Attitudes and Achievement in Statistics: A Meta-Analytic and Functional Near-Infrared Spectroscopy Approach

A thesis submitted in fulfilment of the requirements for the degree of

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by

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ABSTRACT

Statistics anxiety describes the extensive worry and apprehension that students may experience when faced with statistics content as part of their university curriculums. Student's perfunctory disposition towards statistics has been indicated to negatively affect performance outcomes in statistics courses. Two meta-analyses were conducted to investigate the relationship between statistics anxiety and achievement in statistics. The first meta-analysis was inclusive of 22 studies investigating the relationship attitudes towards statistics and achievement, whilst the second meta-analysis focused on the relationship, primary amongst Psychology students. Student's attitudes towards statistics were measured using the Survey of Attitudes Towards Statistics (SATS), whilst achievement in statistics courses was quantified using different outcome measures. Finding from the meta-analysis were supplemented by cortical mapping of the neural correlates of statistical reasoning using functional near-infrared spectroscopy (fNIRS).

Results from the meta-analysis indicated a small significant relationship between university students' *Affect*, r = 0.28, *Value*, r = 0.22 and *Difficulty*, r = 0.18, and subsequent achievement in statistics courses. A medium significant relationship between *Cognitive Competence*, r = 0.31, and achievement was also noted. Findings from the second meta-analysis, indicated a medium, significant relationship between *Affect*, r = 0.32, and *Cognitive Competence*, r = 0.35, and achievement. Moreover, a small significant relationship was found between *Value*, r = 0.24, and *Difficulty*, r = 0.23, in relation to achievement in statistics courses. Case study analysis of the neural correlates of statistics reasoning revealed varied signal quality findings of cortical mapping of the neural correlates of statistics in the dorsolateral prefrontal cortex (DLPFC). Moreover, seed-based correlation analysis indicated cortical activation of the dorsolateral prefrontal cortex paired with diverse prefrontal regions. Recommendations from the study include improvements to the fNIRS research design and the inclusion of larger samples to investigate the cortical mapping of the DLPFC in relation to statistics reasoning and statistics anxiety.

Keywords: attitudes towards statistics, statistics achievement, statistics anxiety, fNIRS, functional near-infrared spectroscopy, statistics education, statistical reasoning, dorsolateral prefrontal cortex

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LIST OF ACRONYMS

fNIRS: Functional Near-Infrared Spectroscopy

FET: Further Education and Training

SATS: Survey of Attitudes Towards Statistics

SAS: Statistics Attitude Survey

ATS: Attitudes Toward Statistics

STARS: Statistics Anxiety Rating Scale

ATR: Attitudes Towards Research

CSSE: Current Statistics Self-Efficacy

SELS: Self-Efficacy to Learn Statistics

SCI: Statistics Concept Inventory

SRA: Statistical Reasoning Assessment

ANOVA: Analysis of Variance

STEM: Science, Technology, Engineering and Mathematics

COSSAA: Composite Survey of Statistics Anxiety and Attitudes

MRI: Magnetic Resonance Imaging

DLPFC: Dorsolateral Prefrontal Cortex

DMN: Default Mode Network

MARS: Mathematics Anxiety Rating Scale

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CHAPTER 1
INTRODUCTION

Statistics is an important aspect of most higher education degrees. Whether a student finds themselves interpreting existing data or contributing to their field's body of knowledge, statistics and quantitative research courses are likely to be there with them for the duration of their academic studies. It has, however, been noted that there are significant factors that hinder the process of acquiring statistical knowledge. Two such phenomena are (a) 'statistics anxiety'- a performance anxiety observed when students undertake statistics tasks, and (b) negative predispositions towards learning statistics. Statistics educators, as well as educators in the fields of science, commerce and social science are increasingly interested in researching the impact of these phenomena on students' experiences and achievement in statistics and quantitative research methods courses[1]. Significantly, a relationship between attitudes towards statistics and achievement in statistics courses has been noted, with students having lower achievement outcomes in statistics courses or examinations when they report negative attitudes towards statistics. My research is particularly interested in investigating the phenomenon of 'statistics anxiety' and its relation to achievement in statistics courses amongst Psychology students.

Given the above interest, the enquiry of this dissertation was to document university students' attitudes towards statistics and how this relates to achievement in the subject, as indicated by outcomes such as grade attainment in statistics courses. Further to the above objective, the current study sought to objectively assess the phenomenon of 'statistics anxiety' and statistics education in a sample of Psychology students, by using a neuroimaging technique called functional near-infrared spectrometry (fNIRS). The technique was used to depict neural cortical activation whilst students engaged in statistical content. In summary, this chapter (Chapter 1) introduces the structure of my research study that will shape our enquiry and concludes with the research questions that the study sought to investigate.

1.1 Context and Rationale

It is important for university students and researchers to possess statistical literacy. Statistical literacy, defined as the mathematical approach to identifying patterns and significance, seeks to take a statistical approach to interpret, and communicate research and other findings using numeric considerations (Koh & Zawi, 2014). Ramirez, Schau and

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[1] In the context of course naming in statistics education, the terms, "Statistics" and "Quantitative research" are often used interchangeably.

Emmioğlu (2012) further describe the goal of statistics education as teaching students to critically apply statistical thinking to explain everyday phenomenon of interests. The ubiquity of statistics education is far reaching and is found in multiple disciplines such as Psychology, Biological Sciences, Mathematics and Commerce. Nonetheless, as noted by Bose (2017) most University level students neglect to realise that the scope of their studies may include auxiliary subjects such as Statistics, and this often causes anxiety when undertaking these courses, either at graduate on postgraduate level.

Specific to Psychology, statistics education is a core component of professional training in the discipline and is seen as vital to psychological research and clinical training in the discipline (Coetzee & van der Merwe, 2010). A perpetuating problem within the Social Sciences (e.g., Psychology, Anthropology, Sociology) is that statistics and quantitative research methods curricula continue to be treated as auxiliary subjects, taught to enhance research at postgraduate level, instead of being integrated throughout the curriculum of social science courses (Onwuegbuzie, 2000). According to Onwuegbuzie (2000), this disjuncture causes a negative disposition towards statistics courses, affecting achievement in the aforementioned courses.

1.2 Statement of the Research Problem and Research Objectives

At a local level, the South African Department of Basic Education does not include sufficient statistical training in the Mathematics curriculum beyond introducing descriptive statistics functions (Department of Basic Education, 2011), which can present as a problem for South African students pursuing higher education. According to Illowsky and Dean (2018), the South African syllabi for statistics in the Further Education and Training (FET) phase[2] only encompasses three topics in basic statistics education – *Sampling and Data*, *Descriptive Statistics*, and rudimentary levels of *Regression and Correlation*. According to the authors, this content is not an adequate foundation, as other fundamental statistical concepts such as *Probability*, *Distributions*, *Confidence Intervals*, *Hypothesis Testing* and *Analysis of Variance*, are to be encountered in the University curriculum (Illowsky & Dean, 2018). To this end, a study by Malik (2014), found that university students' previous education in mathematics and statistics, is a significant predictor of Statistics Anxiety and achievement at university level. Findings from early studies such as the ones by Malik (2014), have made recommendations to

[2] The Further Education and Training Phase (FET) comprises grade 10-12. It is the final schooling years of South African learners that will also determine entry into tertiary education.

ensure comprehensive statistical concept training in high school mathematics curricula, yet the execution of these suggestions, continues to be a major challenge.

Based on the above, research indicates that students have a perfunctory disposition towards statistics and statistics education. For example, Ngantweni (2019) investigated postgraduate Psychology students' attitudes towards statistics at a South African university using a mixed methods approach. Findings from the study indicated that postgraduate Psychology students had positive to neutral responses to learning statistics, with some students raising concerns regarding the difficulty of the subject (Ngantweni, 2019). Qualitative findings from the study further indicated that students had a "fear of failure", regarding statistics, and that "the late introduction to statistics courses" to their Psychology curriculum was a major source of statistics anxiety (Ngantweni, 2019, pp. 6). Of particular concern to my research objectives, statistics anxiety as indicated by Ngantweni, (2019) and other researchers (e.g., Ramirez et al., 2012) is linked to underachievement in statistics courses.

To this end, Emmioğlu and Capa-Aydin, (2012) performed a meta-analysis to investigate the relationship between attitudes towards statistics and achievement in statistics courses. The authors used the Survey of Attitudes Towards Statistics (SATS) (Schau, 2000) in their study and found a significant correlation coefficient between Cognitive *Competence* and *Affect* in relation to achievement in statistics courses. Moreover, the study found a significant relationship between the *Value* students place of statistics and achievement in statistics courses. Suggestions emanating from the study by Emmioğlu and Capa-Aydin, (2012), which are key to my research objectives, included that (a) future studies should investigate the relationship between achievement and attitudes to by including a greater number of studies, and (b) employing a broad range of outcome measures to evaluate achievement to describe the relationship between statistics anxiety and achievement. Further, suggestions from Emmioğlu and Capa-Aydin, (2012), included (c) an improved account of heterogeneity measures between studies within the meta-analysis.

1.3 Addressing the Research Problem

The meta-analysis by Emmioğlu and Capa-Aydin (2012) was published over 10 years ago, and no follow up meta-analysis has since been conducted. Importantly, the meta-analysis by Emmioğlu and Capa-Aydin (2012) summarized and collated key data regarding the relationship between attitudes towards statistics and statistics achievement, which led to further research on this research topic. Nonetheless, no updated meta-analysis exists since the initial study by the above authors, eleven years ago. Given this limitation, the first aim of my study was to expand on the early work of Emmioğlu and Capa-Aydin (2012) by updating their initial meta-analysis investigating the relationship between attitudes towards statistics and achievement amongst university students.

Subsequently, no data exists regarding the neural correlates of statistics anxiety. A previous study by Pletzer et al. (2015) employed MRI neuroimaging techniques to compare cortical activation during arithmetic tasks in high mathematics anxiety and low mathematics anxiety individuals and found that mathematics anxiety impairs deactivation of the default mode network. The neural correlates of arithmetic tasks was confirmed to be the dorsolateral prefrontal cortex (Artemenko et al., 2018; Pfurtscheller et al., 2010). The value of studying the neural correlates of statistics anxiety is that subjective experience of attitudes towards statistics and factors that lead to the phenomenon of 'statistics anxiety' can be explored objectively through quantitative neuroimaging designs (Albarracín et al., 2005). Such an exploration could thus assist in designing interventions for educators, to understand the antecedents of statistics anxiety and how these can be remediated (Gal et al., 1997).

Given the account identified above, the second part of my study was to conduct a pilot study investigating the neural correlates of statistical reasoning using functional near-infrared spectrometry (fNIRS) neuroimaging techniques. The value of fNIRS in monitoring mathematical-type reasoning has been undertaken in educational contexts (Hong et al., 2015; Pletzer et al., 2015), and a recently published research study has advocated for further research on the use of fNIRS in education settings within the South African education context (Barreto & Soltanlou, 2022). Barreto and Soltanlou, (2022), further highlight the value of neuroimaging in the educational context, by stating that it adds an alternative to behavioural approaches mostly used in educational research, that cannot account for how students learn on a neurobiological level and what strategies are best implemented in addressing individual differences in learning.

1.4 Research Methods, Procedure and Methodology

There are two parts to the current research study. Firstly, a meta-analysis was performed to investigate university students' attitudes towards statistics and their subsequent achievement in statistics. This follows a similar methodology used by Emmioglu and Capa-Aydin (2012). The second part of the study made use of fNIRS cortical mapping to investigate statistical reasoning. Previously, MRI techniques (Pletzer et al., 2015) and fNIRS (Artemenko et al., 2018; Hong et al., 2015) were used to monitor participants' brain activity while completing arithmetic tasks. Given that two studies are executed in my research study, I report on both methods (meta-analysis and cortical mapping) in the Methodology Chapter. Specific to the meta-analysis, two types of meta-analysis were run, one investigating statistics anxiety and achievement in a composite sample of *all* University students. The second meta-analysis concentrated on statistics anxiety and achievement, *exclusively* on Psychology students.

In the second part of the study, I detail the neural correlates and brain activation of regions of interest (dorsolateral prefrontal cortex), whilst students complete tasks assessing statistics reasoning. It is worth noting that statistical reasoning is a distinct but related concept to mathematical reasoning, so the dorsolateral prefrontal cortex remained the region of interest for this research (Cashin, 2000; Zeidner, 1991). No research participants were recruited for the execution of the meta-analysis, since data was attained from existing published studies. Research participants were recruited for the second part of the study (cortical mapping of statistics education, using a case study approach.

1.5 Research Questions

My study sought to answer three primary research questions. The first two research questions are focused on quantifying attitudes towards statistics and statistics achievement by conducting a meta-analysis. Following Emmioǧlu and Capa-Aydin, (2012), four research questions related to components of the SATS (i.e., *Affect*, *Cognitive Competence*, *Value*, *Difficulty*) were investigated as detailed below. The third research question concerned cortical mapping of the dorsolateral prefrontal cortex whilst completing a statistics reasoning task.

Research Questions

1. What is the relationship between **university students'** attitudes towards statistics and achievement in statistics?
    1.1. What is the relationship between students' *affect* toward statistics as a subject and statistics achievement?
    1.2. What is the relationship between students' self-perceived *cognitive competence* and cognitive skills concerning statistics and statistics achievement?
    1.3. What is the relationship between students' measure of the *value* of statistics in their own lives and professional identities and statistics achievement?
    1.4. What is the relationship between students' perceived *difficulty* of statistics and statistics achievement?
2. What is the relationship between **Psychology students'** attitudes towards statistics and achievement in statistics?
    2.1. What is the relationship between Psychology students' *affect* toward statistics as a subject and statistics achievement?
    2.2. What is the relationship between Psychology students' self-perceived *cognitive competence* and skills concerning statistics and statistics achievement?

2.3. What is the relationship between Psychology students' measure of the *value* of statistics in their own lives and professional identities and statistics achievement?
2.4. What is the relationship between Psychology students' perceived difficulty of statistics and statistics achievement?
3. Can the neural correlates of statistical reasoning be defined using Functional Near-Infrared Spectroscopy?

1.6 Thesis structure

This Chapter (Chapter 1) provides context to my research study, including the structure of the study. Chapter 2 provides a review of published research related to statistics anxiety, attitudes towards statistics and achievement in statistics courses. The chapter further details the value of neuroimaging, namely fNIRS imaging in education. Chapter 3 outlines the methodologies used in this thesis, followed by the procedures for data collection and analysis for each study. Chapter 4 details findings from the meta-analysis segment of the study (Research Questions 1 and 2). Chapter 5 provides findings from the cortical mapping of statistics reasoning. Chapter 6 discusses findings from my study, and details recommendations emerging from the research study, including the deployment of fNIRS in psychological research within the African continent. The study concludes by detailing recommendations for promoting statistical and mathematical literacy in South Africa, and other contexts.

1.7 Summary and Key Findings

For the first meta-analysis, the study found a small but significant relationship between university students' *Affect*, *Value* and *Difficulty* and achievement in statistics. Moreover, the study found a medium significant relationship between university students' *Cognitive Competence* and achievement in statistics. Within the Psychology sample, the study found a medium significant relationship between *Affect* and *Cognitive Competence* on achievement. A small but significant relationship was found between *Value* and *Difficulty* and achievement in statistics courses. Further, findings from the fNIRS imaging indicated cortical activation in the dorsolateral prefrontal cortex whilst participants completed statistical reasoning tasks.

CHAPTER 2
LITERATURE REVIEW

2.1 Statistics in Higher Education

Statistics is an inevitable aspect of almost all tertiary-level education subjects. The relevance of the subject is summarised by Illowsky and Dean, (2018, pp. 6) who state that training in the fields of "economics, business, psychology, education, biology, law, computer science, police science, and early childhood development require at least one course in statistics" Ramirez, Schau and Emmioğlu (2012) state that at its core, the role of statistics education is to produce individuals who are statistically literate and can hence make appropriate use of statistical thinking to solve everyday problems. Indeed, possessing statistical literacy is of advantage to any student who may find themselves needing to manage or organize data in their studies. Beyond this, statistical literacy allows for successful interpretation of data (Illowsky & Dean, 2018) and a better understanding of what this data may mean for our fields.

2.1.1 Statistics Education in Higher Education

It is important to establish how statistical literacy is defined at tertiary institutions, and to determine where Statistics fits within the curricula of university students. Usually, Statistics is a standalone introductory course that students are encouraged to enrol in, or the course is incorporated into their set degree curriculum. Statistics is unique as a discipline of study in the sense that when offered to students an as introductory Statistics course, it is assumed that skills gained in the introductory course will cement further understanding regarding the core discipline (e.g., economics, business, psychology, education, etc.) undertaken by the student (Ramirez et al., 2012). Additionally, statistics courses seek to promote the advancement of research in core study disciplines, hence, its relevance in tertiary education (Onwuegbuzie, 2000).

A case in point regarding the relevance of statistics education is illustrated at the institution where the current study was conducted. At Rhodes University, the Department of Statistics offers Statistics is a pre-requisite first-year subject for students majoring in Chemistry, Geology or Ichthyology. Statistics is also a recommended first year course for students planning to major in Applied or Mathematical Statistics, Computer Science, Environmental Science, Human Kinetics and Ergonomics, Physics and Zoology (Rhodes University, 2020). Further, first-year statistics courses appear in recommended curricula for

Entomology, Biochemistry, Microbiology, Geography, and Psychology (Rhodes University, 2020).

Key to my research, Gal et al., (1997, pp. 2) state that an important consideration of statistics education is the development of "flexible statistical problem-solving, statistical literacy and related communication skills,", rather than simply teaching computational or mathematical procedural skills to solve statistical problems. This "process considerations" of statistics education, has been linked to the study of attitudes and beliefs regarding statistics education and has been found to be a major influence in the teaching and learning of statistics. Educators thus infer that an ideal environment for statistics education is one that addresses attitudes and beliefs about statistics, and thus allows students to move through their statistics curriculum within minimum encumbrance. Pedagogically, it is thus emphasized that students should be able to (1) feel safe to explore and grapple with statistical tools and methodologies, (2) feel comfortable in dealing with obstacles such as uncertainty, inconclusive results or confusion, (3) believe in their own ability to overcome such obstacles, and (4) be motivated to keep working through their coursework and activities, and not simply arriving at computerised statistical solutions (Gal et al., 1997). Given the above framework, it is important to explore the etiology of negative attitudes towards statistics, in order to inform approach in the teaching of statistics education.

