education ($\beta = 2.24$, $p < .001$). Task 1 (symbol matching) demonstrated weaker but significant prediction (adjusted $R^2 = 0.26$, $F(3, 222) = 27.85$, $p < .001$).

Motor function models showed moderate prediction for finger tapping (dominant hand) (adjusted $R^2 = 0.15$, $F(3, 222) = 14.10$, $p < .001$), with age ($\beta = -2.10$, $p < .001$) and education ($\beta = 9.36$, $p < .001$) as key predictors. Working memory (number span) and verbal learning models were non-significant (all $p > .05$), indicating minimal demographic prediction. Demographic variables explained 15–39% of variance in significant models, with age and education consistently outperforming SES. These results underscore domain-specific susceptibility to demographic influences, with processing speed and visual discrimination most affected, while working memory and learning remain relatively independent.

4.8 Comparative performance against Manhattan HIV Brain Bank (MHBB; New York cohort)

The between-group analyses compare the cohort's performance against established normative populations, serving two key objectives: (1) contextualizing performance relative to broader demographic standards, and (2) evaluating the screening tool's viability by assessing its sensitivity to known population-level differences in cognitive performance. These comparative analyses provide empirical evidence for interpreting results within a clinically meaningful framework.

A one-sample t-test compared neurocognitive performance between the Asenze cohort and Robbins et al.'s (2014) HIV-positive sample (Table 7). The MHBB cohort ($N = 50$) comprised 61% male participants (M age = 53.4 years, $SD = 7.0$; M education = 11.8 years, $SD = 2.4$), with 43% Black/African American, 30% Hispanic/Latino, and 18% non-Hispanic White participants (Robbins et al., 2014). Neurocognitive impairment prevalence was 75%. The Asenze cohort showed mixed performance across cognitive domains compared to the reference cohort. For verbal learning and memory, the learning list total score ($M = 8.29$, $SD = 1.20$) was slightly lower than Robbins et al.'s (2014) mean [$(M = 8.5$; $SD = 1.20$), $t(238) = -2.73$, $p = .007$], while delayed recall performance ($M = 3.42$, $SD = 1.45$) exceeded their mean [$(M = 1.6)$, $t(238) = 19.39$, $p < .001$].

Working memory capacity, measured by the number span test ($M = 4.49$, $SD = 1.28$), was significantly lower than the reference mean ($M = 8.8$), [$t(238) = -51.98$, $p < .001$]. Processing speed measures revealed domain-specific differences: performance on visual discrimination task 1 (symbol matching; $M = 7.81$, $SD = 4.09$) was substantially below the reference [$(M = 27.0)$, $t(238) = -72.40$, $p < .001$], while visual discrimination task 2 (symbol-number matching) showed no significant difference [$(M = 12.21$, $SD = 7.35$) vs. ($M = 12.0$), $t(238) = 0.43$, $p = .666$].

Executive function tasks showed consistently slower performance in the Asenze cohort. Trail Making Task 2 (numbers with alternating colours) completion times ($M = 62.16$, $SD = 29.99$) were significantly longer than the reference [$(M = 14.2)$, $t(238) = 24.57$, $p < .001$], as were number speed task times ($M = 73.77$, $SD = 38.67$ vs. $M = 46.0$), [$t(238) = 11.06$, $p < .001$]. Motor function assessment through finger tapping showed reduced speed for both dominant [$(M = 155.68$, $SD = 66.32$ vs. $M = 236.6$), $t(238) = -18.82$, $p < .001$] and non-dominant hands [$(M = 165.39$, $SD = 62.67$ vs. $M = 208.1$), $t(238) = -10.52$, $p < .001$].

These comparative analyses revealed a consistent pattern of domain-specific differences. The Asenze cohort demonstrated particular challenges in working memory, processing speed, and motor function tasks, while showing relative strengths in delayed recall. The mixed profile across cognitive domains suggests both shared and distinct neurocognitive characteristics between cohorts, potentially reflecting differences in population characteristics, cultural factors, or assessment conditions. The findings underscore the importance of population-specific normative data for accurate neuropsychological assessment.

4.9 Comparative Performance Against the Cape Town Cohort (Masivukeni Study)

A series of one-sample t-tests compared neurocognitive performance between the Asenze cohort and Robbins et al.'s (2018) Cape Town sample (Table 8). The Masivukeni cohort ($N = 102$) comprised predominantly HIV-positive, isiXhosa-speaking South African adults (81.4% female; M age = 33.31 years, $SD = 7.46$; 59.8% with ≥ 12 years education; Robbins et al., 2018). Participants had been on antiretroviral therapy for ≥ 12 months (M CD4 = 501.31 cells/ μ L, $SD = 287.41$; 91% virally suppressed).

Table 8*Regression Analysis of NeuroScreen Task Performance by Demographic Factors*

Model #	Dependent variable	Adjusted R ²	F (df)	P (Model)	Age β (SE)	P	Level of education β (SE)	P	Socioeconomic status β (SE)	P
1	Completion time	.21	21.47 (3, 223)	P<.001	0.16 (0.04)	P<.001	-1.11 (0.27)	P<.001	-0.78 (0.45)	P=.089
2	Trail making task 1	.19	18.01 (3, 220)	P<.001	0.18 (0.21)	P<.001	-6.29 (1.56)	P<.001	-5.51 (2.57)	P=.033
3	Trail making task 2	.20	19.78 (3, 220)	P<.001	0.99 (0.21)	P<.001	-5.68 (1.59)	P<.001	-3.24 (2.62)	P=.217
4	Trail making task 3	.02	2.56 (3, 220)	P=.056	-	-	-	-	-	-
5	Finger tapping: Dominant hand	.15	14.10 (3, 222)	P<.001	-2.10 (0.42)	P<.001	9.36 (3.56)	P<.001	4.72 (5.89)	P=.801
6	Finger tapping: Nondominant hand	.12	11.01 (3, 222)	P<.001	-1.98 (0.46)	P<.001	6.05 (3.42)	P=.078	3.96 (5.67)	P=.485
7	Visual discrimination task 1	.26	27.85 (3, 222)	P<.001	-0.09 (0.03)	P=.002	1.26 (0.20)	P<.001	0.57 (0.33)	P=.091
8	Visual discrimination task 2	.39	48.00 (3, 222)	P<.001	-0.29 (0.05)	P<.001	2.24 (0.33)	P<.001	0.73 (0.55)	P=.186
9	Number speed	.39	49.48 (3, 221)	P<.001	1.91 (0.23)	P<.001	-8.02 (1.74)	P<.001	-7.41 (2.88)	P=.011
10	Number span: Forwards	-.00	0.73 (3, 222)	P=.533	-	-	-	-	-	-
11	Number span: Backwards	.01	2.08 (3, 222)	P=.104	-	-	-	-	-	-
12	Verbal list learning slope	-.01	0.65 (3, 223)	P=.585	-	-	-	-	-	-
13	Verbal list learning delayed recall	.02	2.32 (3, 223)	P=.076	-	-	-	-	-	-

Table 7

Comparison of NeuroScreen Task Performance Between Robbins et al. (2014) and Asenze Cohort

NeuroScreen tasks	Robbins et al (2014)	Asenze cohort			
	Mean	Mean	SD	t-value	p-value
Verbal list learning total (raw; both trials added together) (words recalled)	8.50	8.29	1.20	-2.73	.007
Verbal list learning delayed recall (words recalled)	1.60	3.42	1.45	19.39	<.001
Number span total (forwards and backwards added together) (calculated score)	8.80	4.49	1.28	-51.98	<.001
Visual discrimination task 1 (total correct responses)	27.00	7.81	4.09	-72.40	<.001
Visual discrimination task 2 (total correct responses)	12.00	12.21	7.35	0.43	.666
Number speed (time; seconds)	46.00	73.77	38.67	11.06	<.001
Trail making task 1 (time; seconds)	9.70	55.00	29.09	23.92	<.001
Trail making task 2 (time; seconds)	14.20	62.16	29.99	24.57	<.001
Finger tapping dominant hand (total taps)	236.60	155.68	66.32	-18.82	<.001
Finger tapping: nondominant hand (total taps)	208.10	165.39	62.67	-10.52	<.001

Motor speed, assessed via the finger tapping task, was significantly lower in the Asenze cohort ($M = 321.06$, $SD = 126.54$) compared to Robbins et al.'s (2018) mean [$(M = 454.37$, $SD = 60.00)$, $t(238) = -16.25$, $p < .001$]. Visual discrimination tasks revealed lower Asenze scores for task 1 (symbol matching) ($M = 7.81$, $SD = 4.09$ vs. $M = 11.28$, $SD = 3.67$; $t(238) = -13.09$, $p < .001$) and task 2 (symbol-number matching) [$(M = 12.21$, $SD = 7.35$ vs. $M = 25.97$, $SD = 7.97$; $t(238) = -28.90$, $p < .001$]. Working memory, measured by the number span test, was reduced in the Asenze cohort [$(M = 4.49$, $SD = 1.28$ vs. $M = 5.87$, $SD = 1.29$; $t(238) = -16.63$, $p < .001$].

For learning and delayed recall/memory, delayed recall scores did not differ [(M = 3.42, SD = 1.45 vs. M = 3.39, SD = 1.20; $t(238) = 0.30$, $p = .762$)], while total learning scores were marginally lower [(M = 8.29, SD = 1.20 vs. M = 8.45, SD = 1.51; $t(238) = -2.08$, $p = .038$)]. Processing speed measures showed slower Asenze performance: Trail Making Task 3 [(M = 24.01, SD = 18.70 vs. M = 18.18, SD = 16.32; $t(238) = 4.27$, $p < .001$]. Attention, assessed via Trail Making Task 1 (numbers only), had longer completion times [M = 54.99, SD = 29.09 vs. M = 18.95, SD = 18.17; $t(238) = 19.04$, $p < .001$]. Executive functioning, measured by Trail Making Task 2 (numbers with alternating colours), also showed prolonged times [M = 62.16, SD = 29.99 vs. M = 31.95, SD = 21.21; $t(238) = 15.47$, $p < .001$]. Whilst number speed task performance was markedly slower as well [M = 73.77, SD = 38.67 vs. M = 45.02, SD = 18.08; $t(238) = 11.45$, $p < .001$]

The Asenze cohort required significantly longer total assessment time [(M = 29.17, SD = 5.33 vs. M = 23.88, SD = 5.21; $t(238) = 15.36$, $p < .001$]. Across domains, systematic differences emerged in motor speed, working memory, visual discrimination, and processing speed, with relative parity in delayed recall and minimal divergence in total verbal learning. These findings suggest distinct neurocognitive profiles between cohorts, potentially reflecting demographic, cultural, or methodological factors.