2.1.2 Students' Attitudes Towards Statistics

In designing an introductory statistics course for university students, Ramirez et al. (2012) explain that an important outcome of statistics education is the appropriate attitude towards statistics that will ensure success in using and understanding the work that is taught. During this course, it must be ensured that students have self-belief in their ability to understand and then use statistics, acknowledge the usefulness in statistics in their professional and personal lives, recognize how statistics could be interesting, pledge to invest effort into learning the subject matter, and also see that while statistics is not an easy subject, it is not beyond understanding in terms of difficulty (Ramirez et al., 2012). The authors quote Garfield, Hogg, Schau and Whittinghill (2002) in labelling attitudes towards statistics as the "other" important outcome in statistics education (Ramirez et al., 2012). Indeed, as outlined above, statistical literacy is important, but one's approach and attitudes to learning have long been an important predictor in the implementation of what has been learned.

The nature of attitudes was explored by Albarracín, Zanna, Johnson and Kumgale (2005) in *The Handbook of Attitudes*, a resource that is foundational in most research endeavours on students' attitudes towards statistics. As noted by Albarracín and colleagues, humans evaluate whether they deem objects, events, themselves or others as favourable, or likeable based on subjective judgement. The study of attitudes is thus concerned with investigating how our judgements are formed and changed, and also how memories of these attitudes affect human actions (Albarracín et al., 2005). The definition of an 'attitude' often includes the affect, beliefs, and observable behaviours towards what is being evaluated or judged by a subject (Albarracín et al., 2005). The authors define *affect* as the feelings that a subject experience, and this may or may not involve or be in relation to another object, person, or event. *Beliefs* are defined as particular cognitive evaluation or associations attributed to an object, person, or event. Finally, *behaviour* is the actions of the subject, and is the most observable component of attitudes (Albarracín et al., 2005). With this being noted, a singular definition of an *attitude* is vexatious.

Eagly and Chaiken (1993), further state that "an attitude is a psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour" (Albarracín et al., 2005, pp. 4). McLeod (1992) further define an attitude as "relatively stable, intense feelings that develop as repeated positive or negative emotional responses are automatized over time" (Gal et al., 1997). No matter the particulates of what comprises an 'attitude', it is agreed that there is an evaluative aspect that is important, and its representation in memory should be considered (Albarracín et al., 2005). Positioning an 'attitude' as a process of a judgment being passed by a subject, rather than simply a passive recollection of evaluative memory, also allows for the consideration of how an attitude forms and importantly, how an attitude may change (Albarracín et al., 2005). Importantly, for my research endeavour, there is *subjectivity* to 'an attitude', as such, this dynamic concept can be investigated at a subjective level (Albarracín et al., 2005).

From a biological perspective, 'attitudes' and beliefs are viewed as non-cognitive factors that should be considered as important aspects of the learning process (Berens, 2018). From this perspective, being biological systems, 'attitudes' can either impede or assist knowledge acquisition (Gal et al., 1997). Based on the above frameworks, within the field of statistics education, 'attitudes towards statistics' are described as "a multifunctional concept referring to distinct, but related dispositions pertaining to favourable or unfavourable responses with regard to statistics and statistics learning" (Vanhoof et al., 2011). Based on the definition by Vanhoof et al. (2011) it is important to access various dimensions within an attitude to accurately describe it. It thus follows that beyond the acquisition of statistics knowledge, instructors must consider how students' attitudes and beliefs towards statistics affect how 'easy' or 'difficult' student perceive and engage with statistical coursework (Gal et al., 1997).

In summary, when applying our definitions of attitudes to statistics, we see that beliefs that a student holds about statistics, their positioning as a statistics student, and social contexts of learning statistics, can still closely coincide with our understanding of students' experiences with statistics. What is clear from these definitions is the subjectivity that goes along with attitudes, and how emotions can come into factor while acquiring and reinforcing an attitude. Statistics anxiety can often develop from negative emotions around statistics.

2.1.3 Defining Statistics Anxiety

Onwuegbuzie (2000) states that negative attitudes towards statistics often lead to statistics anxiety. In fact, research such as Macher et al. (2013) has established that statistics and statistics education are one of the most anxiety-inducing courses in students' higher education curricula (Zeidner, 1991) and that this problem is noted across many fields. Statistics anxiety is conceptualised as a performance anxiety, similar to stage fright and mathematics anxiety (Macher et al., 2013). This classification is relevant since statistics anxiety is situation-specific and occurs when one is required to complete a task – namely, a statistics task (Macher et al., 2013). Onwuegbuzie (2004) particularly states that statistics anxiety results in performance impairment which can results in a habitual and enduring anxiety.

Further to the above, Zeidner (1991) defines statistics anxiety as a *subjective* experience of extensive worry, intrusive thoughts, mental disorganization, tension, and even physiological arousal when confronted with statistical concepts or problems. Moreover, this subjective experience impairs performance of the individual in statistics tasks. Similarly, Macher et al. (2012, pp. 2) describe statistics anxiety as a subjective experience of apprehension when confronted with "statistics content, problems, instructional situations, or evaluative contexts".

Based on the above definition, Onwuegbuzie (2004), summarises the experience of statistics anxiety as including factors such as: the *worth* of statistics, anxiety in the *interpretation* of results, anxiety regarding *statistical assessments* including tests and classes, not wanting to ask for help, and *fear* of those teaching statistics. Some issues noted by statistics educators in their students are reported to have stemmed from attitudes they carried from previous experiences. Understanding where negative attitudes towards statistics come from will help to inform our approach to statistics education. This will also assist in mitigating feelings of statistics anxiety in our students, particularly in the Social Sciences where this is particularly a concern.

2.1.4 Antecedents of Statistics Anxiety and Negative Attitudes Towards Statistics

Research by Sesé et al. (2015) and Onwuegbuzie and Wilson (2003) on attitudes towards statistics have revealed possible antecedents to negative attitudes towards statistics. Onwuegbuzie and Wilson (2003) assert the defining effect that introductory courses have on students' lifelong perceptions of statistics, and their willingness to engage with statistics in their personal and working life. This can provide valuable input into the exact source of negative attitudes towards statistics that are unrelated to the current course itself, and a student's beliefs are hence explored as an extension of attitudes.

The above review of literature by Onwuegbuzie and Wilson (2003) showcased antecedents of statistics anxiety. Three categories emerged: *situational*, which are factors surrounding statistics and the statistics classroom, *dispositional*, referring to internal factors brought to the setting (statistics classroom) by the student, and *environmental*, which are past events and external factors that play a role in the current settings (Onwuegbuzie & Wilson, 2003). These antecedents stem from research by Zeidner (1991), which investigated students' experiences with anxiety around statistics and mathematics, with correlational analysis investigating the relationship to mathematics proficiency and self-efficiency.

Prior statistics and mathematics knowledge, course grades, poor previous achievement and mathematics anxiety arise in literature as playing a role in statistics anxiety (Onwuegbuzie & Wilson, 2003). It was suggested by Gal et al. (1997) that the first source of a negative attitudes towards statistics could be a previous negative experience learning statistics or making use of statistics in research. The research by Zeidner (1991) on 431 students found a statistically significant positive relationship between statistics anxiety and parental pressure for mathematics achievement ($p < 0.05$), past mathematics anxiety ($p < 0.001$) and difficulty of statistics ($p < 0.001$). Additionally, there was a negative relationship between statistics anxiety and prior mathematics achievement ($p < 0.01$) (Zeidner, 1991).

Oguan et al. (2013) attribute students liking or disliking statistics to their teachers' beliefs, methods being taught, approaches to teaching, and their learning environment. Particularly, negative experiences with teachers have been shown to lead to negative attitudes, as students feel that teachers expect too much of their students at the tertiary level (due to the research emphasis at many universities), and that teachers do not address questions about the subject adequately to clarify doubts (Oguan et al., 2013). Since statistics is often taught within a research methodology course, negative attitudes towards research in students have been shown to be a source of negative statistics attitudes (Berens, 2018).

An individual's measure of statistics ability and self-efficacy can also lead to statistics anxiety (Onwuegbuzie & Wilson, 2003). This may include mathematics self-concept and self-esteem, which were found to be inversely related to statistics anxiety in the study by Zeidner (1991). Additionally, Onwuegbuzie (2004) found that procrastination also increased statistics anxiety. 135 students in an introductory research course were assessed for procrastination and statistics anxiety using the Statistics Anxiety Rating Scale (STARS) (Onwuegbuzie, 2004). Findings from canonical correlation analysis revealed that procrastination of statistics assignments was common in students and was as a result of a fear of failure and negative attitudes towards the coursework; in turn, this procrastination then led to statistics anxiety (Onwuegbuzie, 2004).

2.2 Measuring Attitudes Towards Statistics Anxiety

An array of surveys have since been developed to study attitudes towards statistics. The subsequent sections provide a purview of the key instruments used to assess attitudes towards statistics and provide a foundation for my research objectives.

2.2.1 The Survey of Attitudes Towards Statistics (SATS)

The Survey of Attitudes Towards Statistics (SATS), created by Candace Schau (2000) is one of the most popular instruments validated to measure attitudes towards statistics. This scale is favoured for being comprehensive, thorough, and non-threatening in nature. Two validated versions of the SATS exist, namely the SATS-28 and SATS-36. The SATS-28 consists of four components to measure attitudes towards statistics, assessed with 28 items, whereas the SATS-36 consists of six components and 36 items.

Affect measures of how students *feel* about Statistics as a subject. *Affect* has six items that include statements such as "I will like statistics" and "I am scared by statistics" (Gal et al., 1997). It is concerned with feelings that students have towards statistics (Schau, 2000). Emotive language is used, such as "I will feel insecure ...", "I will get frustrated ...", "I will be under stress" (Schau, 2000). A Cronbach's alpha range of considerable value of 0.80-0.89 was reported for *Affect* (Schau, 2019). *Cognitive Competence* contains six items that investigate how students view how their own intellectual knowledge and skills will be able to assist them in their statistics studies (Schau, 2000). The items pertain to understanding statistics based on how the student thinks, knowing the structure of the course, fear of making mathematical errors in analyses, confidence in ability to learn statistics, understanding statistics equations, and finally difficulty in understanding concepts (Schau, 2000). Most items are worded in the future continuous tense. *Cognitive Competence* had an acceptable Cronbach's alpha range of 0.77 to

0.88 (Schau, 2019). *Value* comprises nine items about the usefulness, relevance and worth of statistics to the individual in their personal and professional life (Gal et al., 1997). It questions the student's self-determined measure of the value of statistics in their own professional career, as well as its value to typical professionals (Schau, 2000). There are also items that enquire about the prevalence and frequency of the use of statistics in the student's life, and how often they encounter statistical conclusions (Schau, 2000). A wider range of Cronbach's alpha values was reported for *Value*, 0.74 to 0.90 (Schau, 2019), but this was still within an acceptable range.

Difficulty has seven distinct items which simply ask the student about how difficult they perceive statistics to be (Schau, 2000). Some items include aspects of statistics that students may find challenging, such as utilising formulae and computation of statistical measures (Schau, 2000). A wide range of Cronbach's alpha values was also reported for *Difficulty*, at 0.64 to 0.81 (Schau, 2019). This component has the lowest range, and the minimum value is below the recommended range of acceptable Cronbach's alpha values, at 0.70. Finally, *Interest* and *Effort* each have four items, but these components are not of interest for this enquiry. The previous version of the survey, the SATS-28, does not include *Interest* and *Effort*, which means that research that made use of the SATS-28 rather than the SATS-36 is also applicable for investigation.

Items on the SATS are worded as statements requiring a response on a 7-point Likert. All stems in the SATS require a response from 1 = "*Strongly Disagree*", to *7 = "Strongly Agree"* (Ramirez et al., 2012). Higher scores on the scale correspond to positive attitudes towards statistics (Schau, 2000). Some items are reverse scored, where a high rating actually corresponds to a negative attitude (e. g., Item 4 "I will feel insecure when I have to do statistics problems"). This ensures that some items are negatively worded and varies response styles (Schau, 2019).

2.2.2 Other survey-based measures of statistics

In addition to the SATS, the Statistics Attitude Survey (SAS), the Attitudes Toward Statistics (ATS), and the STARS continue to be widely used to assess statistics anxiety The Statistics Attitude Survey (SAS) is a 33-item unidimensional measure derived from assessing mathematics achievement and results in a global attitude score (Roberts & Bilderback, 1980). Like the SATS, it also makes use of Likert-type items that are read as statements to which the participant can respond (Roberts & Bilderback, 1980). The Attitudes Towards Statistics (ATS) survey contains two subscales to assess statistics anxiety, namely: attitudes toward the field of statistics, and attitudes toward statistics courses (Wise, 1985).

The STARS is a popular scale comprising of two parts – 23 statements regarding statistics anxiety and 28 items about statistics education. There are six subscales including the *Worth of Statistics*, *Interpretation Anxiety*, *Test and Class Anxiety*, *Computational Self-concept*, *Fear of Asking for Help*, and *Fear of Statistics Teachers* (Baloğlu, 2007). It is worth further noting that although the SATS-28 and SATS-36 are favoured, the SAS and STARS possess high structural, content, substantive and external validity with internal consistency (Nolan et al., 2012).

With the background of viewing statistics as a language of research, i.e., a way to communicate research, other scales have been developed to investigate students' feelings towards research in general. In this regard, the Attitudes Towards Research (ATR) scale has since been developed (Papanastasiou, 2005). The scale is a five-dimension scale made up of factors *Usefulness of research*, *Anxiety*, *Affect*, *Relevance of research in daily lives*, and *Difficulty of research* (Papanastasiou, 2005), which aim to measure attitude components similar to items seen in the SATS. The widespread use of the SATS compared to these above scales makes it the preferred measure for statistics attitudes.

2.2.3 Achievement in Statistics As a Comparative Measure to Attitudes

A key aspect of assessing attitudes towards statistics is relating this to the student's performance in the subject – namely, achievement in statistics courses. This is due to the effects that feelings of statistics anxiety and negative attitudes have on academic performance. To this end, attitudes have been demonstrated to play a role in statistics achievement (Zimprich, 2012). There have been varied measures of what constitutes 'achievement' in statistics and quantitative research methods courses. In an academic context, achievement is commonly understood to be an indication that the individual has attained a certain standard or measurable proficiency in a subject, measured by a grade or a symbol. Simply then, research would report students' current statistics grades and exam grades as a measure of statistics achievement. Most often, research would use bivariate analysis to investigate the relationship between SATS components as measures of statistics attitudes and achievement, reporting Pearson's correlation coefficient (r) values.

For example, research by Schutz et al. (1998) investigated academic performance of 94 graduate students from nursing, counselling and school psychology and education backgrounds who were enrolled in a beginning-level statistics course. Prior experience with mathematics and statistics were found to be correlated to their course grades ($p < 0.01$) (Schutz et al., 1998). Additionally, the SATS components *Affect* and *Value* were administered to the students, as

Schutz et al. (1998) believed the items were most aligned with achievement. *Affect* having a statistically significant relationship to course grade, r = 0.21*(p* < 0.05), while *Value* was not found to have a statistically significant correlation (Schutz et al., 1998). Regression analysis along with these results lead Schutz et al. (1998) to conclude previous knowledge from mathematics and statistics courses could predict achievement, and motivation and positive attitudes were also integral for good performance.

The validity of using mathematics results as a measure of statistics achievement was confirmed by modelling by Zimprich (2012). This aligns with assertions made by Onwuegbuzie (2003) on the relationship between statistics and mathematics. This approach was seen in research by Scott (2001) which sought to investigate attitudes towards statistics of 155 students enrolled in an introductory statistics course. The SATS was administered as pre- and post-course versions (Scott, 2001). The multivariate relationship of variables in the study such as students' mathematics background, performance in statistics and participant demographics were investigated using path analysis (Scott, 2001). Students' grades in a prerequisite algebra course were used to measure mathematics aptitude, which had been previously noted as a statistics attitude correlate (Scott, 2001). Pearson correlations between SATS and mathematics grades were all statistically significant and revealed a positive relationship for *Affect*, *Difficulty* (both $p < 0.05$), *Cognitive Competence* and *Value* (both $p < 0.01$). Scott (2001) concluded that there is a small to moderate relationship between attitudes and achievement, but no significant changes in attitudes were noted from the beginning to the end of the course, and that students had generally positive attitudes towards statistics. A limitation of the study was that attitudes were not assessed closer to final exams when the relationship between achievement and attitudes is proposed to be higher (Scott, 2001).

Research by Sorge and Schau (2002) assessed the attitudes of 264 engineering students when undertaking an introductory prerequisite statistics course. The SATS was used, with statistics achievement being measured as course grades (Sorge & Schau, 2002). The research was modelled using Eccles' Expectancy Value Model (Sorge & Schau, 2002), which provided descriptive information on the relationship between attitude components and achievement, along with Pearson correlation coefficients. As in Schutz (1998), Value did not have a statistically significant relationship to achievement. Additionally, Sorge and Schau (2002) found through modelling that *Difficulty* had a large positive direct impact on *Cognitive Competence*, and *Cognitive Competence* on *Affect*, and *Affect* on *Value* and achievement. *Cognitive Competence*, and *Difficulty* to a smaller extent, had positive, indirect impacts on achievement. The authors concluded that a combination of high Cognitive Competence and

Affect were found to lead to higher achievement, meaning higher self-concept is important in achievement (Sorge & Schau, 2002).

Finney and Schraw (2003) investigated the self-efficacy of 103 Educational Psychology students and relationships between Statistics course percentages and their attitudes towards statistics. The Current Statistics Self-Efficacy (CSSE) and Self-Efficacy to Learn Statistics (SELS) were developed for use in this study (Finney & Schraw, 2003). Importantly, statistics self-efficacy and achievement had a significant relationship, $r = 0.40 – 0.50$, and Finney and Schraw (2003) stressed the importance of measuring these components closely in time. Students' course percentage for their introductory statistical methods course were found to be statistically significant ($p < 0.01$) for *Affect* ($r = 0.387$) and *Cognitive Competence*, $r = 0.390$, and *Difficulty,* $r = 0.387$ ($p < 0.05$), but not for *Value* (Finney & Schraw, 2003). There was a moderate relationship between statistics self-efficacy and statistics anxiety, $r = -0.57$ as well as self-efficacy and SATS responses, $r = 0.461 – 0.651$, demonstrating how attitudes towards statistics, which are predetermined ideas, can affect Psychology students' feelings of self-efficacy in learning statistics (Finney & Schraw, 2003). Post-test SATS scores had significantly stronger correlations to self-efficacy measures, which speaks to the confidence that students feel in their statistics abilities (Finney & Schraw, 2003). This use of multiple instruments to measure statistics attitudes and statistics anxiety is seen in other studies as well, and this study demonstrates the interconnectedness of statistics anxiety, attitudes, and self-efficacy, and their effects on achievement.