4.10 Comparative performance against the 2021 New York cohort (CASA-H cohort)

A series of one-sample t-tests compared neurocognitive performance between the Asenze cohort and Robbins et al.'s (2021) New York sample (Table 9). The CASA-H cohort (N = 62) comprised adolescents and young adults (median age = 24 years, IQR = 22–26), including 33 with perinatally acquired HIV (PHIV) and 29 perinatal HIV-exposed uninfected (PHEU) controls (64% male; 46% Latinx, 44% African American; M education = 13.17 years, SD = 1.30; Robbins et al., 2021). PHIV participants demonstrated stable immune function (median CD4 = 475, IQR = 172.5–763.5) and virological suppression (median viral load = 46 copies/mL, IQR = 20–5203).

Table 8

Comparison of NeuroScreen Task Performance Between Robbins et al. (2018) and Asenze Cohort

NeuroScreen Tasks	Robbins et al (2018)		Asenze cohort			
	Mean	SD	Mean	SD	t-stat	p-value
Finger tapping task (total taps; both hands combined)	454.37	60.00	321.06	126.54	-16.25	<.001
Visual discrimination task 1 (total correct responses)	11.28	3.67	7.81	4.09	-13.09	<.001
Visual discrimination task 2 (total correct responses)	25.97	7.97	12.21	7.35	-28.90	<.001
Number span total (calculated score)	5.87	1.29	4.50	1.28	-16.63	<.001
Verbal list learning delayed recall (words recalled)	3.39	1.20	3.42	1.45	0.30	.762
Verbal list learning total (words recalled)	8.45	1.51	8.29	1.20	-2.08	.038
Trail making task 1 (time; seconds)	18.95	18.17	55.00	29.09	19.04	<.001
Trail making task 2 (time; seconds)	31.95	21.21	62.16	30.00	15.47	<.001
Trail making task 3 (time; seconds)	18.18	16.32	24.01	18.70	4.27	<.001
Number speed (time; seconds)	45.02	18.08	73.77	38.67	11.45	<.001
Completion time (time; minutes)	23.88	5.21	29.17	5.33	15.36	<.001

Processing speed measures revealed substantial differences. Trail Making Task 3 (dotted line) completion times were significantly longer in the Asenze cohort ($M = 24.01$, $SD = 18.70$) compared to Robbins et al.'s (2021) mean [$(M = 9.62$, $SD = 6.19)$, $t = 11.82$, $p < .001$]. Attention, assessed via Trail Making Task 1 (numbers only), showed markedly slower Asenze performance ($M = 54.99$, $SD = 29.09$ vs. $M = 7.61$, $SD = 4.05$; $t = 25.26$, $p < .001$).

For executive functioning there was a large difference between their means assessed through the second Trail Making Task (numbers with alternating colours) ($M = 62.16$, $SD = 29.99$ vs. $M = 22.48$, $SD = 9.06$; $t(238) = 20.33$, $p < .001$) as well as the number speed task

where performance was slower ($M = 73.77$, $SD = 38.67$ vs. $M = 25.89$, $SD = 4.66$; $t = 19.06$, $p < .001$).

Visual discrimination tasks exhibited pronounced disparities: task 1 (symbol matching) scores ($M = 7.81$, $SD = 4.09$ vs. $M = 20.14$, $SD = 4.44$; $t = -46.52$, $p < .001$) and task 2 (symbol-number matching) scores ($M = 12.21$, $SD = 7.35$ vs. $M = 42.14$, $SD = 7.20$; $t = -62.86$, $p < .001$) were both lower in the Asenze cohort. Working memory, assessed via number span forwards ($M = 3.08$, $SD = 0.94$ vs. $M = 5.07$, $SD = 0.91$; $t = -32.66$, $p < .001$) and backwards ($M = 1.41$, $SD = 0.74$ vs. $M = 3.39$, $SD = 1.24$; $t = -41.26$, $p < .001$), showed reduced spans in the Asenze cohort.

All comparisons reached statistical significance ($p < .001$), with consistently larger standard deviations in the Asenze cohort indicating broader performance variability. These results underscore marked cross-cohort differences in processing speed, visual discrimination, working memory, and executive functioning, with no domain showing parity. The systematic disparities highlight potential influences of demographic, developmental, or cultural factors on neurocognitive task performance.

4.11 Comparative Performance Against the PREDICT Cohort (Thai Sample)

A series of one-sample t-tests compared neurocognitive performance between the Asenze cohort and Robbins et al.'s (2022) Thai sample (Table 10). The PREDICT cohort ($N = 100$) comprised Thai adolescents/young adults (M age = 17.77 years, $SD = 2.75$; 50 HIV-uninfected; 57% female; M education = 11 years; Robbins et al., 2022).

Table 9

Comparison of Neurocognitive Performance Between Robbins et al. (2021) and Asenze Cohort

NeuroScreen tasks	Robbins et al (2021)		Asenze cohort		t-value	p-value
	Mean	SD	Mean	SD		
Trail making task 1 (time; seconds)	7.61	4.05	55.00	29.09	25.26	<.001
Trail making task 3 (time; seconds)	9.62	6.19	24.01	18.70	11.82	<.001

Visual discrimination task 1 (total correct responses)	20.14	4.44	7.81	4.09	-46.52	<.001
Visual discrimination task 2 (total correct responses)	42.14	7.20	12.21	7.35	-62.86	<.001
Number speed (time; seconds)	25.89	4.66	73.77	38.67	19.06	<.001
Number span forwards (calculated score)	5.07	0.91	3.08	0.94	-32.66	<.001
Number span backwards (calculated score)	3.39	1.24	1.41	0.74	-41.26	<.001
Trail making task 2 (time; seconds)	14.62	5.70	62.16	29.99	24.35	<.001

Culturally and linguistically adapted NeuroScreen assessments were administered in Bangkok and Chiang Mai.

Processing speed measures showed consistently slower Asenze performance. Task 3 (dotted line) ($M = 24.01$, $SD = 18.70$ vs. $M = 8.36$, $SD = 4.06$; $t(238) = 12.86$, $p < .001$) followed similar patterns. Visual discrimination tasks revealed substantial differences: task 1 (symbol matching) scores ($M = 7.81$, $SD = 4.09$ vs. $M = 22.10$, $SD = 4.34$; $t(238) = -53.91$, $p < .001$) and task 2 (symbol-number matching) scores ($M = 12.21$, $SD = 7.35$ vs. $M = 36.86$, $SD = 6.28$; $t(238) = -51.77$, $p < .001$) were both lower in the Asenze cohort.

This was similar for attention measure through Trail Making Task 1 (numbers only) as well as completion times ($M = 54.99$, $SD = 29.09$) which exceeded Robbins et al.'s (2022) mean ($M = 18.67$, $SD = 4.54$), $t(238) = 19.19$, $p < .001$. Working memory, assessed via number span forwards ($M = 3.08$, $SD = 0.94$ vs. $M = 5.40$, $SD = 1.46$; $t(238) = -38.07$, $p < .001$) and backwards ($M = 1.41$, $SD = 0.74$ vs. $M = 3.26$, $SD = 1.29$; $t(238) = -38.55$, $p < .001$), showed reduced spans.

For executive functioning the number speed task also demonstrated slower Asenze performance ($M = 73.77$, $SD = 38.67$ vs. $M = 23.83$, $SD = 6.20$; $t(238) = 19.88$, $p < .001$)

Learning and delayed recall/memory scores were lower for total learning ($M = 8.29$, $SD = 1.20$ vs. $M = 9.46$, $SD = 0.73$; $t(238) = -15.13$, $p < .001$) and delayed recall ($M = 3.42$, $SD = 1.45$ vs. $M = 4.15$, $SD = 0.99$; $t(238) = -7.80$, $p < .001$). Motor speed, measured by finger tapping (dominant hand) ($M = 155.68$, $SD = 66.32$ vs. $M = 283.86$, $SD = 30.40$; $t(238) = -29.82$, $p < .001$) and non-dominant hand ($M = 165.39$, $SD = 62.67$ vs. $M = 259.02$, $SD = 29.70$; $t(238) = -23.05$, $p < .001$), was significantly reduced.

All comparisons reached statistical significance ($p < .001$), with larger Asenze standard deviations indicating greater performance variability. Cross-cohort disparities spanned processing speed, visual discrimination, working memory, verbal learning, and motor function, suggesting systemic differences potentially linked to cultural, developmental, or assessment-related factors.

4.12 Summary

Significant variability was observed in cognitive performance metrics. For instance, the total completion time had a median duration of 28 minutes, with a range of 21 to 50 minutes. Motor speed tasks showed median finger-tapping scores of 159 for the dominant hand and 177 for the non-dominant hand. Attention and executive functioning tasks, such as Trail Making Tasks, exhibited substantial variability in completion times, indicating diverse cognitive abilities within the cohort. Comparative analyses revealed significant differences in cognitive performance when stratified by age, education, and socioeconomic status. Age-related declines were particularly pronounced in motor function and processing speed, with older age groups showing prolonged completion times and reduced motor speed. Educational attainment strongly influenced performance, especially in processing speed and visual discrimination tasks, where higher education levels were associated with better outcomes. Regression analyses highlighted age and education as the primary predictors of cognitive performance, explaining up to 39% of the variance in certain tasks. These findings underscore the critical role of demographic factors in interpreting neurocognitive assessment results.

Table 10*Comparison of Neurocognitive Performance Between Robbins et al. (2022) and Asenze Cohort*

NeuroScreen tasks	Robbins et al (2022)		Asenze cohort		t-value	p-value
	Mean	SD	Mean	SD		
Trail making task 1 (time; seconds)	18.67	4.54	55.00	29.09	19.19	<.001
Visual discrimination task 1 (total correct responses)	22.10	4.34	7.81	4.09	-53.91	<.001
Visual discrimination task 2 (total correct responses)	36.86	6.28	12.21	7.35	-51.77	<.001
Trail making task 3 (time; seconds)	8.36	4.06	24.01	18.70	12.86	<.001
Number speed (time; seconds)	23.83	6.20	73.77	38.67	19.88	<.001
Number span forwards (calculated score)	5.40	1.46	3.08	0.94	-38.07	<.001
Number span backwards (calculated score)	3.26	1.29	1.41	0.74	-38.55	<.001
Verbal list learning total (words recalled)	9.46	0.73	8.29	1.20	-15.12	<.001
Verbal list learning delayed recall (words recalled)	4.15	0.99	3.42	1.45	-7.80	<.001
Finger tapping; dominant hand (total taps)	283.86	30.40	155.68	66.32	-29.82	<.001
Finger tapping; nondominant hand (total taps)	259.02	29.70	165.39	62.67	-23.05	<.001
Trail making task 2 (time; seconds)	22.48	9.06	62.16	29.99	20.33	<.001

Chapter 5: DISCUSSION

5.1 Summary of main aims and results

This study evaluated the feasibility of implementing NeuroScreen, a cognitive screening tool primarily validated in high-resource urban settings, within a peri-urban South African population in KwaZulu-Natal. The Asenze cohort, situated in the Valley of a Thousand Hills, represents a transitional setting with limited infrastructure but greater connectivity to healthcare and educational hubs than purely rural areas. The findings confirmed that NeuroScreen effectively differentiated cognitive performance variations linked to age and education. Participants with limited formal schooling (≤ 8 years) exhibited slower processing speed, reduced visual discrimination accuracy, and weaker executive functioning (Trail Making Task 2). Older adults (70–79 years) demonstrated declines in motor speed and processing speed, aligning with broader literature on neurocognitive ageing and educational attainment (Casaletto & Heaton, 2017; Laher & Cockcroft, 2019).

However, sensitivity alone does not guarantee equitable application. Pronounced disparities emerged between the Asenze cohort and international reference groups, particularly in processing speed and visual discrimination tasks. These discrepancies highlight the risks of applying unadjusted normative thresholds from Western, urban, and highly educated populations to peri-urban older adults, potentially inflating rates of perceived impairment (Bilder & Reise, 2019; Olson & Jacobson, 2014). Notably, delayed verbal recall (learning list delayed recall) aligned closely with international norms, suggesting domain-specific resilience potentially linked to cultural practices such as oral memory retention, as documented in cross-cultural neuropsychology.

Crucially, observed performance gaps were not uniformly attributable to cognitive capacity. Lower scores in technology-dependent tasks, such as number speed, appeared partially mediated by "test-wiseness", participants' familiarity with digital interfaces and assessment protocols. More educated (≥ 12 years schooling) or socioeconomically advantaged individuals (high SES subgroup) showed stronger alignment with normative benchmarks, indicating that technological literacy, rather than intrinsic cognitive ability, influenced outcomes (Gasquoine, 2022; Wong et al., 2024). These findings resonate with broader

debates on disentangling true cognitive deficits from systemic inequities in test exposure (Cipolotti & Warrington, 1995; Kiselica et al., 2024).

Despite these challenges, NeuroScreen demonstrated consistency in detecting subtle age- and education-related differences in executive functioning and working memory. Regression analyses confirmed its ability to isolate domain-specific cognitive changes associated with aging, such as processing speed declines. This precision, combined with its portability and scalability, supports its viability in peri-urban low-resource settings where traditional neuropsychological assessments remain inaccessible (Shuttleworth-Edwards et al., 2004; Roebuck-Spencer et al., 2017).

The absence of significant differences in delayed verbal recall—despite participants' advanced age, peri-urban residence, and heterogeneous educational backgrounds—offers important insights into cognitive resilience. This pattern, broadly aligned with global normative expectations, suggests that some cognitive domains, particularly well-practised verbal abilities, may remain relatively robust across diverse settings (Epelbaum & Cacciamani, 2023; Prince & Bruhns, 2017). Indeed, crystallised and highly automated verbal skills appear especially resistant to age-related decline, unlike visuo-spatial abilities, which typically deteriorate earlier due to age-related changes in the right hemisphere (D'Antuono et al., 2022). Such resilience reinforces the possibility that NeuroScreen can identify core, universal markers of cognitive health—provided its interpretations are sensitive to contextual factors. This further underscores the importance of embedding performance within culturally and structurally informed interpretive frameworks that recognise both sociocultural strengths and systemic disparities (Watts & Shuttleworth-Edwards, 2016).

In sum, while NeuroScreen exhibited operational feasibility in this peri-urban LMIC setting, equitable implementation requires contextual adaptations, including demographically stratified norms and compensatory strategies for digital literacy gaps. These adjustments would enhance its capacity to distinguish genuine cognitive trajectories from artefacts of systemic disadvantage, reinforcing its promise as a scalable screening tool for underserved ageing populations (Mattar et al., 2015; Tan et al., 2021).

5.2 Influence of Age on Cognitive Performance

Advancing age exhibited strong associations with declining performance across time-dependent and motor tasks, consistent with global evidence of age-related cognitive changes. Participants aged 70–79 years demonstrated significantly slower processing speeds and diminished motor function. These patterns aligned with established literature linking processing speed deficits to prefrontal cortex vulnerability and age-related white matter atrophy (Salthouse, 1996; Casaletto & Heaton, 2017). However, in peri-urban KwaZulu-Natal, a setting marked by healthcare disparities, high rates of untreated chronic illness, and median education levels of 8 years, such age effects likely reflected a confluence of biological ageing and lifelong socioeconomic adversity. Factors such as manual labour exposure, limited healthcare access, and undiagnosed comorbidities may have exaggerated apparent cognitive declines, challenging attributions of deficits solely to neural ageing in the absence of biomarker validation.

Certain cognitive domains, however, appeared resistant to age-related decline. Delayed verbal recall performance among the oldest cohort aligned with international norms, contrasting sharply with deficits in digitally mediated tasks such as number speed. This discrepancy suggested that culturally embedded cognitive practices, such as intergenerational storytelling and communal memory-sharing, may sustain verbal recall abilities even as technological unfamiliarity contributed to deficits in novel, speeded tasks (Arentoft et al., 2015; Mindt et al., 2019). Similarly, number span forwards scores remained stable across age groups, whereas backwards spans, requiring executive manipulation, declined, consistent with global patterns of preserved rote memory amid executive decline (Harada et al., 2013).

These findings raised critical implications for NeuroScreen’s feasibility. While the tool effectively captured expected age gradients, supporting its utility for identifying domain-specific declines, the conflation of biological ageing with structural inequities risked pathologising normative ageing in underserved populations. For instance, a 70-year-old participant with slowed processing speed might be misclassified as cognitively past the cutoff point using WEIRD-based norms, overlooking contributory factors such as limited education or physically demanding occupational histories (Shuttleworth-Edwards et al., 2004; Daugherty et al., 2017). This underscored the necessity for localised, age-stratified norms to disentangle context-driven disparities from genuine cognitive decline. Future research should integrate sociocultural and biomedical data, including longitudinal assessments, to refine risk

stratification models and ensure NeuroScreen's outputs inform equitable, contextually relevant interventions rather than perpetuate diagnostic biases in peri-urban LMIC settings.

5.3 Educational Attainment as a Critical Determinant

Educational attainment emerged as a critical determinant of NeuroScreen performance, with pronounced disparities across tasks requiring visual discrimination, psychomotor speed, and executive functioning. Participants with completed secondary education significantly outperformed those with ≤ 8 years of schooling in visual discrimination and number speed. These findings align with cognitive reserve theory, which posits that prolonged formal education fosters adaptive neural networks that buffer against age-related decline (Stern, 2006). However, in peri-urban KwaZulu-Natal, where only 16.7% of participants completed secondary education, these disparities also reflect systemic inequities in schooling quality, including language barriers (isiZulu vs. English instruction) and the enduring educational deficits linked to apartheid-era policies (Gallo, 2020).

Performance gaps likely stemmed from intersecting factors: lower-educated participants faced dual challenges in deciphering abstract task instructions (e.g., symbol-number matching) and executing time-sensitive cognitive operations, compounded by limited prior exposure to structured testing paradigms. For instance, executive functioning, assessed via Trail Making Task 2, diverged sharply by education level, a disparity exceeding age-related declines. This suggested that "test-wiseness", familiarity with rule-based problem-solving, mediated outcomes as much as intrinsic cognitive capacity, particularly in digitally mediated tasks (Fernandez, 2019).

Notably, some low-education participants (≤ 8 years) performed comparably to higher-educated peers in delayed verbal recall and number span forwards. Such resilience may reflect compensatory mechanisms fostered through communal practices, including frequent collaborative decision-making and multilingual engagement (isiZulu/English), which could enhance auditory-verbal memory despite limited schooling (Cockcroft & Laher, 2022). Yet these exceptions did not negate the broader trend: education-stratified norms proved indispensable to avoid misclassifying systemic inequities as cognitive impairment (Daugherty et al., 2017).

For NeuroScreen’s feasibility in peri-urban LMICs, these results underscored two imperatives. First, raw scores must be interpreted against local educational benchmarks, a participant with six years of schooling and a Trail Making Task 2 time of 75s might fall within normative ranges for their demographic, rather than meeting pathological thresholds. Second, task designs should minimise language-dependent instructions and integrate culturally familiar stimuli (e.g., locally relevant symbols) to reduce exclusionary cognitive demands. Without such adaptations, the tool risks conflating educational disadvantage with neurocognitive decline, undermining its utility in underserved ageing populations (Van der Berg & Gustafsson, 2019).

5.4 Socioeconomic Status and Environmental Factors

Socioeconomic status exhibited a weaker but significant association with NeuroScreen performance compared to age and education, underscoring its complex, multidimensional influence on cognitive outcomes. Higher SES correlated with modest improvements in processing speed, as evidenced by faster number speed and Trail Making Task completion times. These patterns align with evidence that resource security, such as access to digital devices and reduced psychosocial stress, enhances procedural literacy and task engagement (Noble et al., 2015). However, limited effect sizes suggested that SES influenced cognition through nuanced pathways extending beyond financial indicators. In peri-urban KwaZulu-Natal, traditional SES metrics such as income failed to capture the compounded effects of educational inequities, digital literacy gaps, and differential healthcare access on cognitive functioning (Gallo, 2020).

It is important to emphasise that SES is not a singular causal factor in cognitive development or in shaping the neural structures that support it. Rather, SES reflects a constellation of interrelated variables—including but not limited to income, education, occupation, healthcare access, and social capital—that interact in multifaceted ways.

The study’s SES classification, based on occupation and household assets, omitted critical contextual factors such as nutritional stability, healthcare accessibility, and intergenerational wealth transfer, disproportionately compromised in low SES groups due to apartheid’s structural legacies (Shuttleworth-Edwards et al., 2004). Lack of access to consistent healthcare could potentially exacerbate undiagnosed vascular risks that accelerate

cognitive decline (Jinabhai et al., 2003). Additionally, subsistence livelihoods (e.g., informal farming) common among low SES groups involve cognitively demanding tasks not reflected in standard SES indices, potentially distorting perceptions of ability in structured testing (Manly et al., 2005).

It must also be clarified that the SES index employed in this study was constructed to enable comparative grouping into ‘low’, ‘middle’, and ‘high’ SES categories. These categories are inherently relative rather than absolute. For example, individuals in the ‘high SES’ group may not be considered affluent by broader economic standards and certainly do not represent fixed classifications such as “wealthy” or “elite”. Instead, they reflect relative positioning within the studied population.