The author of the SATS presented a model of the structural relationship between attitudes and achievement in statistics (Schau, 2003). The SATS was administered to 268 university students in an introductory statistics course at the start of the course and at the end of the course once assessments had been completed; course achievement data was also collected for these students (Schau, 2003). Observations made by Schau (2003) include how students' spoken attitudes were more negative than their SATS responses, and many students attributed attitudes to past instructors and previous achievement. Results indicated small to moderate positive relationships between attitudes and achievement, for *Affect,* $r = 0.35$, *Cognitive Competence,* $r = 0.36$, *Value,* $r = 0.30$, and *Difficulty,* $r = 0.17$, that were of statistical significance (Schau, 2003). Modelling of these results led Schau (2003) to conclude that attitudes towards statistics and course achievement do causally impact each other, and that methods for promoting positive attitudes must be explored by statistics educators.

A structural model was also utilized by Nasser (2004) to study the effects of various cognitive factors – statistics and mathematics anxiety and attitudes, motivation and mathematical aptitude – on statistics achievement. The SATS, STARS and related mathematics scales were administered to 162 teaching students undertaking an introductory statistics course, and examination results were used to measure statistics achievement (Nasser, 2004). Results indicated a statistically significant relationship between achievement and *Affect,* $r = 0.18$ ($p < 0.05$) and *Cognitive Competence,* $r = 0.28$ ($p < 0.05$). The relationship between achievement and the *Value* and *Difficulty* components were small and not statistically significant ($p > 0.05$). A limitation of the study was the lack of variability in the sample, where most students were female and had a strong mathematical aptitude (Nasser, 2004). Additionally, modelling provided evidence for the argument that feelings towards statistics are related to feelings towards mathematics, and that the STARS and SATS targeted similar dimensions of attitudes and anxiety (Nasser, 2004).

Cashin and Elmore (2005) conducted a construct validity study of the SATS in continuing their review of statistics attitude scales. 342 university students enrolled in an inferential statistics course completed the Statistics Attitude Scale (SAS), Attitudes Towards Statistics Scale (ATS) and SATS, and course grades were obtained as a measure of statistics achievement (Cashin & Elmore, 2005). Cronbach's alpha estimates showed all scales had good internal consistency, and in keeping with research by Schau (2000), *Difficulty* showed the lowest estimate (Cashin & Elmore, 2005). Correlation analysis showed a positive, statistically significant relationship between achievement and *Affect,* $r = 0.36$, *Cognitive Competence,* $r = 0.32$, *Value,* $r = 0.28$, and *Difficulty,* $r = 0.26$ (Cashin & Elmore, 2005). Multiple regression analysis indicated post-course attitudes could predict statistics course achievement, and no gender differences were noted (Cashin & Elmore, 2005). Cashin and Elmore (2005) conclude that educators should have knowledge of students' attitudes and feelings of self-efficacy in order to facilitate success in the course and in future careers.

Research by Chiesi and Primi (2009, 2010) had sought to investigate the relationship between SATS responses of Psychology students and their course performance. A confirmatory factor analysis investigated the use of the translated Italian SATS on students, and a multi-group analysis investigated pre- and post-SATS administration at the start and end of the course (Chiesi & Primi, 2009). The Attitudes Towards Statistics (ATS) scale was also administered in the 2009 study to 232 Psychology students, and significant correlations were noted between ATS and SATS scores (Chiesi & Primi, 2009). A statistically significant relationship was also found between all attitude components and achievement, where *Affect* and *Cognitive Competence* had the same correlation coefficient, $r = 0.29$ ($p < 0.001$) and were more highly correlated than *Value,* $r = 0.20$ ($p < 0.01$) and *Difficulty,* $r = 0.17$ ($p < 0.05$)

(Chiesi & Primi, 2009). Comparisons of mean attitudes at the start and end of the course revealed that students had higher *Cognitive Competence* and less perceived *Difficulty* of statistics (Chiesi & Primi, 2009). The authors concluded that attitudes had a significant impact on course achievement and improved throughout the course, and students became more confident in their statistics knowledge and perceived statistics as less difficult (Chiesi & Primi, 2009).

This research modality was repeated later by Chiesi and Primi (2010). This research study aimed to investigate cognitive and non-cognitive factors that could affect statistics achievement of 487 Psychology students (Chiesi & Primi, 2010). A structural equation model approach was utilized to model achievement, which was measured as course results, and impacts of attitudes and mathematics backgrounds were investigated (Chiesi & Primi, 2010). A mathematics ability scale was used to measure mathematics background – the cognitive factor – and SATS was used to measure attitudes, the non-cognitive factor (Chiesi & Primi, 2010). High school mathematical knowledge and attitudes towards statistics were both found to affect achievement (Chiesi & Primi, 2010). Statistically significant correlation ($p < 0.01$) was found between achievement and *Affect,* $r = 0.27$, *Cognitive Competence,* $r = 0.26$, *Value,* $r = 0.19$ and *Difficulty,* $r = 0.20$. The authors concluded that attitudes were found to have improved in students at the end of the course regardless of previous mathematical background and would impact achievement in a positive relationship (Chiesi & Primi, 2010), which is encouraging given non-STEM students' dislike or inexperience with mathematics.

Research by Dempster and McCorry (2009) employed a longitudinal design to investigate the role of prior achievement and experiences in mathematics and statistics in the formation of statistics attitudes, and how this may be a predictor for statistics course outcomes. 82 Psychology students participated in the SATS survey at the start of their statistics curriculum within their Psychology course programme. Results indicated a statistically significant relationship between assessment results and *Affect,* $r = 0.233$ ($p < 0.05$), *Cognitive Competence,* $r = 0.305$ ($p < 0.01$), and *Value,* $r = 0.231$ ($p < 0.05$) (Dempster & McCorry, 2009). Additionally, the relationship between achievement and attitudes was stronger than achievement and prior experience with mathematics, statistics, or computing (Dempster & McCorry, 2009), suggesting that how Psychology students feel about their statistics abilities is more important than previous teaching in related subjects. This agrees with notions by Finney and Schraw (2003) on self-efficacy, and Dempster and McCorry (2009) suggest the use of self-efficacy teaching approaches such as asking students to estimate statistical conclusions and discuss these before making calculations, hence relying on Psychology students' built-in intuition.

In a doctoral thesis by Emmioğlu (2011), a structural equation model was used to examine the relationships between mathematics achievement, statistics attitudes, and outcomes in statistics. A pretest-posttest design was utilized in assessing 247 students' responses to the SATS questionnaire at the beginning and end of their test, and statistics achievement was measured as their course grade in statistics courses (Emmioğlu, 2011). A statistically significant relationship ($p < 0.05$) was found between achievement and *Affect,* $r = 0.38$, *Cognitive Competence,* $r = 0.35$, *Value,* $r = 0.51$, *Interest,* $r = 0.57$, and *Effort,* $r = 0.44$ (Emmioğlu, 2011). A statistically significant relationship was not found for *Difficulty*, so Emmioğlu (2011) concluded that outcomes do not depend on perceptions of the difficulty of statistics, but rather, a student's interest and value of using statistics are strong predictors. Further, positive feelings towards statistics, strong self-belief in statistics abilities and a willingness to put effort into their statistics coursework had significant impact on their achievement in coursework (Emmioğlu, 2011).

Research by Hood, Creed and Neumann (2012) also made use of the Eccles' Expectancy Value Model to investigate the relationship between statistics attitudes and achievement, similar to Sorge and Schau (2002). The SATS was administered to 149 Psychology students enrolled in a psychology research methods and statistics course, with final Statistics course results used as a measure of achievement (Hood et al., 2012). Results indicated a statistically significant correlation ($p < 0.05$) between achievement and *Cognitive Competence,* $r = 0.28$, and *Value,* $r = 0.23$ (Hood et al., 2012). It was also found through the Expectancy Value Model that perceptions of statistics being difficult was related to lower *Cognitive Competence* in the Psychology students (Hood et al., 2012), and it was concluded that showing students that statistics is not difficult can increase their self-belief, and in turn their achievement.

Zhang et al. (2012) examined medical postgraduate students' attitudes towards statistics using the SATS, with regression analysis to assess effects of research backgrounds and experiences on attitudes. 539 students from a medical statistics course participated and completed the SATS-28, and course examination scores were used as a measure of achievement (Zhang et al., 2012). A statistically significant relationship was found between achievement and all components ($p < 0.05$), namely *Affect,* $r = 0.40$, *Cognitive Competence,* $r = 0.43$, *Value,* $r = 0.32$ and *Difficulty,* $r = 0.17$ (Zhang et al., 2012). Overall, students had a positive attitude towards statistics and would have more positive attitudes if they had strong mathematical backgrounds and prior experiences learning statistics; additionally, younger students were found to have more positive attitudes and no gender differences were noted (Zhang et al., 2012). The authors concluded that interventions must be designed to help students overcome statistics anxiety (Zhang et al., 2012).

The SATS-36 was used to conduct research on 346 Psychology students at the University of Zurich who were enrolled in a compulsory statistics course (Zimprich, 2012). To measure achievement in Statistics, the students rated their school Mathematics grades and took a written Statistics test (Zimprich, 2012). Confirmatory factor analysis showed that *Affect* and *Cognitive Competence* had a strong effect on achievement, and mathematics achievement was a strong predictor of statistics attitudes (Zimprich, 2012). Bivariate analysis was additionally performed on *Difficulty* and statistics achievement, and a positive correlation was found, $r = 0.25$. Comparing this to the negative regression weight of *Difficulty* led Zimprich (2012) to conclude that perceiving statistics as easy often overestimate *Cognitive Competence* and *Affect*, which led to lower performance in tests due to less time spent on test preparation. Zimprich (2012) believes future attitude interventions must focus on assessing subjective and objective achievement in statistics, where students should reflect on their own performance in statistics as a measure of understanding important statistics concepts.

Clark (2013) investigated undergraduate students' attitudes towards statistics while being enrolled in an introductory statistics course. 1125 students participated and reported their prior experiences with statistics and mathematics; the SATS was administered and students' course grades were accessed as a measure of achievement (Clark, 2013). Positive correlations were noted between achievement and *Affect,* $r = 0.255$, *Cognitive Competence,* $r = 0.251$, *Value,* $r = 0.160$, and *Difficulty,* $r = 0.209$, and were statistically significant ($p < 0.05$) (Clark, 2013). Clark (2013) notes a limitation in that only a pre-course version of the SATS was administered, hence regression models did not fit as well to achievement. The author concluded that study and homework interventions in the statistics course could assist in improving attitudes towards statistics by improving self-belief, motivation and learning skills (Clark, 2013).

A descriptive survey and associational research design were employed by Oguan et al. (2013) to explore students' attitudes and performance toward statistics, and to see if attitudes differ across disciplines. 863 students who were enrolled in a statistics course were administered the SATS and disclosed their performance in the course (Oguan et al., 2013). Results indicated students had positive attitudes overall, although negative attitudes for *Difficulty* were observed, and students attributed this to the amount of effort put into studying statistics and their interest in the subject (Oguan et al., 2013). Students enrolled in Biology and Statistics degrees did not find statistics as difficult as their peers and reported higher *Interest* and *Value* (Oguan et al., 2013). A statistically significant relationship ($p < 0.01$) was found between achievement (course performance) and *Affect,* $r = 0.340$, *Cognitive Competence,* $r = 0.427$, *Difficulty,* $r = 0.580$, and *Interest,* $r = 0.693$ (Oguan et al., 2013). Relationships between achievement and *Value* and *Effort* components were not statistically significant ($p > 0.05$) (Oguan et al., 2013). Additionally, Oguan et al. (2013) report male students had significantly more positive attitudes towards statistics, although a noted limitation of the study is that 76.25% of participants were female in this sample.

Like Zhang et al. (2012), medical students' attitudes towards statistics during a medical statistics course were investigated by Stanisavljevic et al. (2014). 415 students participated in the study, completing a SATS-36 and an assessment set by course instructors as a measure of achievement (Stanisavljevic et al., 2014). A significant positive relationship was reported between statistics achievement and *Affect,* $r = 0.23$, *Cognitive Competence,* $r = 0.27$, and *Effort,* $r = 0.26$ (Stanisavljevic et al., 2014). The correlation between achievement and other SATS components and sex was not significant. A positive correlation was also noted between achievement and self-rated mathematics ability and GPA (Grade Point Average for $n = 141$ students), and a negative correlation between achievement and age (Stanisavljevic et al., 2014). Stanisavljevic et al. (2014) concluded that positive beliefs in understandings of statistics and mathematics, feelings towards statistics, amount of effort applied to statistics courses, being of a younger age and possessing a higher GPA could all predict higher achievement.

Sesé et al. (2015) sought to investigate the relationships between mathematics background, trait anxiety, test anxiety, statistics anxiety, statistics attitudes, and performance in statistics. The Statistical Anxiety Scale (SAS), SATS and other scales were administered to 472 health sciences university students, and students' scores on their statistics midterm exam were used as a measure of achievement (Sesé et al., 2015a). A statistically significant positive relationship ($p < 0.01$) was found between *Affect,* $r = 0.48$, *Cognitive Competence,* $r = 0.45$, *Value,* $r = 0.20$, and *Difficulty,* $r = 0.27$ (Sesé et al., 2015a). Structural modelling showed that statistics anxiety did not have a direct relationship to achievement – rather, statistics anxiety was a direct predictor of statistics attitudes, which has a direct effect on achievement (Sesé et al., 2015a). The authors concluded that attitudes towards statistics was the only factor with a direct effect on statistics achievement, and that mathematics background and lower levels of test and statistics anxiety could assist in developing positive attitudes in students (Sesé et al., 2015a).

The most recent research undertaken is by Melad (2022), who employed a descriptive-correlational research design to investigate 560 business statistics students' attitudes towards statistics and their academic achievements. The design follows most of the above studies, and course grades were the measure of achievement (Melad, 2022). Slightly positive responses were noted for all components apart from *Difficulty*, which also did not have a statistically significant relationship to achievement ($p = 0.064$) (Melad, 2022). Correlation was significant ($p < 0.01$) between achievement and *Affect,* $r = 0.203$, *Cognitive Competence,* $r = 0.231$, *Value,* $r = 0.182$, *Interest,* $r = 0.208$, and *Effort,* $r = 0.243$ (Melad, 2022). Students reported difficulties with the highly technical nature of statistics courses, hence Melad (2022) suggested the introduction of statistical software to assist in computations and interactive, practical lessons in using these packages.

Other researchers have utilised standardised instruments to assess the relationship between achievement and students' reasoning and understanding of statistical concepts (Emmioğlu & Capa-Aydin, 2012). Two commonly used instruments have been used to assess success in statistics knowledge acquisition, which also demonstrates successful achievement. These are the Statistical Reasoning Assessment (SRA) and Statistics Concept Inventory (SCI). The Statistics Concept Inventory was developed by Kirk Allen as part of a doctoral thesis and aimed to assess understanding of introductory statistics topics (Allen, 2006). It assesses basic concepts of statistics and probability and tests for conceptual understanding rather than computing problems (Stone et al., 2003). It was the hope of the authors that the SCI would help improve student learning in statistics by identifying problem areas in the students' understanding and in providing feedback to educators to help improve teaching practices (Allen et al., 2004).

The SCI was used by Stone et al. (2003) as a means to measure achievement as a pilot study for the instrument. 139 students enrolled in introductory statistics courses completed the SCI and the SATS (Stone et al., 2003). A statistically significant relationship ($p < 0.01$) was found between SCI scores and *Affect,* $r = 0.258$, *Cognitive Competence,* $r = 0.315$, *Value,* $r = 0.329$, and *Difficulty,* $r = 0.246$ (Stone et al., 2003). Value was also positively correlated to mathematics and statistics experience, which led Stone et al. (2003) to hypothesize that more exposure to the subjects meant students viewed the content as more relevant and useful. Additionally, social science majors were found to have statistically significant differences in SCI scores to mathematics majors (Stone et al., 2003). The authors concluded that if students found statistics more enjoyable, valuable, and easily done, they would be more motivated to learn statistics, and conversely, successful understanding of statistical concepts meant students enjoyed the subject more (Stone et al., 2003).

The SRA was developed by Joan Garfield to evaluate the effectiveness of a newly formulated high school statistics curriculum in helping students achieve the learning goals (Garfield, 2003). Most instruments for statistics focus on assessing computational skills and problem solving by requiring the application of formulas or graph and chart construction, as opposed to examining statistical reasoning and understanding, and students' abilities to creating and interpreting information (Garfield, 2003). Two studies make use of the SRA to measure achievement (Estrada & Batanero, 2008; Tempelaar et al., 2006).

The study by Tempelaar et al. (2006) investigated the role that statistical reasoning plays in students learning statistics. Since statistical reasoning is a preferred outcome of statistics courses and is the basis by which achievement is gauged, using the SRA is a suitable measure of achievement (Tempelaar et al., 2006). The SATS and SRA were administered to 2031 business and economics students enrolled in a "Quantitative Methods" course as a degree requirement (Tempelaar et al., 2006). Correlation analysis revealed that final exam scores had statistically significant relationships to SRA scores, hence confirming the use of the SRA as an achievement measure (Tempelaar et al., 2006). A statistically significant relationship ($p < 0.001$) was found between SRA scores and *Affect,* $r = 0.12$, *Cognitive Competence,* $r = 0.12$, *Value,* $r = 0.10$, and *Difficulty,* $r = 0.11$ (Tempelaar et al., 2006). A distinction was made by the authors between effort-based course assessment instruments, such as homework assignments and projects, and cognitive-based assessments such as final exams, and Tempelaar et al. (2006) believed that the inclusion of the SRA in assessment portfolios may assist in balancing effort and cognitive assessment and provide more insight into students' reasoning skills and course attitudes.

Estrada and Batanero (2008) aimed to investigate teachers' attitudes towards statistics and statistical knowledge. 367 prospective teachers enrolled in a statistics course completed the SATS and SRA as a measure of statistics achievement (Estrada & Batanero, 2008). Pearson's correlation coefficients between the total score on the SRA and component scores revealed a statistically significant relationship ($p < 0.05$) between achievement and *Affect,* $r = 0.20$, *Cognitive Competence,* $r = 0.26$, and *Value,* $r = 0.22$, but a statistically significant relationship was not found for *Difficulty,* $r = 0.09$ (Estrada & Batanero, 2008). It was believed by Estrada and Batanero (2008) that attitudes tend to improve with increased knowledge. Additionally, it was found through variance analysis that the number of previous statistics courses also positively effects attitudes, and there were no gender differences in attitudes

(Estrada & Batanero, 2008). The authors concluded that educators are responsible for "creating an emotionally and cognitively supportive environment in statistics training" and ensure that students can gain confidence in their abilities (Estrada & Batanero, 2008).

2.2.4 Meta-Analysis Investigating Attitudes Towards Statistics and Achievement

Based on the above cited literature investigating the relationship between statistics anxiety and achievement, Emmioğlu and Capa-Aydin (2012) conducted a meta-analysis to investigate the relationship between student's attitudes towards statistics and their achievement in statistics courses using published data using the SATS (Emmioğlu & Capa-Aydin, 2012). 17 studies were included that reported Pearson correlation coefficients relating achievement in statistics to responses to *Affect*, *Cognitive Competence*, *Value* and *Difficulty* components, and sample sizes, study location and method of measuring achievement were recorded (Emmioğlu & Capa-Aydin, 2012).

Sample size ranged from 49 to 2031 participants. The studies took place in the United States of America (8), Italy (2), Turkey (2 – performed by Emmioğlu), and the remainder in the United Kingdom, Spain, The Netherlands, Switzerland and Israel. Three of the studies made use of standardized assessment instruments to measure achievement (SRA, SCI), two used high school mathematics results, while the rest made use of statistics course or assessment results. The studies were conducted and published between 1998 and 2012.

A global correlation coefficient for each component was calculated from individual effect sizes (Pearson correlation reported by the study and sample size). These were small to medium effect sizes and were all statistically significant ($p < 0.01$), *Affect,* $r = 0.30$ (medium effect size), *Cognitive Competence,* $r = 0.30$ (medium effect size), *Value,* $r = 0.21$ (small effect size) and *Difficulty,* $r = 0.20$ (small effect size) (Emmioğlu & Capa-Aydin, 2012). Global correlation coefficients were significantly higher in US studies (Cashin & Elmore, 2005; Finney & Schraw, 2003; Schau, 2003; Schutz et al., 1998; Scott, 2001; Sorge & Schau, 2002; Stone et al., 2003) than in other countries. The study also found that *Affect* and *Cognitive Competence* had medium effect sizes in US studies, but small effect sizes in non-US studies (Emmioğlu & Capa-Aydin, 2012).

Limitations arising from the study include that some researchers use standardized tests such as the SCI and SRA to measure achievement, while others will formulate their own tests, which means there is a lack of consistency in testing standards (Emmioğlu & Capa-Aydin, 2012). Also, as pointed out by Garfield (2003), statistics assessments can tend to assess the application of formulae and rules rather than assessing understanding and interpretation.

Regardless, both methods have not been assessed enough psychometrically to ensure validity and reliability when compared to well-used instruments such as the SATS (Emmioğlu & Capa-Aydin, 2012). This study served as an important blueprint in how to manage the research in statistics attitudes' relationship to statistics achievement. The review of studies and achievements above show how the achievement measures consistently show statistically significant relationships with attitude components, hence addressing the limitation.

Another concern was the use of two sets of unpublished research results in the meta-analysis, despite Emmioğlu and Capa-Aydin (2012) stating the use of online databases in their methods and design. These were own research completed by Emmioğlu (unpublished doctoral thesis – 2011), and research communicated telephonically to the researchers by Schau, conducted in 2010 (Emmioğlu & Capa-Aydin, 2012). This data will not be considered for this enquiry, as thorough engagement with research and procedures are required for best practice. Additionally, a fixed effects model was employed for the meta-analysis. Field and Gillet (2010) recommend random effects model for social science research, which is more applicable for the current study. Further, the presence of heterogeneity and inferences made by Emmioğlu and Capa-Aydin (2012) make random effects more suitable as the criteria for fixed effects are not met (Hak et al., 2016). This meta-analysis will hence apply a random effects model, and Hak et al. (2016) assert that small effect size variance will result in the model converging to fixed effects. It was also noted only Q-statistics were used to assess heterogeneity, which is a limitation, as I^2 statistics should be included for the nature of this research (Higgins & Thompson, 2002).

2.3 Statistics in Social Science

Research on Statistics education has recently focused more on teaching Statistics in the Social Sciences, and the resultant experiences of Social Sciences students thereto due to the above concerns. We have now seen that there is a well-established body of literature that quantitatively and qualitatively aims to investigate students' experiences with statistics education. Affective and cognitive aspects of students' attitudes and beliefs are often researched by social scientists (Gal et al., 1997), and, fittingly, the experiences of social science students' attitudes towards statistics are of interest to statistics education researchers.

2.3.1 The use of Statistics in the Social Sciences

Rhodes University does not offer a dedicated Statistics teaching course for Social Science students, perhaps because most Social Science subjects are not immediately associated with mathematical thinking as the Commerce and Biological Sciences are. Further, Social

Sciences undergraduate courses typically do not teach the introductory statistical concepts needed for research. An exception is the Department of Psychology which offers a compulsory "Research Methodology" course in both the third year and Honours year of their respective degree programmes; however, the courses also include qualitative research methodology, so the time spent on statistics is limited and the topics covered only include some Descriptive Statistics and Hypothesis Testing, and later ANOVA in the Honours year. While the Department of Statistics does note the use of the Statistics 1S1 course for Social Sciences students as well, no mention is made of the course to Social Sciences students during curriculum selection, and many Social Sciences students remain unaware of the inclusion and use of statistics in their fields.

This is not unique to Rhodes University students: Ruggeri et al. (2008) found that Social Science students tend to underestimate the extent of statistics in their course curricula. Onwuegbuzie (2000) state that often, introductory research methodology or statistics courses are often graduate social science students' only formal exposure to statistics. Further, it is noted that students opting to study psychology, education or sociology are also usually less interested in mathematics and sciences (Macher et al., 2013), and are likely to choose only one or two university mathematics courses (Onwuegbuzie, 2000) – if any.

It is also important to reiterate an observation made by Ncube and Moroke (2015) made previously, where many students in these fields enter tertiary education having taken Mathematical Literacy as a subject in the FET phase of their schooling, and hence they experience statistical concepts late into their formal education. However, as noted, the current CAPS syllabus also does not adequately prepare learners to learn statistical concepts beyond basic data analysis and descriptive statistics. This, coupled with a lack of resources for students whose degrees are typically not mathematical in design, means that Social Sciences students are left vulnerable to feeling overwhelmed and stressed by the sudden implementation of Statistics in their studies. Further, the aim of developing a positive attitude towards Statistics in order to ensure successful engagement with course material, as described by Ramirez *et al.* (2012), is not being met if a large population of students are being left behind in their Statistics education.

2.3.2 Statistics Anxiety in the Social Sciences

Do Social Science students experience Statistics Anxiety more than other fields? Malik (2014) presented findings at the Survey Research Methods section of the 2014 American Statistical Association conference that Statistics Anxiety is higher in non-STEM majors than in STEM[3] majors. Analysis of variance performed by Malik (2014) of students' responses to the Students' Statistics Anxiety Scale (SSAS) report a statistically significant difference, F (2, 195) = 12.14 ($p < 0.05$), in Statistics Anxiety in STEM majors ($N = 117$, $M = 27.44$, $SD = 6.84$) and non-STEM majors ($N = 79$, $M = 32.18$, $SD = 7.6$). Based on these findings, recommendations were made that universities consider offering separate statistics teaching for STEM and non-STEM majors that cater to the students' mathematics background and pace of learning (Malik, 2014). I would like to see Rhodes University assess the possibility of a catered "Statistics for Social Science" course for undergraduate students in the future. Already, optional extra courses facilitated by the Centre for Postgraduate Studies such as "Introduction to *R*" and "Introduction to SPSS" prove to be popular amongst Social Science postgraduates.

Other researchers sought to specifically assess Social Sciences students experiences, rather than delegating them to the "not Science" comparison group. Khavenson et al. (2012) state that a difference in reality and expectations lead to statistics anxiety in Social Sciences students – that is, the structure of their methodology courses are not what the students expected to be engaging in in their Social Sciences degree. Statistics courses are seen by Social and Behavioural Sciences students as intimidating, and the students report feeling insufficiently competent in being able to grasp statistical concepts (Vanhoof et al., 2011). Students in these fields do not believe in their capability in engaging with statistics (Macher et al., 2013) and are observed to experience apprehension during their statistics examinations or when preparing for assessments (Macher et al., 2012). Ncube and Moroke (2015) noted that within the South African context, 913 Behavioural Sciences and Social Sciences students enrolled in introductory statistics courses at the University of South Africa, had a perfunctory disposition towards statistics. It was found that negative self-perception of ability and interest in statistics, as well as low worth and motivation, could lead to a negative attitude towards statistics, which in turn could affect performance in the courses (Ncube & Moroke, 2015).

2.3.3 Psychology students' statistics anxiety and attitudes towards statistics

Statistics is a particularly useful tool in Psychology. However, Bose (2017) quotes a study by Hong *et al.* (2014) where only 57.1% of undergraduate Psychology students were aware of the statistics component of their degree. Research by VanderStoep and Shaughnessy (1997) found that reasoning abilities of Psychology students improved after research methods

[3] STEM is a commonly used acronym in academic circles that denotes scientific fields of study, as in Science, Technology, Engineering and Mathematics. The Social Sciences are not deemed to be included within "Science".

courses. Dempster and McCorry (2009) explain that the inclusion of statistics in undergraduate Psychology programmes greatly enhances critical reasoning among students, and this is a crucial skill for these students to learn. Hood et al. (2012) also assert that statistics is useful for future professional psychologists in practice.

While Ruggeri et al. (2008) acknowledge that feelings of statistics anxiety are widespread across most fields of study, this is particularly noteworthy amongst students in psychology, education and sociology. As previously outlined, Zimprich (2012) reported a certain aversion that Psychology students at the University of Zurich had towards their compulsory statistics course. He accredits this to antiquantitative bias, not understanding the power of analytical models employed in statistics and underestimating how often scientific and statistical methods are used in the social sciences (Zimprich, 2012).

The relationship between statistics achievement and attitudes of Psychology have been explored in ten studies (Chiesi & Primi, 2009, 2010; Dempster & McCorry, 2009; Emmioglu, 2011; Finney & Schraw, 2003; Hood et al., 2012; Oguan et al., 2013; Schutz et al., 1998; Sesé et al., 2015a; Zimprich, 2012). Results indicated a statistically significant relationship between achievement and attitudes. Onwuegbuzie (2004) and Ruggeri et al. (2008) quote multiple studies where statistics anxiety has been shown to negatively affect the performance of Psychology students in Statistics and Research Methodology courses.

A review of literature by Nesbit and Bourne (2018) revealed 11 studies that made use of the STARS to assess Psychology students' experiences with statistics anxiety. Variability in reported scores were noted across studies, and acceptable to excellent reliability statistics were noted, although there were inconsistencies in result interpretation across the studies (Nesbit & Bourne, 2018). Additionally, Nesbit and Bourne (2018) investigated Psychology students' experiences in an introductory statistics course. 315 Psychology students completed the STARS, and students had more positive attitudes and were less anxious than samples in other studies (Nesbit & Bourne, 2018). Similarly, research by Hamid and Sulaiman (2014) aimed to quantify statistics anxiety in Psychology students and examine both statistics anxiety and mathematics skills as possible predictors for statistics achievement. 139 Psychology students enrolled in an introductory statistics course were administered the STARS and a mathematics skills test (Hamid & Sulaiman, 2014). Results indicated that Psychology students experienced statistics anxiety, and regression analysis revealed that mathematics achievement was a predictor of statistics anxiety and statistics course performance (p < 0.001) (Hamid & Sulaiman, 2014).

Griffith et al. (2012) investigated attitudes towards statistics across disciplines. A significant difference was found for attitudes between majors (p < 0.05), and 39% of Psychology majors (n = 171) were shown to have negative attitudes towards statistics as a result of their experiences with the subject (Griffith et al., 2012). Among the students who reported positive attitudes, 60% of the Psychology students valued the use of statistics in their future career and 76% said they would need statistics for graduate school (Griffith et al., 2012). Most Psychology students who reported negative attitudes described by the students as too difficult as well as irrelevant for their future career paths, and a predeveloped dislike for Mathematics (Griffith et al., 2012). It was concluded that Psychology educators needed to inform their students of the use of statistics in their future careers (Griffith et al., 2012).

In another study, Ruggeri et al. (2008) investigated the expectations of Psychology students in an introductory psychology statistic course. The Composite Survey of Statistics Anxiety and Attitudes (COSSAA, comprising of the STARS and SATS) was administered to 196 Psychology students, and focus groups were formed to allow students to discuss their experiences with their course (Ruggeri et al., 2008). It was found that only 46.7% of students were aware of the statistics component of their course, but this was not found to be a predictor of statistics attitudes and anxiety (Ruggeri et al., 2008). A statistically significant improvement in *Cognitive Competence* was noted from the first year to second year, t = 2.123 (p = 0.035) (Ruggeri et al., 2008).

Coetzee and van der Merwe (2010) conducted a cross-sectional survey design that aimed to assess the attitudes of 235 Organisational Psychology students at a South African University. Regression analysis revealed Spearman's correlations between high school mathematics achievement and statistics attitude to be statistically significant (p < 0.01) for *Affect*, *Cognitive Competence*, *Value* and *Difficult*y (Coetzee & van der Merwe, 2010). It was not statistically significant for Interest (p = 0.106) and Effort (p = 0.094) (Coetzee & van der Merwe, 2010). Coetzee and van der Merwe (2010) confirmed the validity and reliability for the SATS-36 for a South African Sample, and also found positive attitudes among students like Scott (2001). It was also concluded that while students were interested in statistics and had mostly positive attitudes towards statistics, the students also reported feelings of insecurity, stress and frustration (Coetzee & van der Merwe, 2010). This indicates that, overall, the subject does seem to be daunting for Psychology students, despite them being enthusiastic for the subject itself – but also that its worth is still underestimated (Coetzee & van der Merwe, 2010).

Research by Ngantweni (2019) employed a mixed methods approach to investigate Psychology students' attitudes towards statistics at a South African university. A sequential explanatory design meant that quantitative data collection and analysis was followed up with qualitative data collection and analysis, and this was then interpreted together (Ngantweni, 2019). 56 postgraduate students enrolled in the "Quantitative Research Methods" course offered by their department completed the SATS-36, and five of the students participated in qualitative interviews (Ngantweni, 2019). SATS responses indicated neutral responses to *Affect,* $M = 3.95$ ($SD = 1.75$), *Cognitive Competence,* $M = 4.76$ ($SD = 1.41$), *Value,* $M = 4.35$ ($SD = 1.58$), *Difficulty,* $M = 3.79$ ($SD = 1.49$) and *Interest* $M = 4.17$ ($SD = 1.66$) (Ngantweni, 2019). Students reported a great deal of *Effort*, $M = 6.31$ ($SD = 0.88$) that went into course assignments and assessments (Ngantweni, 2019). Thematic analysis of the interviews revealed that the Psychology students were afraid of failing statistics, and this was causing statistics anxiety; secondly, students felt that they were introduced to statistics late in their psychology curriculum (3rd year or Honours) which also led to statistics anxiety, and educators were seen as playing a role in alleviating or exacerbating statistics anxiety (Ngantweni, 2019).

Clearly, statistics attitudes have been defined in Psychology students to be correlated to their achievement in statistics. It has also been noted how prior experiences with statistics and the lack of clarity of the extent of their statistics coursework can negatively affect attitudes of Psychology students. Luckily, it has been demonstrated that there are relatively achievable interventions and teaching approaches that can be implemented to mitigate negative feelings towards statistics.

To summarise, the above sections have explained the experience of statistics anxiety that many students are faced with when undertaking statistics courses as part of their degree. Statistics anxiety often stems from negative attitudes towards statistics. Schau (2000) designed the SATS to assess statistics attitude, using components such as *Affect*, *Cognitive Competence*, *Value*, *Difficulty*, *Interest* and *Effort*. The key finding emanating from the above review is that a positive relationship has been noted between attitudes and achievement in statistics has been noted, where negative attitudes have been shown to affect performance. Hence, addressing statistics anxiety and negative attitudes towards statistics is crucial for statistics educators, in order to promote statistics knowledge acquisition and achievement in their students. Limitations identified in the literature are that studies investigating the relationship between attitudes and achievement have not been published in an updated meta-analysis in the last 11 years. Additionally, the previous meta-analysis did not assess differences in achievement measures and included unpublished research. A review of literature of Psychology students' statistics anxiety due to the relationship between attitudes and achievement has also not been explored by quantitative means.

The subsequent section aims to present another quantitative method of assessing *subjective* experiences such as statistics anxiety and attitudes, using neuroimaging techniques. This research has been performed in mathematics studies, and the interrelatedness of mathematics and statistics as outlined in the above literature does suggest the expansion of this research into statistics. The technical nature of neuroimaging and reliance on statistical methods for more complex operations also coincides with statistics research.

2.4 Neuroimaging as an investigative tool in Mathematics and Statistics Anxiety

Neuroimaging software such as functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS) have been utilized to successfully quantify statistical reasoning and mathematical reasoning. Given the interrelatedness, of statistics and mathematics, the neuroimaging of these constructs is valuable for the advancement of education, and studying the neural constructs of statistics and mathematics anxiety.

2.4.1 Mathematics Anxiety as a related concept

Statistics Anxiety is seen as a discrete concept similar to Mathematics Anxiety. Similarly, statistics education and mathematics education are separate, but interrelated fields of study (Malik, 2014). In the South African Curriculum Assessment Policy Statements (CAPS), statistics is a section within the mathematic curriculum (Department of Basic Education, 2011). So interrelated is statistics to mathematics, to the extent that statisticians often admit to not realising that statistics is a separate discipline to mathematics in their early careers, all the while acknowledging considerable overlap between the fields (Malik, 2014).

Mathematics Anxiety is defined as (1) the feelings and experiences of anxiety and nervousness as well as bodily symptoms related to engaging in mathematics, or (2) apprehension and tension around performing mathematical tasks and solving mathematical problems (Malik, 2014). Macher et al. (2012) view both Statistics and Mathematics Anxiety as types of performance anxiety. With particular reference to statistics, students are thought to experience negative feelings towards statistics due to the perception that statistics education is complicated because of its associating to mathematics (Berens, 2018).

Nonetheless, although the mental procedures involved in statistics are different to those involved in mathematics, which requires more processing; mathematics achievement is often a predictor of positive or negative attitudes towards statistics, and a key antecedent of statistics anxiety (Zimprich, 2012).

2.4.2 The Use of Neuroimaging in Assessing Mathematics Anxiety

Research using Magnetic resonance imaging (MRI) and near-infrared spectroscopy (NIRS), has been demonstrated that mathematical reasoning and mathematics anxiety often occurs in the dorsolateral prefrontal cortex (DLPFC) (Artemenko et al., 2018; Pfurtscheller et al., 2010; Pletzer et al., 2015). For example, Artemenko et al. (2018), investigated arithmetic processing in adolescents using fNIRS. The authors designed a self-paced block design type of fNIRS study, where arithmetic tasks were presented to participants in 45 seconds (block length), intervals, followed by a break of 20 seconds (Artemenko et al., 2018). Findings from the study indicated activation in fronto-parietal network, including he dorsolateral prefrontal cortex. The authors highlighted the novelty of fNIRS with adolescent participant due to the non-invasive nature of the technology, and the ability for participants to freely move during calculation of mathematical tasks (Artemenko et al., 2018). The authors concluded that fNIRS imaging allowed for an ecologically valid assessment similar to what would have been expected in a classroom setting (Artemenko et al., 2018).