These limitations mirror broader debates about SES in cognitive research. While higher SES often covaries with enriched environments (e.g., technology exposure, literacy resources), its effects are mediated by structural inequities transcending individual attainment (Van der Berg & Gustafsson, 2019). A low SES participant with robust communal problem-solving skills might underperform on Trail Making Task 2 due to digital unfamiliarity rather than impaired executive functioning—a disconnect amplified by NeuroScreen’s reliance on WEIRD normative frameworks (Henrich et al., 2010).

For NeuroScreen’s feasibility in peri-urban LMICs, these findings necessitate two refinements. First, SES measures should integrate context-specific indicators such as nutritional diversity, digital literacy, and healthcare access to disentangle socioeconomic privilege from cognitive capacity (Cockcroft, 2024). Second, score interpretation must prioritise ecological validity: a low SES individual’s slower number speed may reflect systemic exclusion from technology, not intrinsic impairment. Incorporating such refinements would acknowledge the complex, context-bound nature of SES and may prevent the conflation of structural barriers with individual deficits. Addressing these dimensions could transform NeuroScreen from a diagnostic tool into an instrument for identifying and mitigating structural barriers to cognitive equity in resource-limited settings (Daugherty et al., 2017).

5.5 Digital Assessment in LMIC Settings: Strengths and Challenges

NeuroScreen's digital format offered practical advantages for cognitive screening in peri-urban KwaZulu-Natal, including automated scoring, reduced reliance on specialist personnel and potential for decentralised administration. These benefits aligned with its original aim of addressing resource constraints in low- and middle-income countries (LMICs; Robbins et al., 2021). However, systemic challenges stemming from digital inequities risked undermining equitable application.

The idea that touchscreen familiarity may influence outcomes in digital assessments warrants closer exploration. It's worth considering whether this factor disproportionately impacts older adults and individuals with limited education, potentially contributing to unintended disparities. These patterns might resonate with broader observations from LMICs (Selwyn & Facer, 2013), where unequal technology access entrenches gaps unrelated to cognitive ability. This suggests that digital assessments may be inadvertently prioritising prior exposure to technology against intrinsic cognitive capacity. Exploring this possibility may reveal important insights into the fairness and applicability of such tools in diverse contexts.

The feasibility of task design might be shaped by cultural alignment. For instance, visual discrimination tasks that relied on abstract Western iconography (e.g., geometric shapes) appeared to result in lower accuracy within the Asenze cohort. This observation could point towards potential cultural misalignment within the task design. Interestingly, delayed verbal recall, which places less emphasis on visual abstraction, showed outcomes consistent with international norms. This alignment could possibly reflect the communal decision-making practices commonly observed in this population.

The necessity for population-specific normative data was further underscored by education-stratified differences. For example, executive functioning (Trail Making Task 2) times for participants with ≤ 8 years schooling exceeded international impairment thresholds (≤ 40 s) but aligned with local education-matched percentiles. Without contextual calibration, automated scoring systems risked pathologising normative profiles (Manly et al., 2002).

Addressing the digital divide requires targeted interventions. While NeuroScreen's portability mitigated geographic barriers, given some participants spent nearly 50 minutes on the assessment, nearly 20 minutes above the median completion time. Solutions such as pre-

assessment orientation or interfaces mimicking locally familiar activities (e.g., radio dials for number inputs) could enhance usability without compromising validity.

In sum, this study supports digital screening as a viable approach to expanding neurocognitive assessment access in LMICs but cautions against technocentric optimism. Without concurrent investments in digital literacy and contextually appropriate norms, such tools risk exacerbating health disparities rather than ameliorating them.

5.6 Comparisons with International Norms and Their Interpretations

The systematic comparison of the Asenze cohort's performance against international benchmarks (Robbins et al., 2014, 2018, 2021, 2022) revealed significant disparities, particularly in timed and technology-mediated tasks. Participants from peri-urban KwaZulu-Natal exhibited slower processing speeds and reduced motor dexterity, patterns empirically linked to their unique demographic profile: an older cohort (median age = 52 years) with lower educational attainment (median = 8 years) and strong age-education-performance correlations (e.g., $\rho = -0.34$ for motor speed, $\rho = 0.57$ for number speed). These discrepancies were most pronounced against cohorts with higher educational attainment (e.g., CASAH: mean education = 13.17 years vs. Asenze) and younger age profiles (e.g., PREDICT: mean age = 17.8 years; CASAH: median age = 24 years), reflecting structural inequities in foundational skills development. Limited digital literacy, educational deprivation, and potentially variable ART adherence (given the Cape Town cohort's 91% viral suppression vs. Asenze's unknown treatment consistency) likely contributed more than intrinsic neurocognitive deficits to these domain-specific gaps (Claassen et al., 2001; van der Berg & Gustafsson, 2019).

Interestingly, delayed verbal recall performance aligned closely with the demographically closer Cape Town cohort (both South African, similar age ranges), suggesting shared linguistic/contextual factors. This parity reflects the Asenze cohort's relative resilience in verbal memory (median delayed recall = 4.00, IQR = 1;), a domain less affected by age ($\rho = -0.16$, $p = .011$) or education (non-significant correlation) compared to digitally mediated tasks. Culturally embedded practices like communal oral exchanges may sustain this resilience despite educational disparities (Manly et al., 2004). In contrast, tasks requiring abstract symbol manipulation (e.g., visual working memory) highlighted acute mismatches with younger, higher-educated international cohorts (e.g., CASAH's number span backwards: mean

= 3.39 vs. Asenze's mean = 1.41). These divergences align with the Asenze cohort's education-stratified performance gaps in symbol-number matching ($p = 0.53$, $p < .001$) and underscore how such tasks measure familiarity with Western academic paradigms, exacerbated by $\leq$ Grade 10 education in 41.2% of participants.

Performance variability within the Asenze cohort markedly exceeded all reference groups (e.g., finger tapping SD Asenze = 66.32 vs. SD PREDICT = 30.40), reflecting the cohort's demographic heterogeneity: robust age effects ($p = -0.32$ to -0.34 for motor tasks), educational stratification (e.g., Trail Making Task 2 time gaps by education level), and SES nuances (e.g., $p = 0.16$ for Trail Making Task 3). This variability—rooted in heterogeneity of educational quality (e.g., 41.2% with $\leq$ Grade 10), healthcare access, and technology exposure—contrasts sharply with comparison cohorts' homogeneous samples (O'Bryant et al., 2004). Consequently, uniform diagnostic thresholds from high-income populations prove inadequate. For example, applying Robbins et al.'s (2018) Trail Making Task threshold (≤ 40 s) would pathologise 82% of the Asenze cohort, despite their scores aligning with local education-stratified percentiles and the cohort's lack of severe neurocognitive disorders.

Critically, all comparison cohorts (MHBB, Cape Town, CASAH, PREDICT) benefited from consistent ART—a known cognitive protector (Robbins et al., 2014, 2018, 2021)—while Asenze's ART history was heterogeneous. This may partially explain poorer motor/processing speeds in tasks sensitive to HIV neuropathology (e.g., finger tapping, symbol matching), particularly given the cohort's age-accelerated declines in these domains.

These findings emphasise the necessity of demographically stratified local norms that account for age, education, ART status, and cultural exposure. While NeuroScreen detected cross-context variation, its equitable application in peri-urban KZN requires culturally informed adaptations (e.g., untimed administration; Fernández, 2019) and tasks reflecting ecologically valid skills. Without such adjustments, digital tools risk conflating structural disadvantage (e.g., education-mediated "test-wiseness"; Section 5.3) or treatment gaps with neuropathology.

5.7 Processing speed as an outcome measure

Processing speed has historically been regarded as a sensitive measure of cognitive function, particularly in domains such as attention, and motor function, capturing nuanced

variations that binary accuracy metrics may overlook. While widely used in neuropsychological testing to assess cognitive efficiency, its validity as a universal outcome measure has been increasingly questioned, particularly in older adults and non-WEIRD populations. Research demonstrates that processing speed naturally declines with age due to neurobiological changes in cognitive processing and motor coordination, rather than pathological impairment (Ancelin et al., 2006; Lord & Fitzpatrick, 2001). In peri-urban KwaZulu-Natal, cultural norms often prioritise deliberate, contextually appropriate responses over speed, a pattern observed in rural South African settings where slower task engagement aligns with communal practices (Ursenbach, 2024). Consequently, reliance on reaction time as a primary metric risks misclassifying cognitive impairment in individuals whose performance reflects cultural or age-related norms rather than neurocognitive deficits. This caution is particularly relevant for digital tools like NeuroScreen, where processing speed tasks loaded onto a single factor accounting for 56.16% of variance in South African cohorts, with age being the strongest predictor of performance (Katzef et al., 2019).

The ecological validity of processing speed assessments has faced scrutiny in low-resource settings. Traditional tests developed in WEIRD populations frequently fail to account for educational disparities, digital literacy gaps, and culturally specific cognitive strategies (Thompson et al., 2023). In rural South Africa, limited exposure to standardised testing protocols led to poorer performance on processing speed tasks, independent of true cognitive capacity (Ursenbach, 2024). NeuroScreen's demonstrated capacity to detect HIV-associated cognitive slowing in South African adults confirms its sensitivity to neurobiological impairment (Katzef et al., 2019), yet its regression models simultaneously highlight how sex, education, and cultural factors compound performance variations in healthy cohorts. Additionally, tasks requiring rapid motor responses disadvantaged older adults with physical limitations, conflating motor speed deficits with cognitive decline (Özden et al., 2024). For instance, participants with arthritis or manual labour histories exhibited prolonged times on finger tapping and Trail Making Task 3 (dotted line), despite intact executive functioning in qualitative interviews.

These findings underscore the need for caution when interpreting processing speed in non-WEIRD contexts. Population-specific normative frameworks—like those established for NeuroScreen in LMIC settings (Katzef et al., 2019)—must therefore explicitly account for

intersecting biological, educational, and cultural confounds to avoid pathologising normative differences. To mitigate misclassification, complementary measures, such as culturally relevant problem-solving tasks or observational assessments of daily functioning, should accompany quantitative metrics. Such approaches would better disentangle true cognitive trajectories from artefacts of structural disadvantage, aligning with broader calls for contextually adaptive neuropsychological frameworks in peri-urban LMIC settings.

5.8 Theoretical Perspectives: Cognitive Reserve & Luria's Framework

Luria's Functional Systems Theory provides a critical neuropsychological lens for understanding how culturally-contextual factors shape cognitive test performance by delineating the interplay between basic regulatory functions (Unit I), information processing pathways (Unit II), and higher-order executive systems (Unit III). This framework is essential for moving beyond neurobiological determinism when interpreting digital cognitive assessments in non-WEIRD populations. The findings align with two theoretical frameworks: Cognitive Reserve Theory (Stern, 2006) and Luria's Functional Systems Theory (Luria, 1966, 1973). The cognitive reserve perspective explains the observed stratification in NeuroScreen performance, where participants with higher education outperformed lower-educated peers in executive functioning, working memory, and processing speed. Prior research demonstrates that prolonged exposure to cognitively stimulating activities fosters adaptive neural networks mitigating age-related deterioration (Cockcroft, 2024). However, in semi-rural South Africa, marked by historical educational disparities and limited access to cognitively demanding occupations, the protective effects of cognitive reserve may be unevenly distributed, exacerbating neurocognitive outcome disparities.