In another study, using fNIRS, Pfurtscheller et al. (2010), locate the cortical regions of mathematical thinking to bilateral activation of the ventrolateral (VLPFC) and dorsolateral (DLPFC). In their study, Pletzer et al. (2015) investigated the effects of Mathematics Anxiety on mathematical reasoning. The authors found that mathematical processing efficiency is associated with increased activation in the DLPFC and increased deactivation in the default mode network[4] (DMN). Interestingly, the study found lower activity of the DLPFC when participants experienced mathematics anxiety (Pletzer et al., 2015).

The key implication of the above cited research is that the biological representation of mathematical reasoning occurs in the DLPFC. Nonetheless, although the relationship between mathematics and statistics has been established, distinct research in mapping the cortical correlates of statistical reasoning should be explored as separate to mathematical reasoning, since mathematics anxiety and statistics anxiety are seen as separate concepts. To this end, near-infrared spectroscopy imaging (fNIRS) shows promise in unmasking the neural correlates of statistical reasoning. The next section briefly details this technique and application in research.

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[4] The default mode network is activated when the brain is at rest and not focused on the outside world, and during thought processes related to performing external tasks.

2.4.3 Functional near-infrared spectroscopy as a neuroimaging tool

Near-infrared spectroscopy (NIRS) was developed by Frans Jöbsis while exploring non-invasive optical techniques for monitoring in vivo tissue (Ferrari & Quaresima, 2012). In its application, NIRS relies on absorption of light in biological matter as a means of measuring blood concentration. The technique utilizes the concept of the Beer-Lambert Law to convert optical density to changes in oxygenated and deoxygenated haemoglobin (Ferrari & Quaresima, 2012). Within fNIRS, light transmission in biological matter, including cortical tissue, is dependent on the effects of, *reflectance*, *scattering* and *absorption* (Jöbsis, 1977). In terms of light, reflectance refers to light bouncing off the surface of biological matter at certain angles. Light scattering refers to the light particles spread out from their original trajectory upon hitting tissue surface. On the other hand, absorption refers to the light passing through a surface and entering the biological matter. Scattering and absorption can be controlled, where using light with a higher wavelength can reduce scattering, and absorption may only occur at particular wavelengths according to the chemical and physical properties of biological matter (Jöbsis, 1977). Hence, fNIRS research can utilize specific wavelengths to determine the functioning and properties of biological matter in medical and neuroscientific research.

In its application, near infrared spectrometry uses light in the near-infrared range. Visible light is observed by human eyes is in 400-700nm range. Ultraviolet (UV) light, is observed in 700-1000nm is considered infrared (IR) light. In as early as 1977, Jöbsis is reported to have utilised light in the near-infrared range to study brain tissue to measure haemoglobin oxygenation levels in the human cortex (Ferrari & Quaresima, 2012). This is due to light absorption in biological matter being most optimal in the 700nm-1300nm range (Jöbsis, 1977). Jöbsis indicated that near-infrared light is absorbed by chromophores, such as haemoglobin in blood vessels, which allowed for the wide use of the technique (Ferrari & Quaresima, 2012). Based on the early work of Jöbsis, fNIRS, measures cortical activity by utilizing light-emitting diodes, that are used as sources to emit near-infrared light. Sources are attached to detectors that measure the amount of absorption of light by cortical tissue. .

Within a typical data collection setting, sources and detectors are spaced within 30mm apart, with a resulting ‘banana shape’. The resulting ‘banana shape’, represents the shape that is observed when light particles are emitted from a source, experiences a change in trajectory due to being absorbed and scattered by biological matter, curving the path, before then reaching a detector. Using sources and detectors, fNIRS methodology monitors haemoglobin and deoxyhaemoglobin oxygenation changes by assessing the degree of light absorbance and scattering, which is affected by the amount of haemoglobin present. Simply, NIRS measures neurovascular coupling, through haemodynamic responses such as the concentration of oxyhaemoglobin (HbO_2) and deoxyhaemoglobin (HHb), and the concentration of oxidized cytochrome *c* oxidase (oxCCO) and blood flow index (BFI) (Elwell & Cooper, 2011). fNIRS uses these physiological measures to relate haemodynamic responses due to neuronal demand due to cortical activation (Elwell & Cooper, 2011). By studying oxyhaemoglobin and deoxyhaemoglobin concentration in a particular region in the brain, fNIRS can determine if neurons are experiencing cortical activity. Typically, fNIRS measures increases in HbO_2 concentration and decrease in HHb due to arterial vasodilation and indicating increased cerebral blood flow and blood volume due to brain activity (Ferrari & Quaresima, 2012).

2.4.4 Applications of fNIRS technology

In fNIRS, three techniques are available. Continuous wave (CW) systems employ a constant intensity of light that is emitted, so detectors measure light intensity that is scattered back from tissue (Barreto & Soltanlou, 2022). In time domain (TD) systems, a short pulse of light is emitted into the tissue, and the time it takes for photons to reach detectors is also measured (Barreto & Soltanlou, 2022). Frequency domain (FD) systems involves the changing of light intensity, where the phase of light signal is measured to give an absolute HbO_2 and HHb reading (Barreto & Soltanlou, 2022). CW systems are most frequently employed for fNIRS analysis.

There are many advantages to using NIRS over similar methods. While MRI and PET make use of the same technology, they require participants or patients to remain very still throughout imaging (Lloyd-Fox et al., 2014), the process of which can be lengthy. Neuroimaging relies on cortical activation, and in instances where neural networks in motor regions are of interest, this is a significant hinderance. NIRS is suitable due to it being “relatively movement-insensitive [and allowing for] natural body postures” (Artemenko et al., 2018, pp. 3). Indeed, it is very useful for research designs that participants can be seated upright or standing while performing tasks, rather than lying down. Another concern is the use of radioisotopes as seen in PET imaging – this is an essential consideration for studies making use of children (Lloyd-Fox et al., 2014).

Rather than measuring haemodynamic activity, electroencephalography (EEG) measures the electrical charges that result from neural activity using electrodes. NIRS technology is preferred over EEG because it is comparatively more practical and user-friendly for use outside of laboratories (Pfurtscheller et al., 2010). Likewise, PET and MRI machines are large and cumbersome and are hence largely confined to the medical laboratory wherein it is installed. The transportability of NIRS equipment – usually, just the cap with sensors and detectors along with the digital software – cannot be under looked. Lloyd-Fox et al. (2014) cite this factor as one of the most crucial in their study that took place in rural Gambia – highly technical software is now more accessible to those without access to medical facilities or laboratories.

In the mental arithmetic study by Artemenko et al. (2018), the authors sought to investigate the neural correlates of mathematical reasoning. A concern in the study was the region of interest (ROI) implemented during mathematical tasks. The researchers were able to monitor a wide ROI for different age groups and pinpoint significant differences in activation levels by opting to utilize fNIRS (Artemenko et al., 2018). Activation was viewed in the angular, inferior and middle temporal gyri, as well as the superior and inferior parietal lobule (Artemenko et al., 2018) The convenience of fNIRS is the option of simply creating a larger montage to a wider ROI, and its allowance of simultaneous, continuous monitoring of different areas.

Zapała et al. (2022) state that continuous wave fNIRS is a suitable brain-recording method that can be used outside a laboratory setting. In their motion study, fNIRS was used along with virtual reality (VR) equipment to assess performance in an n-back task (working memory assessment) in a virtual environment (Zapała et al., 2022). The regions of interest were the medial frontal gyrus and dorsolateral prefrontal cortex (Zapała et al., 2022). CW-fNIRS is non-invasive and able to pair with other measurement devices, and has high resistance to motion artifacts (Zapała et al., 2022). The authors found that it was possible to use fNIRS to differentiate between working memory and rest periods in the region of interest, showing the neural correlates of enhanced attention and working memory (Zapała et al., 2022). It was concluded that the VR and fNIRS study design could be used to create attention-focused neurofeedback training to achieve symptom improvement in individuals with social anxiety disorder (SAD) (Zapała et al., 2022).

fNIRS has been used in a number of settings, for example, to study developmental and clinical diseases. A systematic review by Ho et al. (2020) investigated the use of fNIRS in the diagnosis and treatment response prediction of major depressive disorder (MDD). Since MDD has no established biomarkers, 64 studies were reviewed for their use of fNIRS in monitoring symptomatology and various treatment responses (Ho et al., 2020). Analysis of the studies found that oxyhaemoglobin concentration values were consistently negatively correlated to the degree of depressive symptoms, and diminished increases in oxyhaemoglobin in recurrent MDD patients compared to first-episode patients (Ho et al., 2020). Haemodynamic changes that were correlated with the improvement of depressive symptoms or social and cognitive functioning showed favourable increases (Ho et al., 2020). These results led Ho et al. (2020) to conclude that fNIRS is a good diagnostic and predictive tool for MDD and the increase of studies on the subject also attest to the use of the technique in psychiatric research and clinical practice (Ho et al., 2020).

From the above cited studies, and multiple other imaging studies, researchers have concluded that fNIRS is suitable for use in many settings, from clinical neuroscientific research in laboratories and hospitals, to studies that require motion to be accounted for; research with children in educational settings can also be conducted. For now, the research of interest is aligned with understanding the neurocognitive mechanisms behind cognitive processes of learning (Barreto & Soltanlou, 2022). While fMRI has been the non-invasive technique used most frequently in educational studies, it is restrictive in its requirements (Barreto & Soltanlou, 2022). A controlled lab setting is needed, and Barreto and Soltanlou (2022) explain that fMRI requires that appropriate for classroom settings and has the correct applications for use in educational research. Successful cortical mapping of mathematical reasoning has occurred as the first step in understanding Mathematics Anxiety, hence the interest in replicating this for the current enquiry in statistics.

2.5 Summary of Reviewed Literature and Link to Research Objectives

This chapter explored university students' experiences with learning statistics as part of their curriculums. Negative attitudes towards statistics were noted to stem from previous adverse experiences with mathematics or experiences from past statistics courses. Other factors noted for a perfunctory disposition to statistics included, insufficient teaching practice by statistics educators, negative self-efficacy and perceptions of students' abilities regarding statistics. Importantly for my research, students' attitudes towards statistics have been shown to negatively impact achievement in statistics courses. To this end, a meta-analysis by Emmioğlu and Capa-Aydin (2012) investigating the relationship between attitudes towards statistics and achievement found a small-to-medium effect sizes between attitudes towards statistics and achievement. To date, no robust analysis has since been performed in the last 10 years to investigate the above relationship.

Researchers has also indicated a relationship between mathematics education and statistics education. To this end, neuroimaging techniques such as fNIRS have been utilised to map the cortical regions involved in mathematical reasoning. Nonetheless, there is a dearth of research investigating the neural correlates of statistical education supported by behavioural measures. The objectives of my study are this to update the early work of Emmioğlu and Capa-

Aydin (2012), and investigate the neural correlates of statistics education (and statistics anxiety), through a case study quantitative approach.

CHAPTER 3
METHODOLOGY AND DESIGN

3.1 Research Objectives and Aims

The aim of this research was to expand on previous research that quantitatively assessed the causal relationship between students' attitudes towards statistics and achievement in statistics. The statistics anxiety of Psychology students had also not been explored through meta-analysis. This expanded into exploring the viability of using neuroimaging techniques to further understand subjective experiences of statistics education. Previously, only mathematics anxiety has been quantified using these methods.

A meta-analysis by Emmioğlu and Capa-Aydin (2012) suggested that there is a small to medium statistically significant relationship between statistics achievement and components of the SATS (i.e., *Affect, Cognitive Competence, Value* and *Difficulty*). As previously mentioned, the key limitations identified within the literature were the inconsistencies in measures of achievement, the use of unpublished research, and the statistical methods used in the study. My study sought to respond to the recommendation made by Emmioğlu and Capa-Aydin (2012) for further research on attitudes towards statistics by consolidating their research findings on statistics anxiety and the SATS questionnaire. No additional meta-analyses have been published in the 11 years since the original study. Specifically, there is an interest in consolidating studies that specifically pertain to the experience of Psychology students and their attitudes towards statistics, and achievements in the course.

This study tackled the above limitations by conducting a meta-analysis of published literature on the relationship between attitudes towards statistics and achievement. The updated, newer studies on the topic of interest were included, and appropriate statistical measures to answer the research question were implemented. An additional meta-analysis with specific reference to studies on Psychology students was also performed. fNIRS was utilized to assess statistics education in a similar way to Artemenko et al. (2018) who used the method to assess mathematics education and mathematics anxiety.

3.1.1 Research Questions

The first two research questions derive from those asked in the meta-analysis by Emmioğlu and Capa-Aydin (2012), which were based on the SATS attitude components. The third question was derived from research in mathematics education and the cortical regions implicated in mathematics education.

The hypothesis for the first research question is that a statistically significant relationship of (small to medium effect size) will be found between university students' attitudes towards statistics and achievement. The hypothesis for the second research question is that a similar effect size (small to medium effect size) will be observed for Psychology students' attitudes and achievement. Lastly, for the third research question, it is hypothesized that the Dorsolateral Prefrontal Cortex (DLPFC) will demonstrate activation during the execution of statistics tasks.

3.1.2 Research Design

There are two distinct components to this research. A meta-analysis was performed to answer the first two questions of the research study. Seed based correlation were undertaken to investigate the cortical mapping of the dorsolateral prefrontal cortex during the execution of the statistical reasoning tasks. Both analyses took the form of a quantitative research design as detailed below. For the sake of synergy, the Methodology related to the meta-analysis will first be discussed, followed by the methodology of the fNIRS experimentation.

3.2 Meta-Analysis Methods and Design

Emmioglu and Capa-Aydin (2012) describe a meta-analysis as a means to reveal patterns of relationships across multiple studies, while also summarising and collating data in a way that corrects for sampling and measurement errors. Similarly, Hak et al. (2016) describe a meta-analysis as a systematic means of assessing the effect of a determinant, intervention or treatment on a defined outcome. The former is done by employing the concept of an effect size, which is described as a standardized measure of an observed effect in a study (Field & Gillett, 2010). An effect size can be calculated as a Pearson's correlation coefficient, *r*, Cohen's *d*, or the odds ratio (Field & Gillett, 2010). For my study, the effect size was described using a Pearson's correlation coefficient.

3.2.1 Study Design and Search Process

The meta-analysis section of the study expands on the four research questions performed by Emmioglu and Capa-Aydin (2012). The independent variable in my study was students' attitudes towards statistics in terms of *Affect*, *Cognitive Competence*, *Value* and *Difficulty*. The dependent variable was achievement in the statistics courses attained by the students. An extensive literature search informed by PRISMA guidelines was performed. The original meta-analysis by Emmioglu and Capa-Aydin (2012) was also analysed for suitable studies. The unit of analysis was literature in the form of journal articles pertaining to (a) statistics anxiety and attitudes towards statistics, and (b) the SATS and achievement. Online databases were used in the search for studies, such as *ResearchGate, PubMed, JSTOR*, *ScienceDirect*, *PsycINFO* and *ERIC*. Relevant studies were obtained through a search of the phrases including the name of the available SATS versions, namely "SATS-36" and "SATS-28". For the search of Psychology students' attitudes towards statistics, the above searches were repeated and paired with "Social Sciences" and "Psychology" filters in order to specify the type of students included.

3.2.2 Eligibility Criteria

The eligibility criteria for studies being included into the meta-analysis was that (a) studies must have been written in English, (b) studies must include the SATS questionnaire as the unit of analysis for attitudes towards statistics; (c) studies had to include a measure of achievement as the outcome variable; (d) studies should have used Pearson's correlation coefficients to report effect size measures between attitudes and achievement. Finally, (e) research participants within the studies must have been university students or tertiary-level students enrolled in a statistics course. Non-experimental studies and studies reporting Spearman's correlation coefficient to measure attitudes and achievement were excluded from the meta-analysis.

The first meta-analysis included participants from all fields of study (Business, Management, Economics, Marketing), sciences (Technology, Engineering, Applied Mathematics), health sciences (Nursing, Medicine, Physiotherapy), and the social sciences (Education, Sociology, Psychology). The second meta-analysis only included Psychology students as the unit of analysis, studies were excluded if Psychology students were not the main unit of analysis.

3.3 Meta-Analysis: Data Synthesis and Analysis

Meta-Essentials Software was employed to run the meta-analysis (Suurmond et al., 2017). Meta-Essentials is based on Microsoft Excel and "facilitate(s) the integration and synthesis of effect sizes from different studies and provide figures, tables and statistics that might be helpful for interpreting them (van Rhee et al., 2015). Pearson's correlation coefficient (r) was used as the measure of the relationship between the attitude component of the SATS and achievement. Fisher's r-to-z transformation was utilized to calculate effect sizes from the correlation coefficient and sample sizes (van Rhee et al., 2015).

A random effects model was used to calculate the meta-analysis and to derive the statistical significance of estimated effect sizes, as well as the magnitude and homogeneity of the statistics model. An effect was evaluated for each of the attitude components separately

(*Affect*, *Cognitive Competence*, *Value*, *Difficulty*) in the form of subgroup analysis, based on the 95% confidence interval (CI). Forest Plots were obtained for each component, indicating the effect size and 95% CIs. Cohen's D criteria were applied when assessing magnitudes of effect sizes, namely large ($r \geq 0.50$), or moderate ($0.30 \leq r < 0.50$), or small ($r < 0.30$) (Emmioğlu & Capa-Aydin, 2012). Heterogeneity measures, including the Q-statistic and I^2 value (Higgins & Thompson, 2002) were assessed for data spread.

3.4 Functional Near Infrared Spectrometry Mapping of Statistical Reasoning

The cortical mapping of statistical reasoning was modelled after Artemenko et al. (2018) who investigated the role of the DLPFC in mathematical processing. Similar to the above study, my study employed the continuous wave (CW) technique to measure optical density and light absorption due to cortical activity.

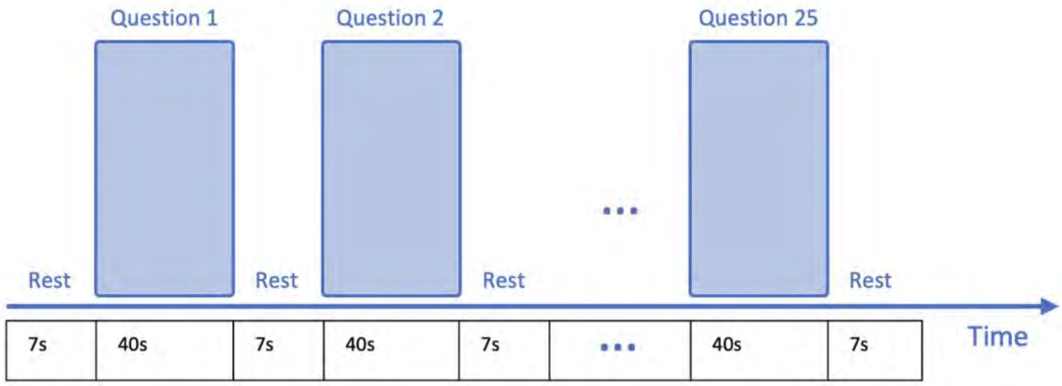
3.4.1 Study design

Experimental designs in fNIRS take either, the block design, or event-related design approach to assess cortical activation (Tak & Ye, 2014). My study took the form of the block design. This design is the most favoured due to its ability to easily evoke the hemodynamic response (Barreto & Soltanlou, 2022). By definition, the block design approach to neuroimaging entails presenting stimuli in block form; meaning stimuli are presented for a period of time (e.g., 30 seconds) followed by a rests period (e.g., 7s). This design is thought to mimic typical neuronal function in response to stimuli (e.g., visual, auditory) (Barreto & Soltanlou, 2022).

For my study, blocked stimuli were presented in the form of 25 multiple choice questions (MCQs), used in the Research Methodology course taught by the supervisor of the current research thesis. Stimuli blocks included content from *descriptive statistics*, *correlation*, *regression*, *t-tests*, and *analysis of variance* (ANOVA). Blocks of stimuli (MCQs) were presented for a period of 40 seconds, followed by 7 seconds of rests, for a total of 25 blocks. The experiment took a total of approximately 20 minutes to complete for each participant. Figure 3.1 depicts the block design approach used for my study.

Figure 3.1

Block design experimental paradigm



Note. Instructions to the test taker were presented for 60s at the start of the stimuli, followed by the first interblock interval. The study comprised of 25 questions (block), with 7 seconds of rest.

3.4.2 Participants

Convenience sampling was used to select 10 research participants for the fNIRS segment of the study. All participants were recruited from the Rhodes University Psychology Honours class (eight General Psychology Honours[5] and two Organizational Psychology students). The research participants are collectively referred to as the "Psychology Honours" class here forth. All participants undertook the "Honours in Research Methodology', course, a compulsory elective course undertaken for completion of the Honours in Psychology course. The course comprises of theoretical seminars in quantitative and qualitative research techniques. The quantitative theoretical seminars are juxtaposed with practical sessions that involved engagement with statical content in the form of independent t-tests, correlation and regression analysis, analysis of variance, and non-parametric statistics. Content from these courses formed the basis of the stimuli used in the cortical mapping study. Table 3.1 provides participant characteristics data pertinent to the study design. Characteristics are presented for each participant along with cranial measurements in Chapter 5.

[5] General Psychology students are differentiated from Organizational Psychology major students based on specialization.

Table 3.1

Participant characteristics in fNIRS study

Characteristic	Experimental group (n=10)
Age (years) at start of Honours year	21-27
Sex (female/male)	n=8 female, n=2 male
Honours degree (General/Organisational)	n=8 General, n=2 Organizational
Expected grade for statistics course component	Responses ranged from 56-65% to above 75%
Time (hours) in a week spent studying statistics	2-25 hours
Overall stress level (1-7) in usual university week	M=5.60, SD=1.71
Cranial measurements (ear-to-ear across top of head (cm), mid-forehead to nape of neck (cm))	Recorded for individual participants at the start of the experimental procedure
Skin pigmentation	Recorded for individual participants
Hairstyle and hair pigmentation	Recorded for individual participants

Note. Age varied for participants (M = 22.4, SD = 1.8). Eight participants were female, while two participants were male. Cranial measurements are presented in Chapter 5.

3.4.3 Materials

Demographics Questionnaire and SATS-36

A Demographics Questionnaire was used to assess participants' age, degree of study (Organisational Psychology or General Psychology Honours), and information from the SATS, namely, "What grade are you expecting to receive in this course for the statistics component?", "In a usual week, how many hours did you spend outside of class studying statistics?".

The Survey of Attitudes Towards Statistics, (36) (Schau, 2000) was used to collect data pertaining to students' attitudes towards statistics. The SATS-36 is based on questions that require a Likert scale response, where 1 = strongly disagree, to 7 = strongly agree. The psychometric properties of the SATS are well attested and include high Cronbach's alpha values for *Affect*, 0.80 – 0.89, *Cognitive Competence*, 0.77 – 0.88, *Value*, 0.74 – 0.90 and *Difficulty*, 0.64 – 0.81 (Schau, 2019). Moreover, Coetzee and van der Merwe (2010) recorded acceptable levels of internal consistency among components of the SATS-36 in a sample of South African students.

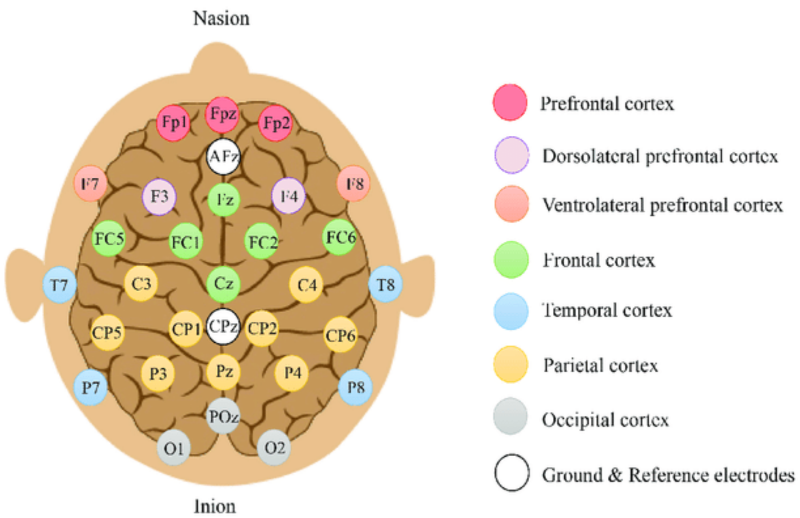
Cortivision Photon Cap (fNIRS)

The Cortivision Photon fNIRS cap was used to record optical signals when participants completed the statistical stimuli mentioned above. The Photon fNIRS cap is a wireless fNIRS device that pairs with stimulus presentation software such as PsychoPy, Presentation, and Eprime. The Photon fNIRS cap employs continuous wave and records optical signals at two wavelengths, namely 760nm and 850nm. The Photon fNIRS cap used for my study included 9

LED sources (emitters), and 4 detectors. The configuration included two short separation channels. Short-channel sources were placed less than 1cm from a detector to allow for more accurate estimations of the neural responses during analysis (Luke et al., 2021). All data was measured at a sampling rate of 7 Hz. The configuration of my sources and detectors allowed for up to 37 channels of data analysis. The montage for my study was created using the Extended International 10-20 System (Klem et al., 1999). Figure 3.2 below provides an example of the 10-20 system used for electrode and optode placement for my study, as detailed in Section 3.5.1.

Figure 3.2

Extended International 10-20 system guide with regions of interest



Note. Model of the 10-20 system from Chai et al. (2019) explaining electrode placement using the Extended International 10-20 system. The 10 represents a distance between electrodes being 10% of the total distance of a front to back or left to right skull measurement, whereas the 20 represents a 20% distance; this usually equates to 20-40mm distance between electrodes. From "Exploring EEG Effective Connectivity Network in Estimating Influence of Colour on Emotion and Memory" by M.T. Chai, H.U. Amin, L.I. Izhar, M.N.M. Saad, M.A. Rahman, A.S. Malik, T.B. Tang, 2019. Frontiers in Neuroinformatics, 13(66). CC BY 4.0

3.5 fNIRS Data Acquisition and Analysis

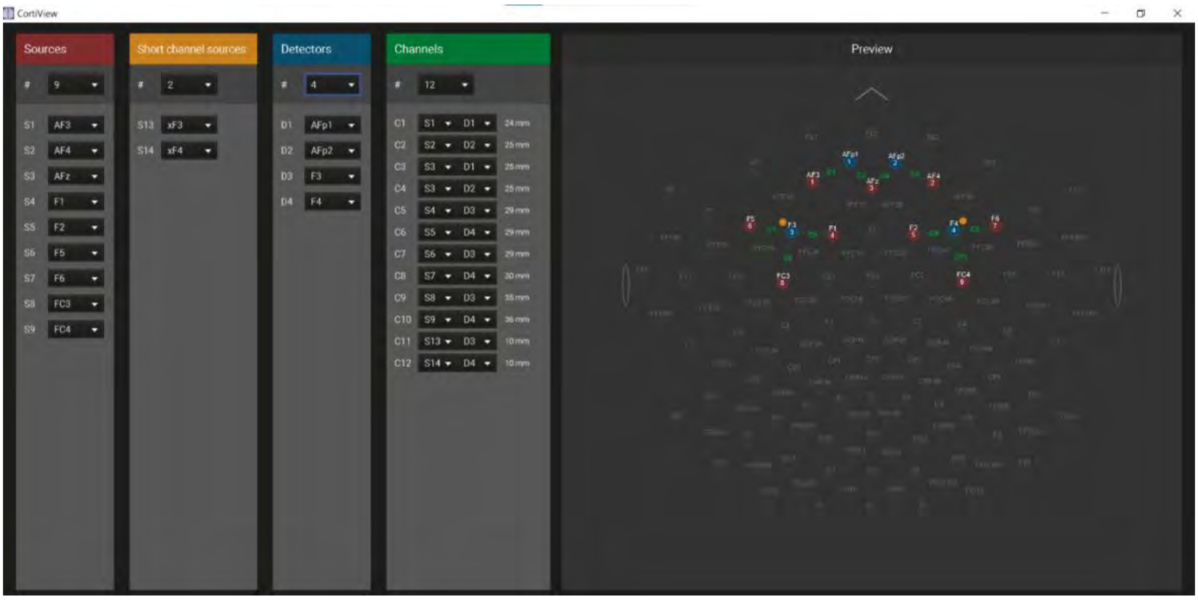
3.5.1 Optode Array Design, Cap and Targeted Brain Regions

A probe design for my study was designed on Cortiview using the fNIRS Optodes' Location Decider (fOLD) software (Morais et al., 2018). The fOLD montage for my study focused on the coordinates of the dorsolateral prefrontal cortex (DLPFC). The region of interests (DLPFC) was chosen due to its activation during mathematical reasoning tasks

(Artemenko et al., 2018) and was hypothesized to be activated during statistical reasoning tasks. The DLPFC montage from Cortiview can be found in Figure 3.3 below.

Figure 3.3

Cortiview screen depicting 10-20 dorsolateral prefrontal cortex montage



Note. Image obtained from Cortiview software. The Extended International 10-20 system labels are used in optode placement. Two separation channels were used as depicted in F3 and F4.

As noted in the above montage, my study covered the prefrontal cortex regions, namely AF3-AFp1-AFz-AFp2-AF4, and the dorsolateral prefrontal cortex (DLPFC), within the left hemisphere F1-F3-F5-FC3, and the right hemisphere, F2-F4-F6-FC4. In total, 9 sources, 2 short-channels and 4 detectors were utilized to measure activation from 12 channels. The neural connections for the cortical measures are summarized in Table 3.2, and Table 3.3.

Table 3.2

Source and detector placement on photon cap

Sources		Short-channel sources		Detectors	
Optode name	Placement on cap	Optode name	Placement on cap	Optode name	Placement on cap
S1	AF3	S13	xF3	D1	AFp1
S2	AF4	S14	xF4	D2	AFp2
S3	AFz			D3	F3
S4	F1			D4	F4
S5	F2				
S6	F5				
S7	F6				
S8	FC3				
S9	FC4				

Note. Placement names are based on 10-20 system names. Sources S1-S3 and detectors D1 and D2 are at the front of the montage, according to Figure 3.2. S4, S6, S8, and S13 along with D3 are found on the left hemisphere. S5, S7, S9, S14 and D4 are on the right hemisphere.

Table 3.3

Channel creation from source-detector connection

Channel name	Source-Detector
C1	S1-D1
C2	S2-D2
C3	S3-D1
C4	S3-D2
C5	S4-D3
C6	S5-D4
C7	S6-D3
C8	S7-D4
C9	S8-D3
C10	S9-D4
C11	S13-D3
C12	S14-D4

Note. As depicted in Table 3.3, and within the montage, channel C1 and C3 are formed from two sources, namely, S1 and S3 respectively. These share one detector, D1. Channels C5, C7, C9 and C11 share D3. The sources for these channels are S4, S6, S8 and short-channel source S13 respectively. In total 12 channels were measures for cortical activation.

3.5.2 Participant Instructions, and Protocol

Testing protocols for my study were based on Artemenko et al. (2018) who assessed cortical activation of the DLPFC, whilst participants completed arithmetic tasks. Participants who consented to the study, were sent an email detailing the purpose of the study including details on how the fNIRS equipment works. The email further contained information on completing the Demographic Questionnaire. Once the above was complete, participants were invited to Department of Psychology to complete the fNIRS procedures.

Once at the department, students were escorted to a quiet, soundproofed experimental room. Once in the room, participants were provided with an answer sheet, pen, and calculator, and had the protocols explained to them.

Once explanations were understood, participants were fitted the Cortivision Photon fNIRS Cap. Cranial measurements were taken of each participant to ensure the correct fitting fNIRS cap was worn. Signal quality emanating from the fNIRS cap was then checked using the Cortivision software. Once the signal was deemed appropriate, participants complete the block stimuli as described in Figure 3.1. Stimuli were presented to participants using Microsoft PowerPoint presentation. After participants had completed the study protocols, the fNIRS device was removed from their head, they were thanked for their participation, and dismissed from the research venue. Table 3.4 details the various phases of participant interaction, from the recruitment stage to the termination of the testing procedure. All appendices related to the recruitment, and procedures of the study can be found in Appendix A and B. The stimuli and test layout for the study can be found in Appendix C.

Table 3.4

fNIRS procedure with participants

Phase	Procedure
Recruitment of participants	1. Emails sent out to participants detailing the procedure, risks, and study details. 2. Students fill out a Google Form including demographics questionnaire and give informed consent to participate in the study. 3. Students provide email addresses with which they can be contacted, and times are set for the experimental procedure.
Arrival and rapport building	1. Students arrive at the Rhodes University Department of Psychology at the time stipulated. 2. They are greeted and escorted to a soundproof room. 3. The procedure is once again explained to participants and participants are invited to ask questions. 4. Verbal consent is given by participants. 5. Participant is placed in front of the stimuli, with a blank screen set until the procedure begins. 6. An answer sheet, pen and calculator are provided to the participant.
Positioning Photon cap on participant	1. Place Cortivision Photon Spectroscope Cap on participant's head, by first positioning it on the forehead and then gently pulling over the rest of the cranium to fit snugly on head. 2. Ensure that "AFz" optode position is squarely in the middle of the forehead. The edge of the cap should hence rest just above the participant's eyebrows. 3. Check that ear loops are in the same position on either side of the head and will allow ears to stick through. 4. Secure the cap by using Velcro chin strap, pulling on the end of the ear loops so that the cap is snug.
Cranial measurements (using measuring tape)	1. Measure across the top of the head, ear-to-ear (width in cm) 2. Measure forehead (AFz) to nape of neck (where gyroscope/power source is attached) (length in cm)
Preparing Cortivision software for use	1. Cover Photon Cap with blackout fabric cap (Velcro strap meets at nape of neck) 2. Attach power supply device to participant's left upper arm and switch on 3. Open Cortivision Cortiview software on computer device 4. Load dorsolateral prefrontal cortex montage from library
Signal calibration	1. Dim room lights as much as possible to mitigate light interference 2. Identify low-quality signals and adjust areas accordingly: this may mean gently pulling the cap downwards by its edge so that the optodes are closer to the skull. It may require moving the participant's hair out the way if this is deemed to be blocking the signal. 3. Once the signals are acceptable quality (mostly green), begin calibration. 4. Ask the participant to sit comfortably in a natural position and remain still. They should be positioned how they will be during the testing procedure. 5. Calibrate NIRS and gyroscope readings on Cortivision
End of testing procedure	1. Once the stimuli has completed, remove cap and power supply from the participant. The participant is then dismissed.

Note. The study protocol was published (dx.doi.org/10.17504/protocols.io.14egn24e6g5d/v1). This can be viewed in Appendix D The testing procedure took approximately 20 minutes, and other protocol steps surmount to 10 minutes.

3.5.3 Data Pre-Processing

Satori 1.6 software was used to pre-process the data and to conduct further statistical analysis of the fNIRS data (Lührs & Goebel, 2017). Data analysis was informed by the statistical procedures followed by Artemenko et al. (2018), as such neural activation of the DLPFC were investigated.

Motion artifacts, due to significant motion whilst participants complete the fNIRS task were corrected using correlation-based signal improvement (CBSI) (Cui et al. (2010). This was necessary as during testing participants had to calculate and write down responses to answers, which resulted in significant motion effects. As noted by Cui et al. (2010), CBSI corrects signals quality based on the assumption of simultaneous increases in oxyhaemoglobin and decreases in deoxyhaemoglobin being an indicator of cortical activation. Spike removal was also applied using temporal derivative distribution repair (TDDR). This technique is based on robust regression and removes baseline shift and spike artifacts which are due to sudden head movement when wearing the fNIRS cap (Fishburn et al., 2019).

3.5.4 Signal Quality and Channel Rejection

Channel rejection was applied based on the scalp coupling index (SCI). SCI measures how the fNIRS optodes (detectors and sources) are coupled to the human scalp. Given this coupling, the SCI is an indicator of signal quality, as it indicates the extent of vascular coupling within the scalp (Yücel et al., 2021). Channels with SCI value below 0.75 Hz were removed from the analysis, as these represented bad signal channels. Channels with SCI values above 0.90 Hz were high quality signals (Yücel et al., 2021). In addition to the above, channels with separation distance between sources and detectors smaller than 20mm and larger than 40mm were removed from the analysis, due to being outside the ideal range for source-detector communication (Luke et al., 2021).

3.5.5 Noise removal

High-pass Butterworth temporal filtering was applied, on the data at 0.01 Hz. Low-pass Gaussian smoothing was also applied at 0.4 Hz. The filters were applied to correct for physiological confounds, such as breathing, and artifact noise due to cranial blood flow (Yücel et al., 2021).

3.5.6 The Modified Beer-Lambert Law (mBLL)

Once the data was pre-processed, and physiological noises were corrected, changes in optical densities were converted into oxygenated (O_2Hb) and deoxygenated (HHb) haemoglobin by applying the modified Beer-Lambert Law (mBLL) (Yücel et al., 2021). The application of the mBLL prepared the data for further statistical analysis, using seed-based correlations.