Luria's Functional Systems Theory provides a framework for understanding interactions between neurocognitive processes and their neural substrates in culturally diverse settings (Ardila, 1992; Glozman, 2020). The theory's three interdependent units are particularly relevant to this study's focus on executive function, working memory, and processing speed in semi-rural older adults (Desmond et al., 2022; Robbins et al., 2014, 2018). Unit I, regulating arousal and attention, may have been compromised in participants due to chronic health conditions (e.g., untreated hypertension) or socioeconomic stressors common in low-resource settings (Yulia & Luis, 2018). Critically, these factors represent potential confounds rather than intrinsic deficits; integrating simple pre-screening for chronic

conditions and stress levels could contextualise Unit I-related performance variations within normative interpretations for this cohort. For older adults experiencing fatigue, NeuroScreen performance could reflect transient arousal deficits rather than intrinsic cognitive impairment, necessitating culturally sensitive adaptations like flexible pacing and simplified instructions to reduce disengagement (Fernández & Abe, 2018; Watts & Shuttleworth-Edwards, 2016; Wong et al., 2024).

Unit II, governing sensory processing and memory storage, is highly sensitive to educational and literacy variations (Mikadze et al., 2019). In semi-rural KwaZulu-Natal, older adults' limited exposure to abstract reasoning tasks or digital technology likely contributed to difficulties in visual discrimination and working memory tasks, challenges stemming from test unfamiliarity rather than cognitive deficits (Korkman, 1999). The Asenze cohort's performance patterns specifically suggest a preference for verbal over visuospatial modalities within Unit II functions, highlighting the need to prioritise auditory-verbal tasks where feasible and to rigorously assess visual and auditory acuity before administering visuospatial or auditory working memory components. This underscores the need for ecologically valid assessments using culturally relevant stimuli (e.g., locally recognisable symbols) to minimise technological novelty effects.

Unit III, governing executive function and self-regulation, is shaped by socio-cultural experiences (Jørgensen & Christensen, 1995). Prolonged task times in this cohort may reflect environmental factors like test anxiety, lack of prior problem-solving exposure, or linguistic barriers (isiZulu/English discrepancies), rather than deficits in executive functioning (Golden & Thomas, 2000; de Vito et al., 2019). The significant divergence from other normative data observed in the Asenze cohort reflects distinct developmental pathways shaped by culturally-specific child-rearing practices, socio-environmental contexts, and historical educational access patterns, rather than limitations in intrinsic cognitive capacity. This underscores the need to evaluate WIERD-derived test paradigms (e.g., timed abstract symbol tasks) through the lens of African epistemologies of cognitive development. Luria's framework highlights the importance of supplementing quantitative scores with qualitative observations to distinguish genuine impairments from contextual influences like test-taking unease (Eilam, 2003).

By interpreting NeuroScreen results through Luria's model, this study advocates for multidimensional assessment in non-WEIRD populations. Rather than attributing deficits

solely to neuropathology, the framework encourages integrating socio-cultural contexts with neural substrates (Hopstaken et al., 2015). Adapting NeuroScreen through this lens, via refined stimuli, population-specific norms informed by pre-screened socio-educational and health confounders, and controlled novelty effects, could enhance equity and accuracy in semi-rural African contexts, aligning digital assessments with local cognitive realities.

5.9 Implications for Clinical Practice

These findings underscore the necessity of contextually informed scoring frameworks when interpreting NeuroScreen results among older South African adults. Given the pronounced influence of educational attainment on processing speed, executive functioning, and visual discrimination, clinicians should implement demographic correction factors to adjust raw scores based on years of formal schooling, as advocated in cross-cultural neuropsychology (Manly et al., 2002). Basic stratification, categorising participants into low (≤ 8 years), moderate (9–11 years), or high (≥ 12 years) educational attainment groups, could mitigate false-positive classifications of cognitive impairment. This aligns with global guidelines emphasising culturally sensitive normative data (Shuttleworth-Edwards et al., 2004), particularly in populations with systemic educational disparities linked to apartheid-era policies (Gallo, 2020). By refining interpretive frameworks to reflect the cognitive diversity of non-WEIRD populations, clinicians can enhance diagnostic accuracy and NeuroScreen's clinical utility in semi-rural settings.

From a public health perspective, NeuroScreen's brevity and portability hold promise for scaling cognitive screening in community health centres or mobile clinics, enabling early detection of decline and timely interventions. This is critical in regions where dementia awareness remains limited, and infrastructural barriers delay diagnosis. However, maximising effectiveness requires further research. Longitudinal studies tracking processing speed and executive functioning trajectories could establish NeuroScreen's predictive validity for mild cognitive impairment and dementia progression. Pre-test training modules to familiarise participants with touchscreen technology may reduce variance attributable to digital unfamiliarity, a key barrier identified in this cohort (Ursenbach, 2024). Additionally, integrating culturally relevant stimuli (e.g., locally recognisable symbols) into tasks like visual discrimination could improve ecological validity and engagement.

Finally, detailed data on participants' daily cognitive challenges, language fluency, and literacy levels should inform tailored scoring frameworks. For instance, a participant with limited schooling but intact delayed verbal recall (median = 3/5) might represent normative performance within their demographic, not impairment. Such nuance is vital to avoid conflating structural inequities with neuropathology, ensuring NeuroScreen informs equitable, contextually grounded care pathways in peri-urban LMIC settings.

5.10 Strengths and Limitations of the Present Research

This is one of the few studies that has utilised digital neuropsychological assessments in South Africa and in peri-rural settings, despite the growing need for scalable screening tools. Another key strength of this study lies in its rigorous quantitative methodology, integrating descriptive statistics, group comparisons, correlational analyses, and regression models to comprehensively evaluate NeuroScreen's feasibility in a semi-rural South African context. The large sample ($N > 200$) and broad age range (40–79 years) enabled robust exploration of demographic variability, while international comparisons with Robbins et al. (2014, 2018, 2021, 2022) underscored the non-transferability of cognitive norms

However, several limitations warrant consideration. The cross-sectional design precluded causal inferences about whether observed performance reflected stable cognitive functioning or incipient decline. Longitudinal follow-up is required to establish NeuroScreen's predictive validity for detecting early impairment. The dataset's lack of systematic detail on participants' prior digital experience limited quantification of technological familiarity's influence, a critical factor given the cohort's variable exposure to touchscreen interfaces. Similarly, sparse data on comorbid conditions (e.g., hypertension, diabetes) and nutritional status restricted contextual insights into health-mediated cognitive effects.

Comparisons with Robbins et al.'s (2014, 2018, 2021, 2022) cohorts, though informative, require cautious interpretation. Demographic and cultural differences, such as the inclusion of HIV-positive participants in some reference groups and divergent socio-environmental contexts (e.g., New York City vs. peri-urban KwaZulu-Natal), complicated direct benchmarking. To address this, future studies should prioritise generating local normative data specific to KwaZulu-Natal's older, predominantly isiZulu-speaking population, ensuring culturally calibrated diagnostic thresholds.

Finally, defining “older adults” those 40 years and above, introduced interpretative challenges. While this broad classification aligned with the Asenze cohort’s composition and facilitated feasibility assessments across age strata, it risks conflating midlife and late-life cognitive profiles. Variability in ageing definitions across literature (e.g., ≥ 40 vs. ≥ 60 years) necessitates caution when generalising findings to South Africa’s ageing population.

Despite these limitations, the study provides foundational insights into adapting digital cognitive tools for under-resourced settings, emphasising the interplay of education, technology access, and cultural relevance in neuropsychological assessment.

5.11 Future directions for research and conclusion

This study demonstrated that NeuroScreen effectively captures cognitive variability among older adults in semi-rural KwaZulu-Natal, with processing speed and motor execution emerging as domains most sensitive to demographic influences. Age and educational attainment were the strongest predictors of performance, while international comparisons revealed pronounced gaps in these domains, likely driven by digital literacy disparities, cultural differences, and limited formal education. These findings underscore the necessity of developing locally relevant normative data and culturally adapted testing protocols to ensure equitable interpretation of cognitive profiles.

Future research should prioritise longitudinal designs to establish NeuroScreen’s predictive validity for cognitive decline, particularly in executive functioning and working memory. Mixed-methods approaches, integrating qualitative interviews with quantitative metrics, could elucidate barriers to touchscreen testing, such as technological unfamiliarity or task abstraction, while targeted digital literacy modules might mitigate artificially prolonged completion times. Such efforts would enhance accessibility and diagnostic precision in low-resource settings, ensuring the tool’s outputs reflect true cognitive capacity rather than systemic inequities.

5.11 Conclusion

In conclusion, while NeuroScreen exhibits sensitivity to demographic differences, its equitable application requires refinement through culturally informed adaptations and population-specific validation. Observed performance disparities highlight the risks of

universal benchmarking in neuropsychological assessment, reinforcing the imperative for frameworks that prioritise local contextualisation. By integrating community insights and structural safeguards against diagnostic bias, digital assessments such as NeuroScreen could evolve into a cornerstone of equitable cognitive healthcare, bridging diagnostic gaps and enabling timely interventions in underserved LMIC populations.

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Appendices

Appendix A. Ethics approval



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

CLEARANCE CERTIFICATE

PROTOCOL NUMBER: MAPSYC-24-06W

PROJECT TITLE:

Investigating the viability of a digital neurocognitive measuring tool in older adults Asenze population-based cohort.