The mBLL is based on the below equation, where *OD* represents optical density. *I* represents incoming light from the detectors, and *Io* represents light absorbed by the detectors. The equation states that a change in optical density, i.e., a change in the amount of light absorption, is a representation of the change in the concentration of a chromophore. Hence, the optical density changes at the wavelength for oxygenated haemoglobin can be monitored as a means of measuring changes in haemoglobin concentration. The same is true for deoxygenated haemoglobin. D_{PF} refers to differential path factor while ε is absorption coefficient and L is the distance between source and detector. These values can be determined and will result in the concentration value of a chromophore.

$$\Delta OD = -log\frac{I(t_2)}{Io(t_1)} = \Delta\varepsilon L D_{PF}$$

3.5.7 Statistical Analyses of Processed fNIRS Data

The General Linear Model (GLM) was applied to compare concentration changes during stimuli exposure (block = statistics stimuli) and rest (interblock interval). Cortical markers to measure brain activation were applied to the data, starting at t = 67s for stimuli 1, which lasted for 40 seconds, followed by 7 seconds of rest. This block format was repeated 25 times. Z-transformation normalization procedures were applied in pre-processing steps pipeline to study the GLM (Lührs & Goebel, 2017).

Due to the case study approach adapted in my analysis, GLM models were conducted using the seed-based correlation approach. This approach to assessing signal detection due to cortical activation based on a node (seed). A seed was selected as a primary activation point, to be correlated which other signal responses (Lührs & Goebel, 2017). In this approach, the seed is based on a channel-based approach, where strong channels with SCI higher than 0.90 Hz are selected for the correlation. For my analysis, the primary seed selected as the correlation seed was C4, C5, C6, C7, C8 or C12 depending on signal strength. 2D and 3D cortical activation of the task, based on the seed were used to indicate cortical activation due to the statistical stimuli.

3.6 Ethical considerations

Ethical clearance for my study was obtained from Rhodes University Human Ethics Committee (Review Reference: 2021-5248-6211). Ethical clearance to conduct cortical mapping amongst university participants was granted to my research supervisor by the Rhodes

University Human Ethics Committee (Review reference: 2021-5308-6453). These clearance letters are attached in Appendix E.

CHAPTER 4
RESULTS: META-ANALYSIS

This chapter presents the results from the two meta-analysis experiments. The selection criteria of the studies, and all retained studies, and their characteristics are detailed through relevant PRISMA Flow Diagrams. Following the above, meta-analysis finding, (a) exploring the relationship between university students' attitudes towards statistics and (b) how this influences achievement in the statistics course is detailed. Forest plots are presented as the main outcome indicator of achievements, supplemented by effect sizes and heterogeneity measures. Results pertaining to functional near infrared imaging (fNIRS) and the neuroimaging of statistics education are presented in the Chapter 5.

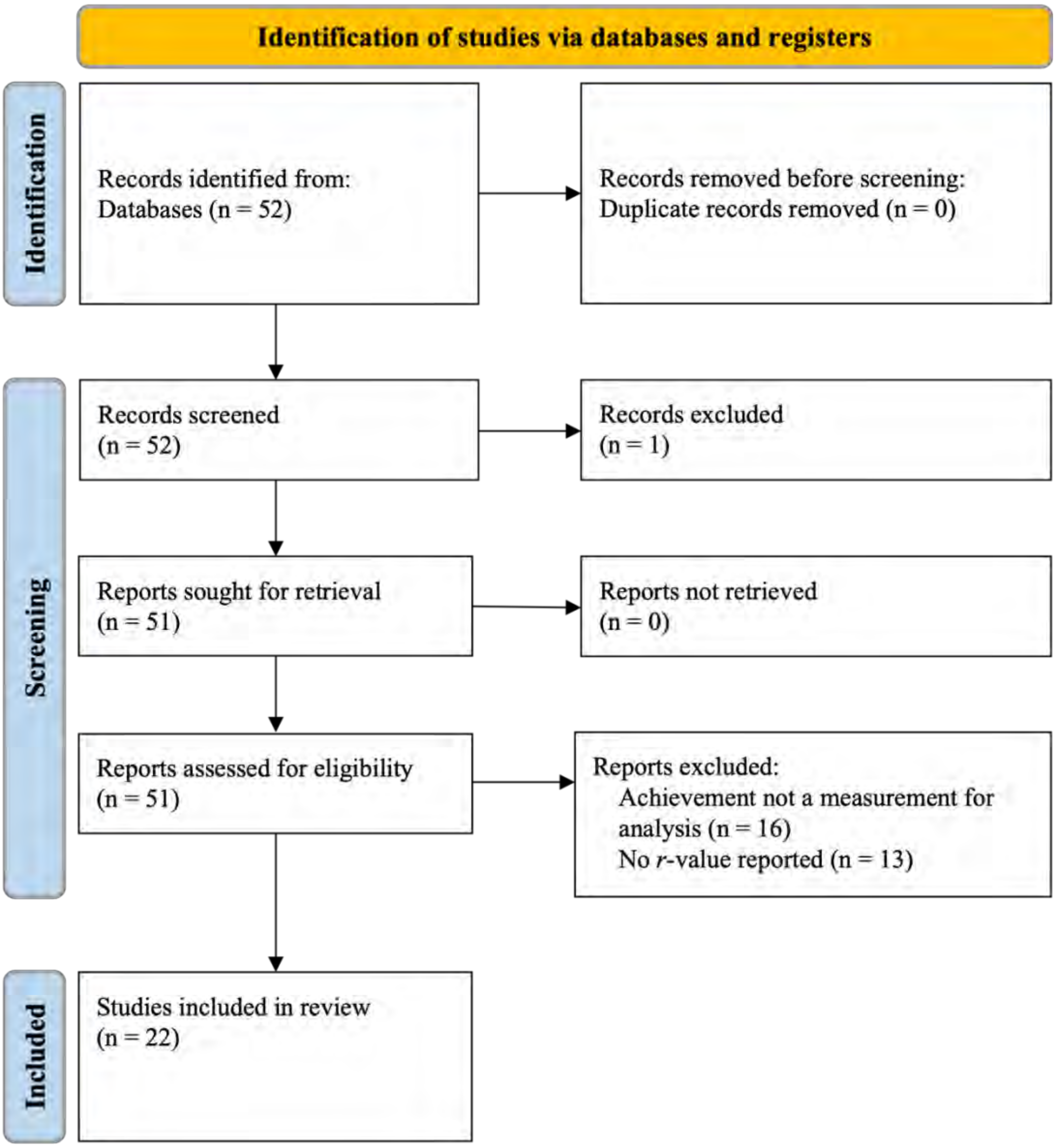
4.1 Study selection

4.1.1 Retained studies

Based on the exclusion criteria established for conducting meta-analysis research, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were followed to identify and screen all studies for eligibility into the meta-analysis (Moher et al., 2009). PRISMA guidelines were supplemented by flow diagrams as indicated on Figures 4.1 and 4.2. The first meta-analysis consolidated all studies that investigated the relationship between tertiary students' attitudes towards statistics and their achievement in statistics. Figure 4.1 represents the flow diagram for the selection of studies to the first segment of the above analysis.

Figure 4.1

2020 PRISMA Flow Diagram of Retained Studies for Meta-Analysis (Tertiary Students)

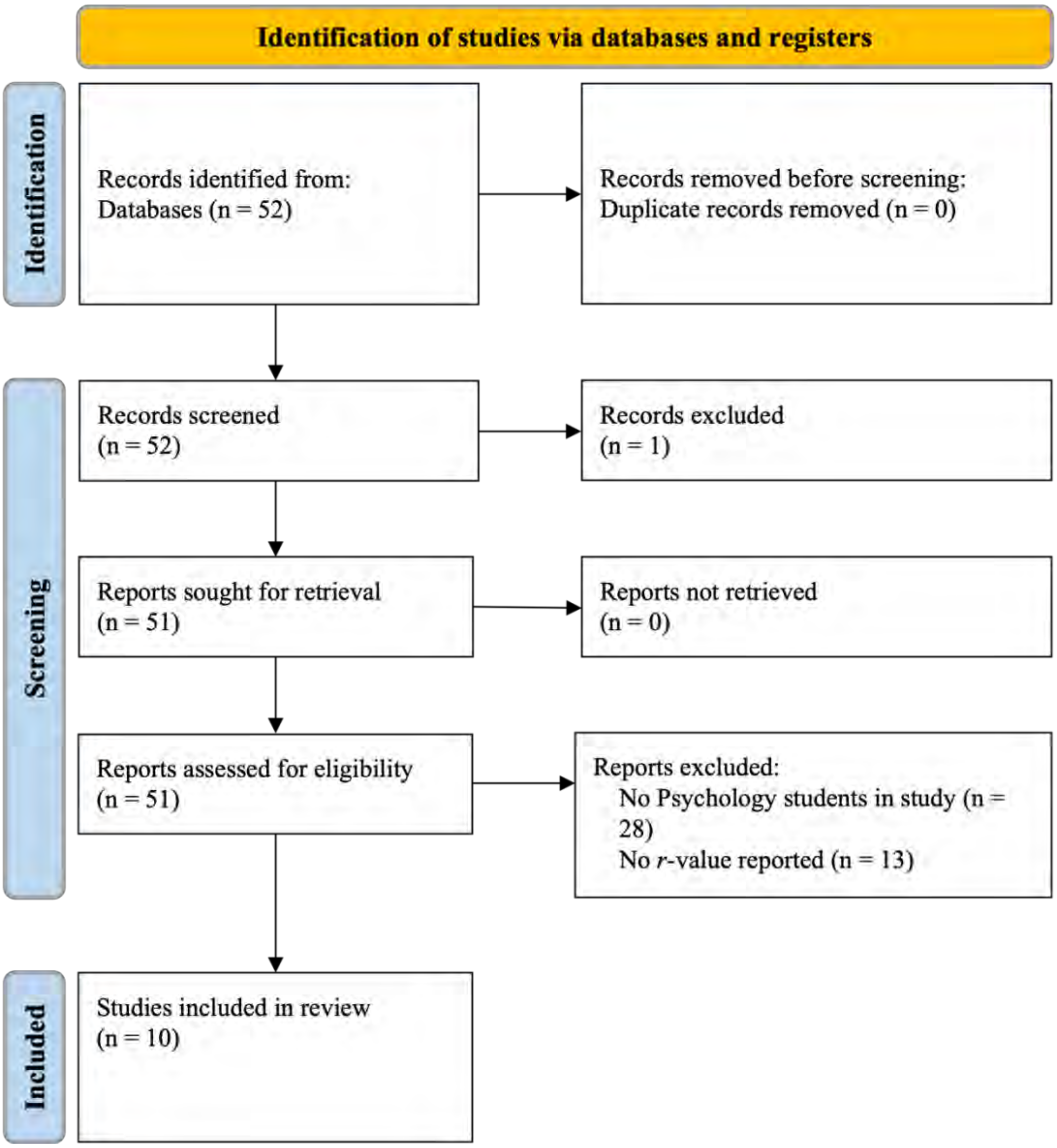


The original meta-analysis by Emmioglu and Capa-Aydin (2012) included 17 studies. A similar approach was followed in the inclusion criteria of the studies for my updated meta-analysis. Only studies written in English were included in the meta-analysis, all my meta-analysis included studies published in the 2012 article by Emmioglu and Capa-Aydin (2012) in addition to studies published in the 11 subsequent years following the original study.

A second meta-analysis was performed to investigate the relationship between attitudes towards statistics and achievement in statistics course amongst Psychology students – i.e., research articles with Psychology students as participants. Figure 4.2 represents the flow diagram illustrating the screening and eligibility criteria of studies meeting the additional criteria, that contain Psychology students.

Figure 4.2

2020 PRISMA Flow Diagram of Retained Studies for Meta-Analysis (Psychology Students)



10 studies were retained for the second meta-analysis. Of the excluded studies, four studies were excluded for not reporting Pearson's correlation coefficient data. More studies were excluded as they did report achievement measurements for Psychology students (Carlson & Winquist, 2011; Chowdhury et al., 2018; Coetzee & van der Merwe, 2010; Jatnika, 2015). Carlson and Winquist (2011) and Coetzee and van der Merwe (2010) opted to use Spearman's correlation coefficient to investigate the relationship and were thus excluded from the meta-analysis. Additionally, some studies with Psychology students that reported on attitudes

towards statistics, did not comment on the relationship between achievement in statistics and attitudes towards statistics and were thus excluded from the analysis (i.e., Counsell & Cribbie, 2019; Emmioğlu Sarikaya et al., 2018; Khavenson et al., 2012; Liau et al., 2014; Ngantweni, 2019; Ruggeri et al., 2008). Counsell and Cribbie reported demographic information and SATS responses of three different groups of Psychology students, and these were treated as three different studies.

4.1.2 Meta-Analysis 1: Study Characteristics for *All* Tertiary Students

Two studies from the original meta-analysis by Emmioğlu and Capa-Aydin (2012) were not included in this meta-analysis, as the authors included a Turkish study, and the other provided details based on author personal consultation. Two additional studies published in the same year as the meta-analysis by Emmioğlu and Capa-Aydin (2012) were included in the overall meta-analysis (Hood et al., 2012; Zhang et al., 2012). Chiesi and Primi conducted a correlational analysis on a pre-and post-attitude towards statistics and subsequent achievement in statistics course comprising 232 Psychology students. The authors later published an additional correlational analysis based on their original sample to include 487 Psychology students (Chiesi & Primi, 2009, 2010). These studies were included in the meta-analysis and recorded as separate studies for the meta-analysis. The first meta-analysis retained 22 studies as summarised in Table 4.1. Further information enclosed in Table 4.1 includes demographic data detailing the location of the study, number of participants (n), student majors, and the achievement indicator.

Table 4.1

Study characteristics of retained studies involving university students for meta-analysis

Study	Country	Student major	n	Measure of statistics achievement
Schutz et al. (1998)	US	Counselling Psychology, Education, Nursing, School Psychology	94	Overall course grade
Scott (2001)	US	Arts & Sciences, Health Sciences, Technology and Business	117	Previous mathematics results
Sorge and Schau (2002)	US	Engineering	264	Overall course grade
Finney and Schraw (2003)	US	Educational Psychology	103	Overall course grade
Schau (2003)	US	Not specified	268	Overall course grade
Stone et al. (2003)	US	Communications, Engineering, Mathematics	139	SCI score
Nasser (2004)	Israel	Teaching	162	Exam result
Cashin and Elmore (2005)	US	Not specified	342	Overall course grade
Tempelaar et al. (2006)	Netherlands	Business, Economics	2031	SRA scores
Estrada and Batanero (2008)	Spain	Teaching	367	SRA scores
Chiesi and Primi (2009)	Italy	Psychology	232	Overall course grade
Dempster and McCorry (2009)	UK	Psychology	82	Exam result
Chiesi and Primi (2010)	Italy	Psychology	487	Overall course grade
Emmioglu (2011)	Turkey	Applied Mathematics, Business Administration, Economics, Education, Engineering, Psychology, Sociology	247	Overall course grade
Hood, Creed and Neumann (2012)	Australia	Psychology	149	Overall course grade
Zhang et al. (2012)	China	Medicine	539	Exam result
Zimprich (2012)	Switzerland	Psychology	346	Created test
Clark (2013)	US	Not specified	1125	Overall course grade
Oguan et al. (2013)	Philippines	Astronomy, Biology, Entrepreneurial Management, Management, Marketing, Political Science, Psychology, Statistics	863	Overall course grade
Stanisavljevic (2014)	Serbia	Medicine	415	Exam result
Sesé et al. (2015)	Spain	Nursing, Physiotherapy, Psychology	472	Exam result
Melad (2022)	Philippines	Accountancy, Entrepreneurship, Financial Management, Legal Management, Marketing Management	560	Overall course grade

Note. *N* = number of participants who completed the SATS survey

Of the included studies, eight studies were conducted in the US (Cashin & Elmore, 2005; Clark, 2013; Finney & Schraw, 2003; Schau, 2003; Schutz et al., 1998; Scott, 2001; Sorge & Schau, 2002; Stone et al., 2003), 11 on the Eurasian continent (Chiesi & Primi, 2009, 2010; Dempster & McCorry, 2009; Emmioğlu, 2011; Estrada & Batanero, 2008; Nasser, 2004; Sesé et al., 2015b; Stanisavljevic et al., 2014; Tempelaar et al., 2006; Zhang et al., 2012; Zimprich, 2012), two in the Philippines (Melad, 2022; Oguan et al., 2013) and one in Australia (Hood et al., 2012). The number of participants ranged from 82 students (Dempster & McCorry, 2009) to 2031 students (Tempelaar et al., 2006). Three studies (Cashin & Elmore, 2005; Clark, 2013; Schau, 2003) did not specify the major of the students. 10 studies included Psychology student's participation (Chiesi & Primi, 2009, 2010; Dempster & McCorry, 2009; Emmioğlu, 2011; Finney & Schraw, 2003; Hood et al., 2012; Oguan et al., 2013; Schutz et al., 1998; Sesé et al., 2015b; Zimprich, 2012) and would be analysed in a subgroup analysis in the second meta-analysis. In summary, the analysis of statistics attitudes and achievement included studies involving students from commerce, science, medical science and social science backgrounds.

As noted in Table 4.1, the measurement of achievement in statistics courses varied greatly amongst studies. Two studies assessed achievement using Statistical Reasoning Assessment (SRA) scores as a measurement of statistics achievement (Estrada & Batanero, 2008; Tempelaar et al., 2006). Stone et al. (2003) made use of their own instrument, the Statistics Concept Inventory (SCI). Twelve studies used students' course grade percentages as a measure of achievement. Five studies utilised results obtained from on a statistics exam set by the course educators as a measure of achievement (Dempster & McCorry, 2009; Nasser, 2004; Sesé et al., 2015b; Stanisavljevic et al., 2014; Zhang et al., 2012). Scott (2001) used prior mathematics results as a measure of statistics achievement. Zimprich (2012) opted to design and administer their own statistics test to measure student's achievement.

4.1.3 Meta-Analysis 2: Study characteristics for Studies *Only* Reporting Psychology Students

From the above summary of study characteristics, the studies involving Psychology students were isolated for further analysis. The 10 retained studies are summarised in Table 4.2. Again, the studies by Chiesi and Primi were recorded as separate studies in aligning with the approach used by Emmioğlu and Capa-Aydin (2012). My updated meta-analysis included four studies that appeared in the original meta-analysis by Emmioğlu and Capa-Aydin (2012).

Information enclosed in Table 2 details data pertaining to the location of the study, number of participants (*n*), student majors (Psychology and other majors), and the achievement indicator.