INVESTIGATOR

Mafalo Mosa

SCHOOL/DEPARTMENT OF INVESTIGATOR

SHCD/Psychology

DATE CONSIDERED

08 July 2024

DECISION OF THE COMMITTEE

Approved unconditionally

RISK LEVEL

No Risk

EXPIRY DATE

31 December 2026

ISSUE DATE OF CERTIFICATE

23 July 2024

CHAIRPERSON

Aline Ferreira Correia
(Prof. Aline Ferreira Correia)

cc: Dr Sahba Besharati (Supervisor)

DECLARATION OF INVESTIGATOR

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

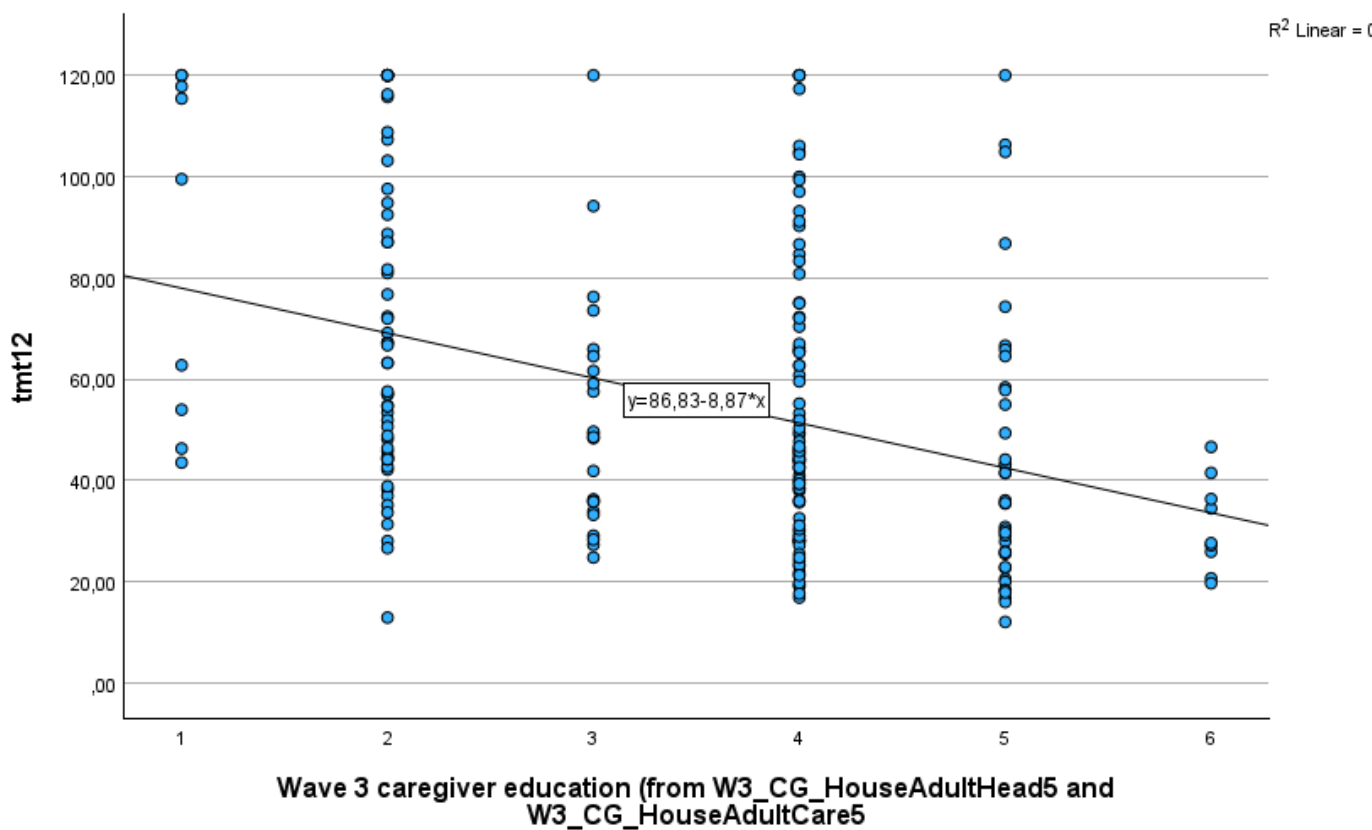
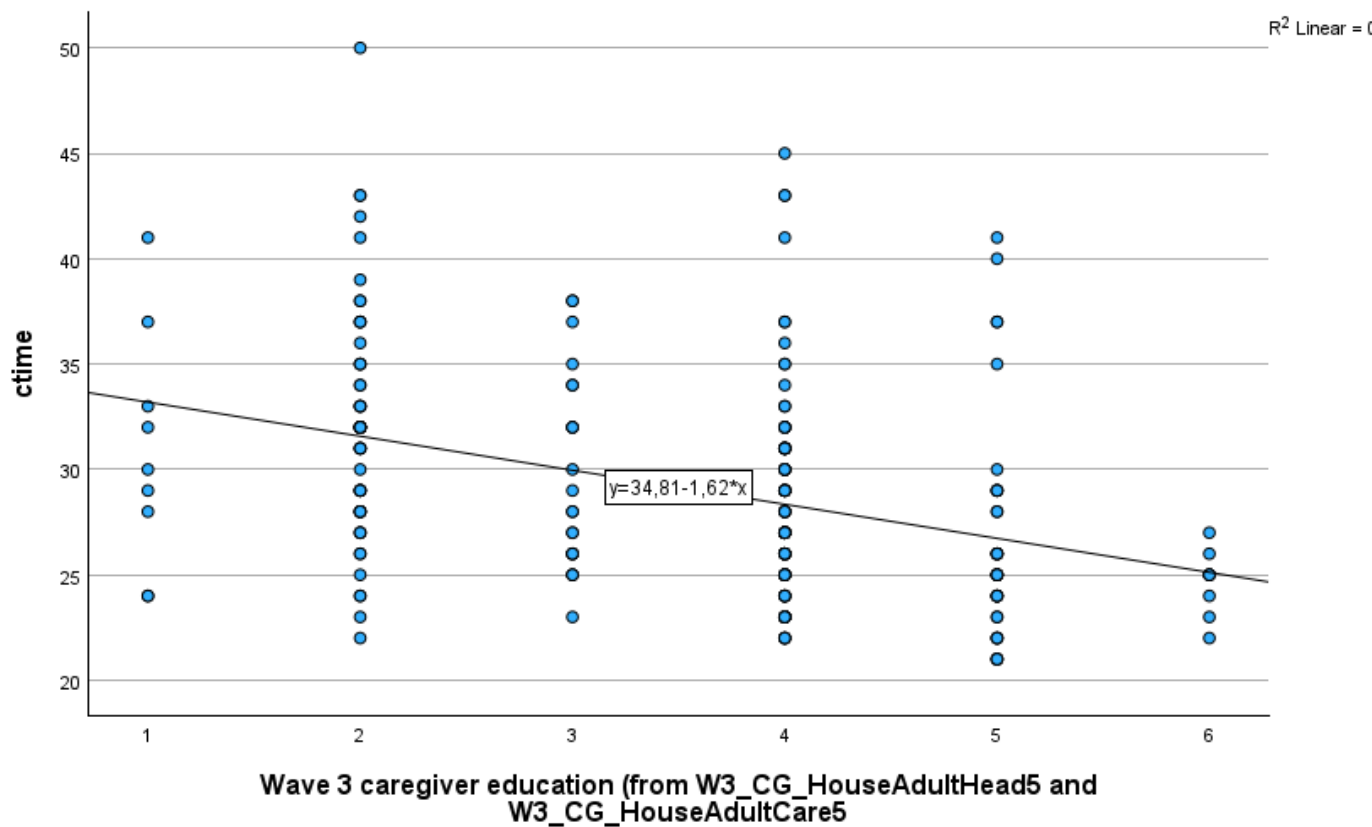
I/we fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure be contemplated from the research procedure as approved, I/we undertake to submit an amendment of the protocol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

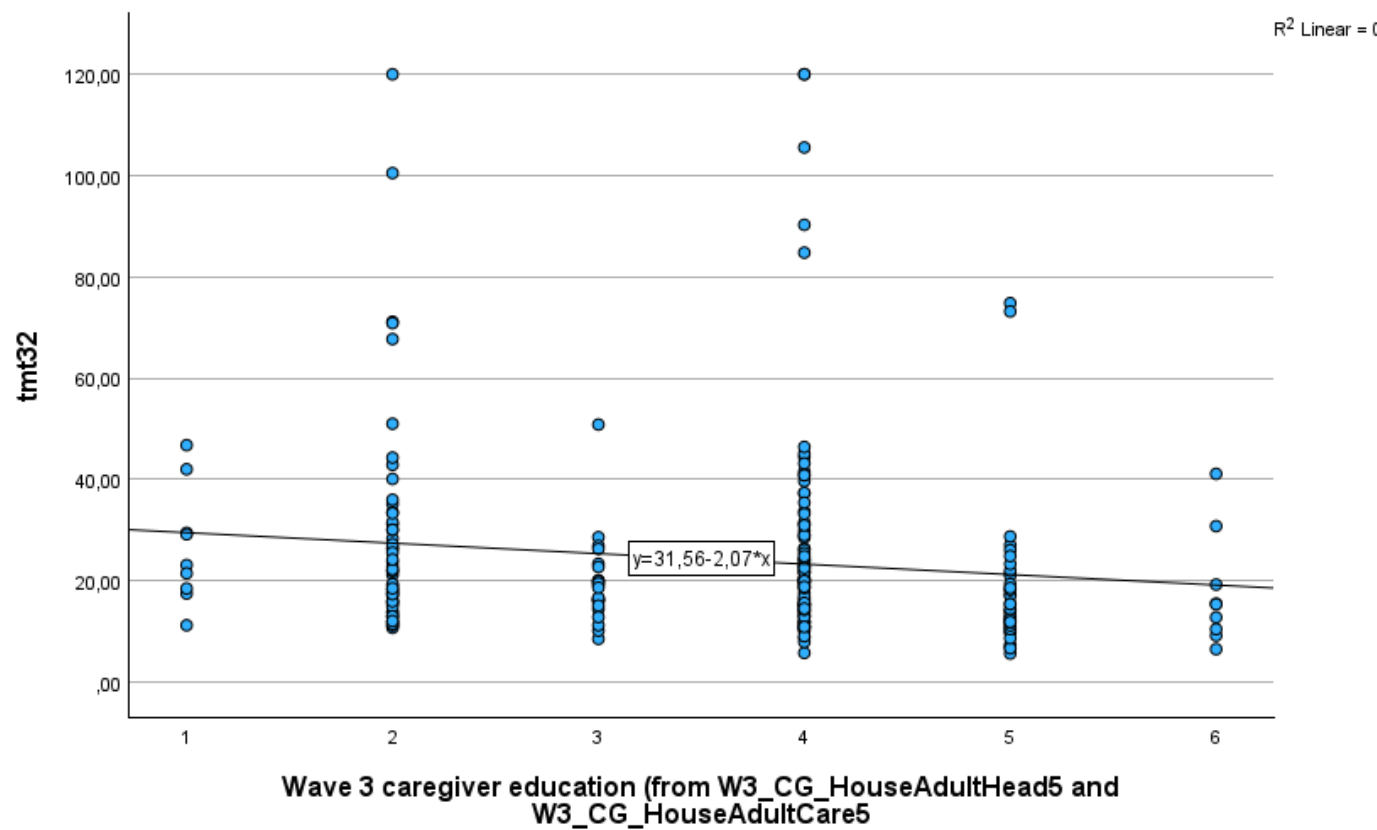
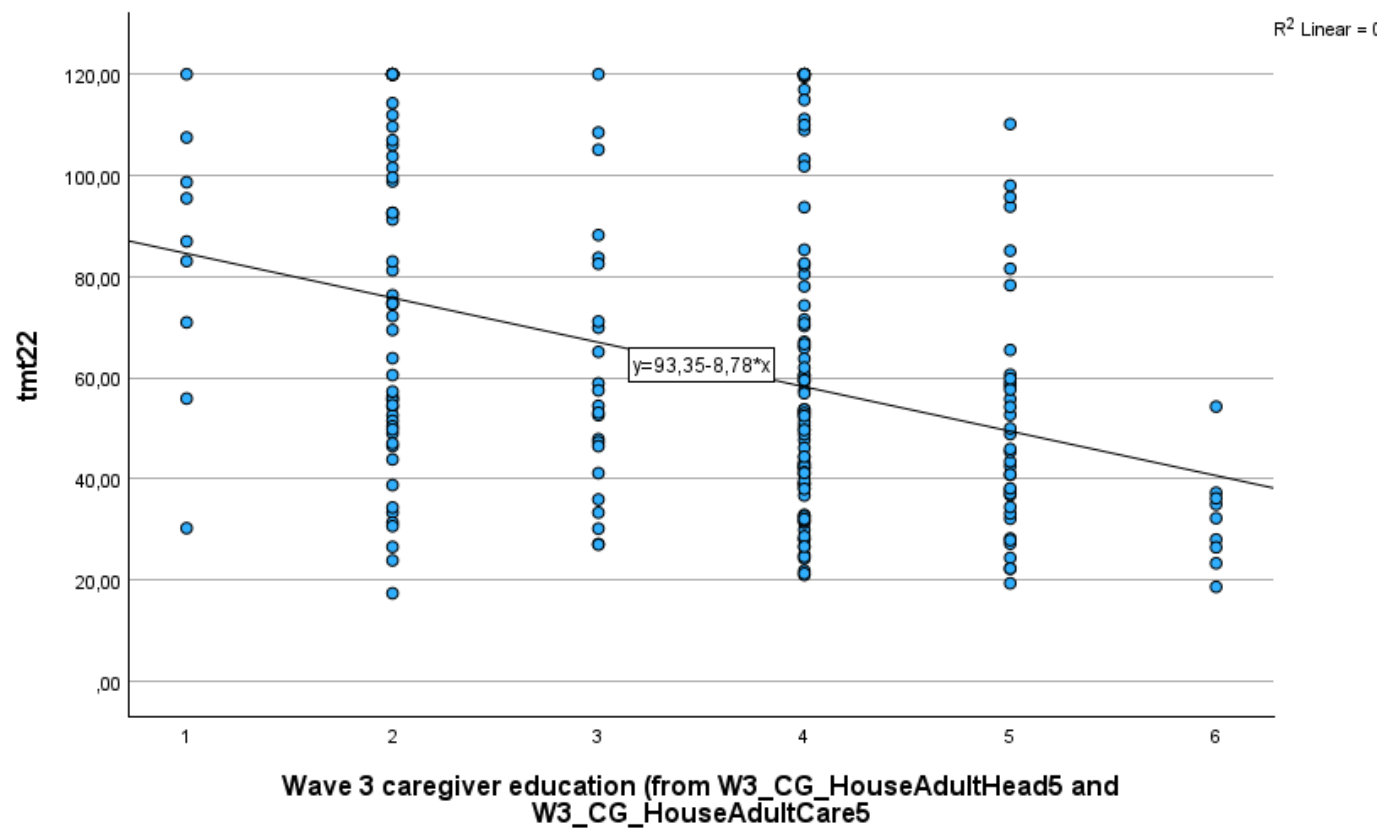
Appendix B. Normality checks

Category	Mean	Standard		Standard error of skewness	Kurtosis	Standard error of Kurtosis		50	75	Minm	Maximum
		Deviation	Skewness			25 Percent	Percent	Percent	Percent	um	
HIV Status	2.000	0.000	-	0.162	-	0.323	2.000	2.000	2.000	2.000	2.000
Gender	1.080	0.272	3.117	0.162	7.785	0.323	1.000	1.000	1.000	1.000	2.000
Race	1.000	1.000	-		-		1.000	1.000	1.000	1.000	1.000
Handedness	1.022	0.148	6.526	0.162	40.954	0.323	1.000	1.000	1.000	1.000	1.000
Language	1.013	0.115	8.543	0.162	71.622	0.323	1.000	1.000	1.000	2.000	2.000
40.00											79.000
Age	53.100	9.351	0.665	0.162	-0.182	0.323	46.000	52.000	58.000	0	
Education Level	3.540	1.250	-0.204	0.162	-0.802	0.323	2.000	4.000	4.000	1.000	6.000
Completion Time											
(Minutes)	29.09	5.347	0.968	0.162	0.865	0.323	25.00	28.00	32.00	21.00	50.00
Trail Making Task 1	55.45	29.468	0.825	0.162	-0.306	0.323	32.88	46.38	72.01	12.06	120.00
Trail Making Task 2	62.27	30.217	0.622	0.162	-0.797	0.323	38.15	54.24	83.01	17.38	120.00
Trail Making Task 3	24.24	19.116	2.981	0.162	10.468	0.323	13.56	19.07	26.97	5.62	120.00
Visual											
Discrimination Task											
1	2.540	1.950	1.426	0.162	4.076	0.323	1.000	2.000	3.750	0.000	13.000
Visual											
Discrimination Task											
2	117.820	7.352	-0.214	0.162	-0.756	0.323	112.000	118.000	125.000	0	130.000
Number Speed Task	2.720	4.857	3.566	0.162	17.447	0.323	0.000	1.000	3.000	0.000	39.000

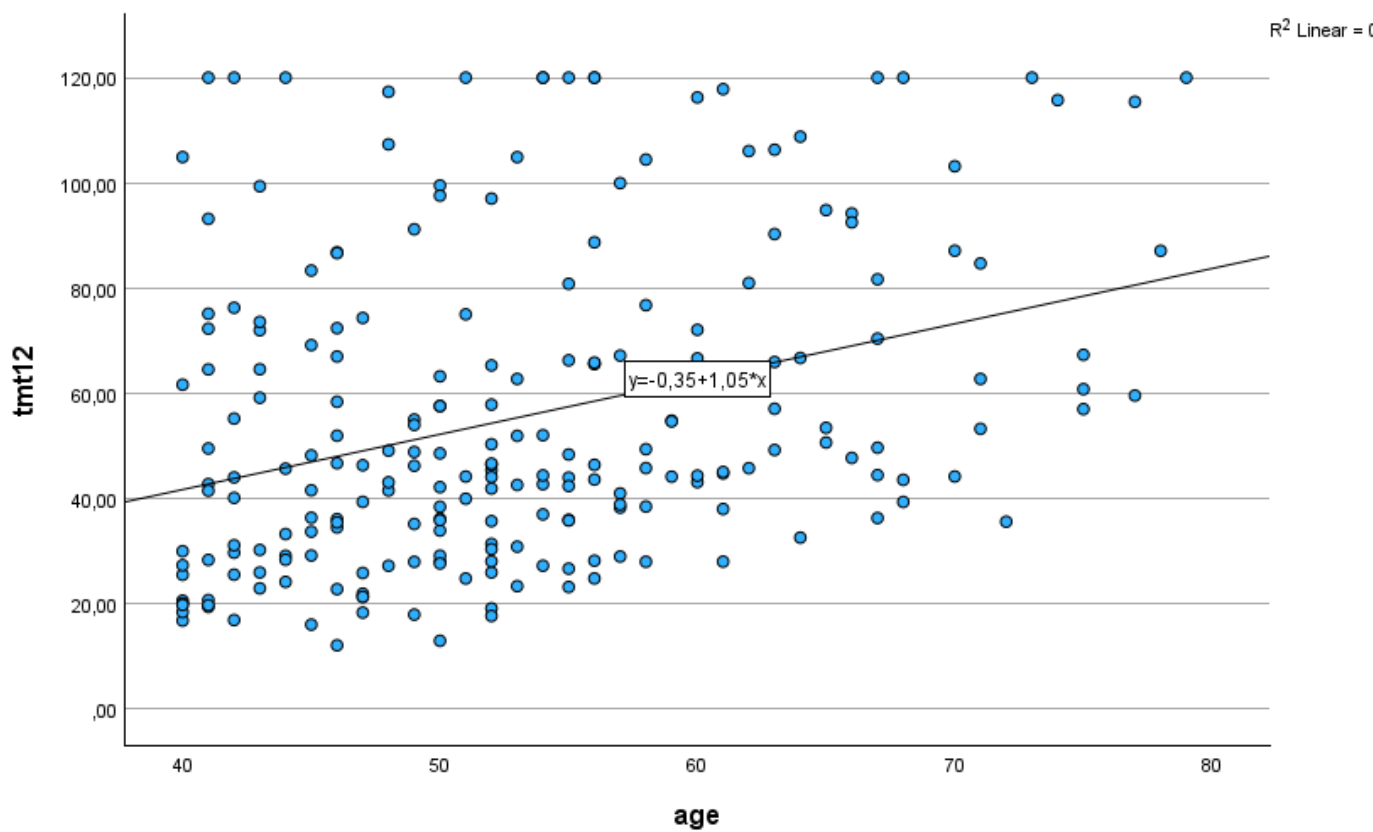
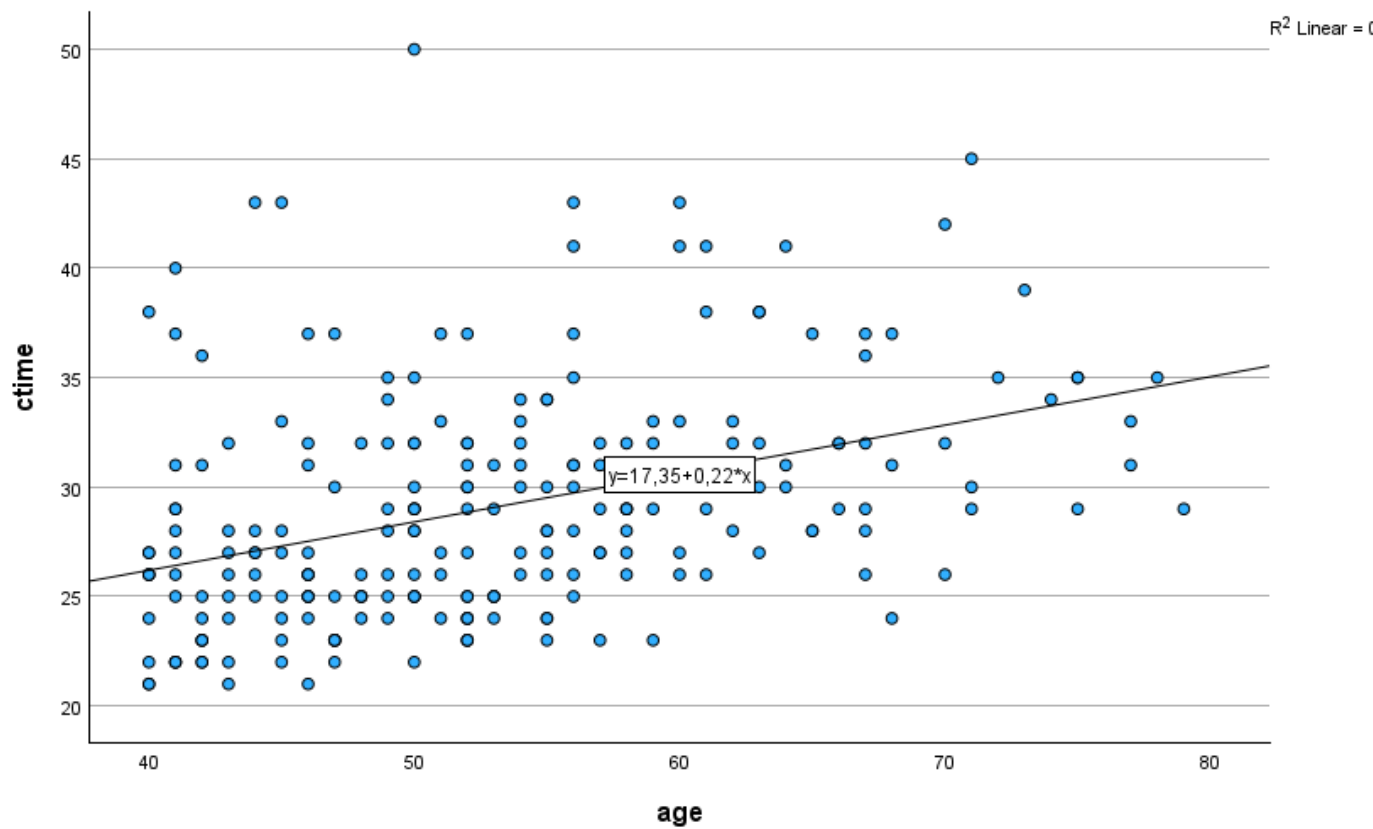
Appendix C-I. Linearity checks (For the regression and correlational analysis)

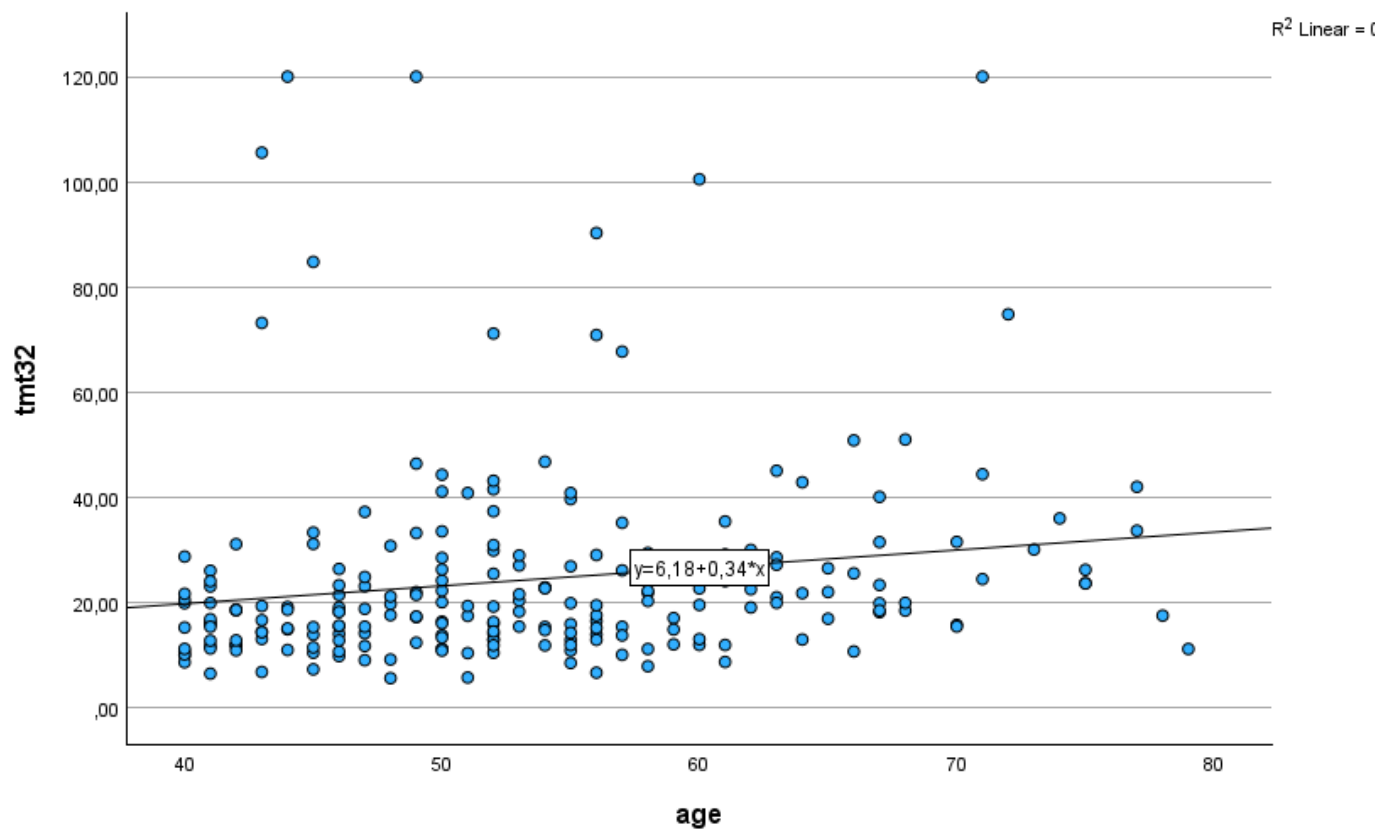
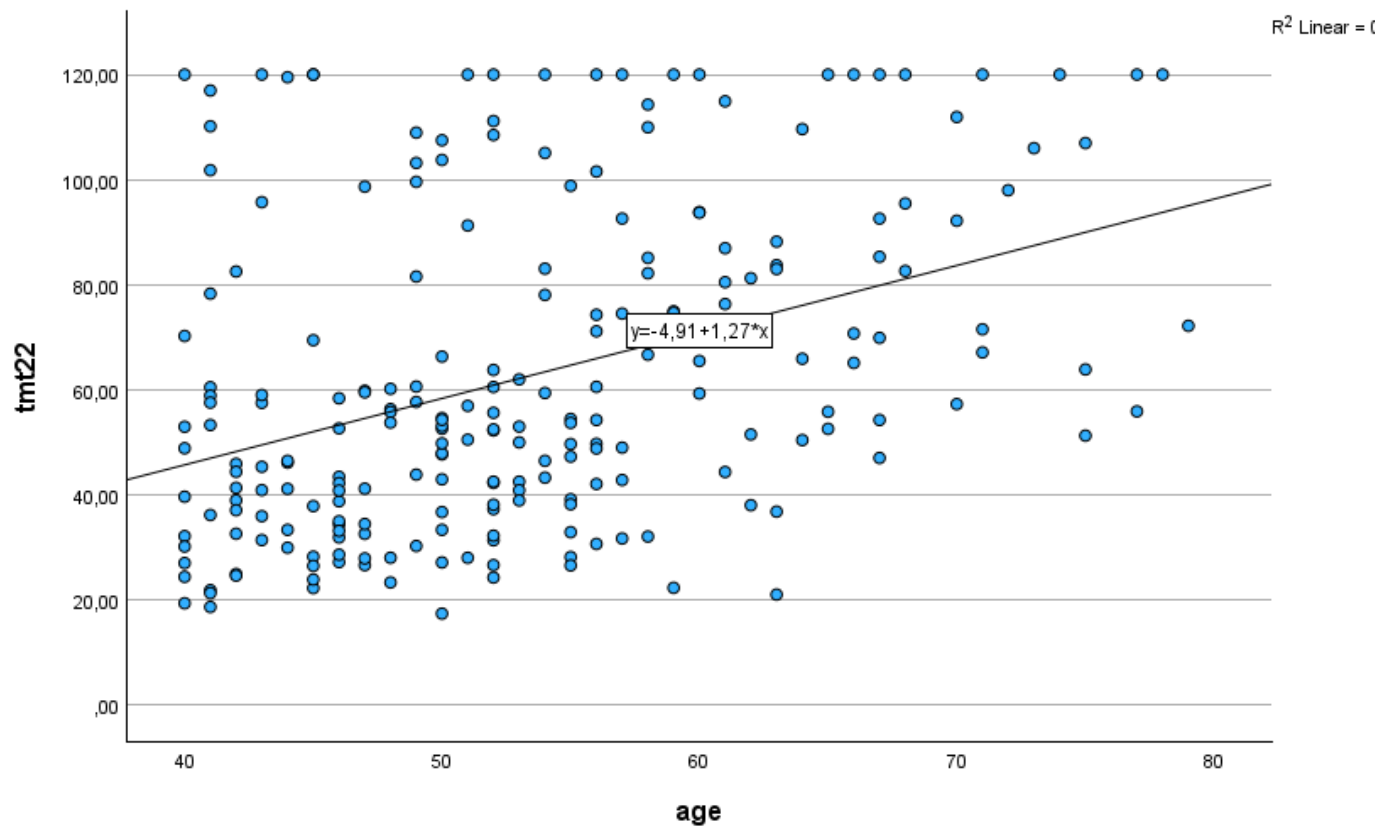
For education





For age





Appendix J. Permission letter to use Asenze data



Asenze Study
Centre for Rural Health
School of Public Health and Nursing
University of KwaZulu Natal

chrisdesmond@libstudies.com

16 May 2024

Dear Chair, WITS ethics review board

This letter is to confirm that Mosa Mafalo (Student Number: 2156642) has obtained permission to utilise data from wave 3 of the Asenze study for the purpose of conducting research for his Masters in Psychological Research degree. The focus of his research is on investigating the viability of a digital neurocognitive measuring tool in older adults using the Asenze population-based cohort.

Once Mr Mafalo has finalised the specifications of his thesis, he is required to submit a data analysis plan to the Asenze team and upon completion of his dissertation, he will be required to submit a copy of the thesis together with his data analysis record. Any subsequent publications will require additional approval by the study PI's.

Sincerely,

Prof Chris Desmond
Asenze PI

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