Table 4.2

Study characteristics of retained studies involving Psychology students for meta-analysis

Study	Country	Student major	n	Measure of statistics achievement
Schutz et al. (1998)	US	Counselling Psychology, Education, Nursing, School Psychology	94	Overall course grade
Finney and Schraw (2003)	US	Educational Psychology	103	Overall course grade
Chiesi and Primi (2009)	Italy	Psychology	232	Overall course grade
Dempster and McCorry (2009)	UK	Psychology	82	Exam result
Chiesi and Primi (2010)	Italy	Psychology	487	Overall course grade
Emmioglu (2011)	Turkey	Applied Mathematics, Business Administration, Economics, Education, Engineering, Psychology, Sociology	247	Overall course grade
Hood, Creed and Neumann (2012)	Australia	Psychology	149	Overall course grade
Zimprich (2012)	Switzerland	Psychology	346	Created assessment
Oguan et al. (2013)	Philippines	Astronomy, Biology, Entrepreneurial Management, Management, Marketing, Political Science, Psychology, Statistics	863	Overall course grade
Sesé et al. (2015)	Spain	Nursing, Physiotherapy, Psychology	472	Exam result

Note. *n* = number of participants who completed the SATS survey

Two studies were conducted in the US (Finney & Schraw, 2003; Schutz et al., 1998), six on the Eurasian continent (Chiesi & Primi, 2009, 2010; Dempster & McCorry, 2009; Emmioğlu, 2011; Sesé et al., 2015b; Zimprich, 2012), one in the Philippines (Oguan et al., 2013) and one in Australia (Hood et al., 2012). The number of participants ranged from 82 students (Dempster & McCorry, 2009) to 863 students (Oguan et al., 2013). Four studies included students with additional majors besides Psychology, from medical science, commerce, science, education and social science faculties (Emmioğlu, 2011; Oguan et al., 2013; Schutz et al., 1998; Sesé et al., 2015b). Seven studies made use of the overall course grade as an indicator of statistics achievement (Chiesi & Primi, 2009, 2010; Emmioğlu, 2011; Finney & Schraw, 2003; Hood et al., 2012; Oguan et al., 2013; Schutz et al., 1998). The results of an examination were used as the achievement measure in two studies (Ruggeri et al., 2008; Sesé et al., 2015), while Zimprich (2012) made use of a self-created statistics assessment.

4.2 Meta-Analysis 1: University Students' Attitudes Towards Statistics

A meta-analysis was performed on the 22 retained studies using Meta-Essentials plugin for Microsoft Excel (Suurmond et al., 2017). The effect sizes were calculated using Fisher's r-to-z transformation, using Pearson's correlation coefficient (r) values and sample size (n) from each of the studies. The correlation coefficient was calculated as the relationship between the SATS components, namely, *Affect*, *Cognitive Competence*, *Value* and *Difficulty.* These measures were correlated to the measure of achievement in Statistics as detailed in each of the studies. As previously noted, achievement measures were denoted in various studies by standardized instruments, including high school mathematics final results, statistics course grades, exam results, or compiled statistics tests. As opposed to a fixed effects model, a random effects model was chosen to calculate effect measures. This method is more appropriate for research in the social sciences such as this which involves students reporting subjective feelings, that can be extrapolated to the population. It was found that the model converged into a fixed effects model, which indicates that enough assumptions were met in the data for this form of analysis.

4.2.1 Forest plots

Forest plots were utilised to depict the overall effect contribution of each study to provide summary effects in the form of point estimates, namely 95% confidence intervals (CIs) (Borenstein et al., 2009; Hak et al., 2016). Forest plots show the extent to which the overall effect is based on the studies used –i.e., the weight that the studies carry. Secondly, forest plots help visualise how the effect sizes of the studies compare and show if these results align (Borenstein et al., 2009). In this meta-analysis, the forest plot indicates the correlations between the attitude components (i.e., Value, Cognitive Competence, Effort, Difficulty) and achievement in statistics. Following Borenstein et al. (2009), a random effects model estimator was used with the raw correlation coefficients coded as the model measure. The effect size in the form of the correlation coefficient is shown on the x-axis of the Forest Plot. The extending lines represent the 95% confidence interval that were utilised, with no moderators applied.

As noted in Figure 4.3-4.6 and later in Figure 4.7-4.10, the correlation coefficient (r), which is the effect, is represented by the middle point within the Forest Plot. Weights of the studies, i.e., the degree to which a study influences overall effect sizes, based on their statistical significance and sample size, are represented by the area of circle surrounding the r point. Large weights were reported for studies with large sample sizes (e.g., Tempelaar et al. (2006)), as indicated in Figure 4.3-4.7. For the first meta-analysis, the global correlation score, i.e., the combined effect size for the analysis was calculated to be $r = 0.25$. This effect was found to be statistically significant at the 5% level ($p < 0.05$). The extending lines in Figure 4.3-4.7 represent the 95% confidence interval. Ideally, confidence intervals are narrow, indicating a greater precision in studies and estimate of where effect sizes in studies are likely to fall (Borenstein et al., 2009).

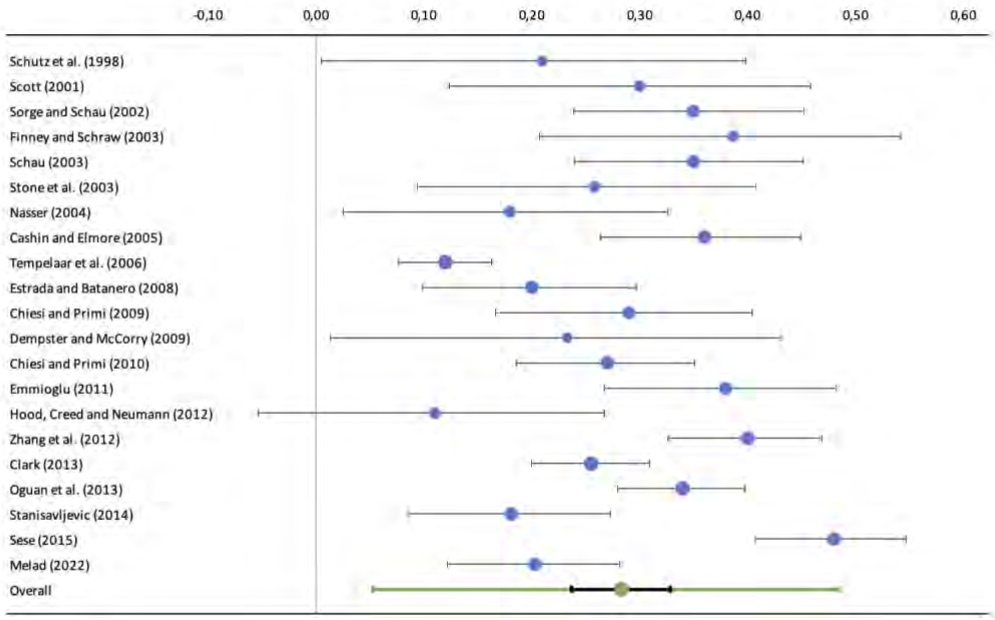
Individual Forest Plots (Affect, Cognitive Competence, Value and Difficulty) and Relationship to Achievement

Affect and Achievement

As indicated in Figure 4.3, the overall effect size for *Affect* was calculated to be a small, yet statistically significant, $r = 0.28$ (95% CI, 0.24 – 0.33, $p < 0.05$). The calculated effect was slightly lower than the effect reported in Emmioglu and Capa-Aydin (2012), $r = 0.30$ (95% CI, 0.05 – 0.49, $p < 0.05$) for *Affect*.

Figure 4.3

Forest plot of Affect and achievement correlation at 95% confidence interval



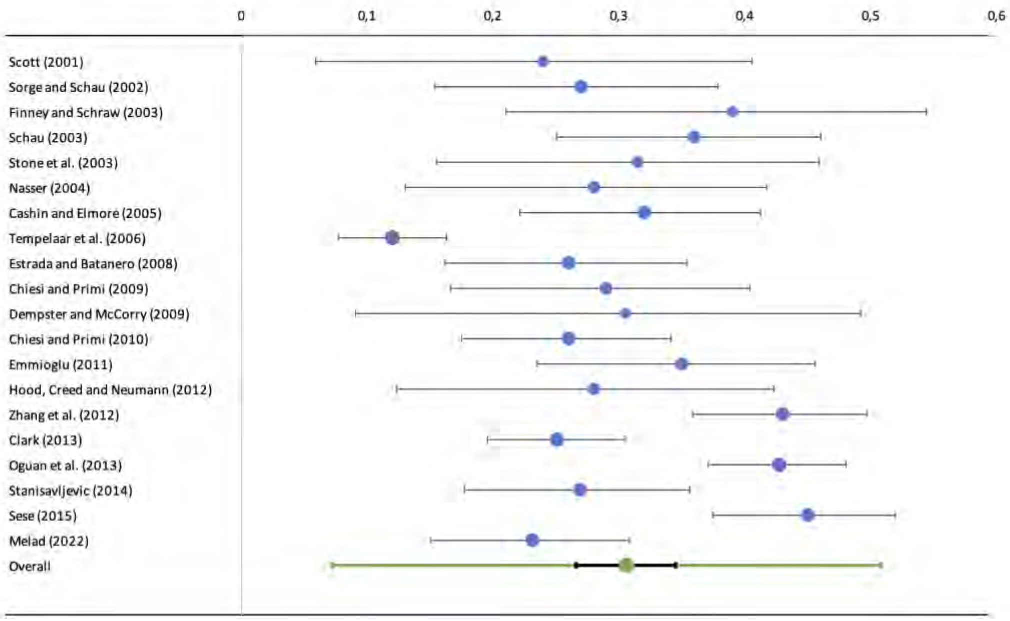
Note. Overall effect size and 95% CI shown as final chart value.

Cognitive Competence and Achievement

As indicated in Figure 4.4, *Cognitive Competence* had the highest overall global correlation score, $r = 0.31$ (95% CI, 0.27 – 0.34, $p < 0.05$), indicating a medium and statistically significant relationship. Emmioglu and Capa-Aydin (2012) also calculated a medium effect size, $r = 0.30$ (95% CI, 0.28 – 0.32, $p < 0.05$).

Figure 4.4

Forest plot of Cognitive Competence and achievement correlation at 95% confidence interval



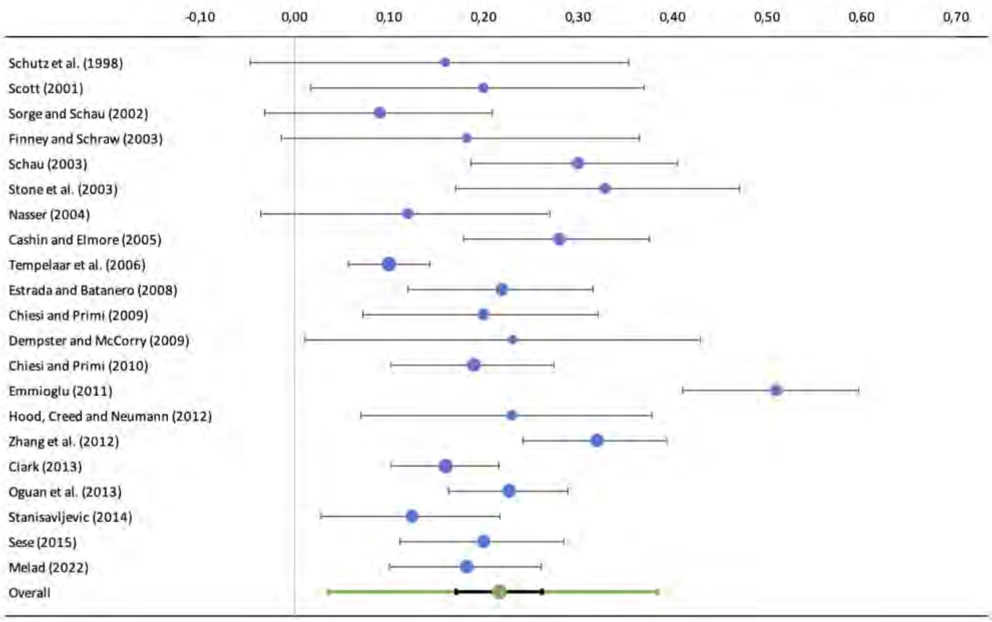
Note. Overall effect size and 95% CI shown as final chart value.

Value and Achievement

As indicated in Figure 4.5, a small, statistically significant overall effect size was calculated for *Value*, $r = 0.22$ (95% CI, 0.17 - 0.26, $p < 0.05$). Emmioglu and Capa-Aydin (2012) also reported a small effect size for Value, $r = 0.21$ (95% CI, 0.19 – 0.23, $p < 0.05$).

Figure 4.5

Forest plot of Value and achievement correlation at 95% confidence interval



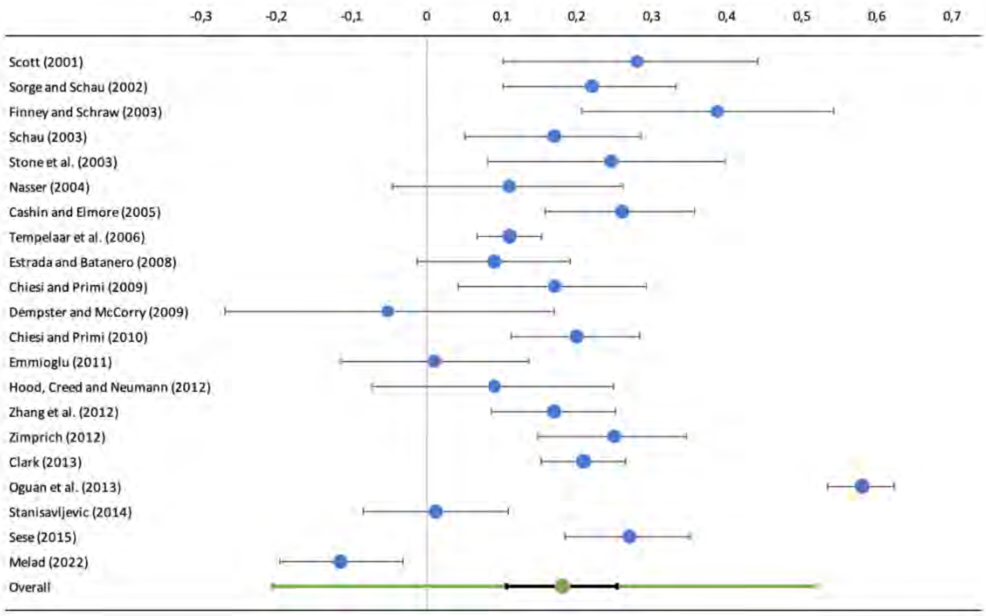
Note. Overall effect size and 95% CI shown as final chart value.

Difficulty and Achievement

As indicated in Figure 4.6, the overall effect size for *Difficulty* was small but statistically significant, $r = 0.18$ (95% CI, 0.11 – 0.25, $p<0.05$). A small effect size $r = 0.20$ (95% CI, 0.17 – 0.22, $p < 0.05$) was also reported by Emmioglu and Capa-Aydin (2012).

Figure 4.6

Forest plot of Difficulty and achievement correlation at 95% confidence interval



Note. Overall effect size and 95% CI shown as final chart value.

4.2.2 Effect sizes of SATS components

To investigate the effect sizes for each SATS component, *Affect*, *Cognitive Competence*, *Value* and *Difficulty*, the components were treated as study subgroups, and subgroup analysis were hence performed. Subgroup analysis allows for better interpretation of forest plot results, as individual study correlations are then analysed for statistical significance. Table 4.3 summarizes the subgroup analysis on the SATS components of the studies, as reported by Pearson Correlation Coefficients.

Table 4.3

Pearson correlation coefficients (r) of SATS components and achievement for university students

Study	n	Affect	Cognitive Competence	Value	Difficulty
Schutz et al. (1998)	94	0.21*	-	0.16	-
Scott (2001)	117	0.30*	0.24*	0.20*	0.28*
Sorge and Schau (2002)	264	0.35*	0.27*	0.09	0.22*
Finney and Schraw (2003)	103	0.387*	0.39*	0.182	0.387*
Schau (2003)	268	0.35*	0.36*	0.30*	0.17*
Stone et al. (2003)	139	0.258*	0.315*	0.329*	0.246*
Nasser (2004)	162	0.18*	0.28*	0.12	0.11
Cashin and Elmore (2005)	342	0.36*	0.32*	0.28*	0.26*
Tempelaar et al. (2006)	2031	0.12*	0.12*	0.10*	0.11*
Estrada and Batanero (2008)	367	0.20*	0.26*	0.22*	0.09
Chiesi and Primi (2009)	232	0.29*	0.29*	0.20*	0.17*
Dempster and McCorry (2009)	82	0.233*	0.305*	0.231*	-0.052
Chiesi and Primi (2010)	487	0.27*	0.26*	0.19*	0.20*
Emmioglu (2011)	247	0.38*	0.35*	0.51*	0.01
Hood, Creed and Neumann (2012)	149	0.11	0.28*	0.23*	0.09
Zhang et al. (2012)	539	0.40*	0.43*	0.32*	0.17*
Zimprich (2012)	346	-	-	-	0.25*
Clark (2013)	1125	0.255*	0.251*	0.160*	0.209*
Oguan et al. (2013)	863	0.340*	0.427*	0.227*	0.580*
Stanisavljevic (2014)	415	0.181*	0.269*	0.124*	0.012
Sesé et al. (2015)	472	0.48*	0.45*	0.20*	0.27*
Melad (2022)	560	0.203*	0.231*	0.182*	-0.115*
Overall		0.28*	0.31*	0.22*	0.18*

Note. * $p < 0.05$

As noted in Table 4.3, there was large variation in the subgroup analysis conducted on the component responses. The largest study included 2031 participants (Tempelaar et al., 2006), whilst the smallest study had 82 participants (Dempster & McCorry, 2009). Most relationships within the subgroup analysis were positively correlated (e.g., Cashin and Elmore (2005), Oguan et al. (2013), Sesé et al. (2015)). Negative relationships between achievement and *Difficulty* were noted in two studies, Melad et al. (2022) r = -0.115, and Dempster and McCorry (2009) r = -0.052. The latter negative correlation was found to be statistically insignificant.

Of the subgroup analysis, the attitude components *Affect* and *Cognitive Competence* had the strongest relationships to achievement. Of the 21 studies included in the subgroup analysis, 20 studies returned statistically significant finding in relationship to *Affect*, with the highest correlation, reported by Sesé et al. (2015) (r = 0.48). Twenty studies were included for *Cognitive Competence,* and all were found to be statistically significant with the highest correlation reported in Sesé et al. (2020), (r = 0.45). While 21 studies were included in the subgroup analysis of *Value*, only 17 studies were found to be statistically significant. The highest correlation was a large, statistically significant effect size, $r = 0.51$ (Emmioğlu, 2011). There were 21 studies in the *Difficulty* subgroup analysis. The largest correlation in the meta-analysis reported for Difficulty, $r = 0.580$ was the study by Oguan et al. (2013). Given significant findings on the subgroup analysis in relation to *Affect*, *Cognitive Competence*, *Value* and *Difficulty,* heterogeneity measures were conducted on the data to study variance effects on the effect sizes.

4.2.3 Heterogeneity measures

Within meta-analysis research, heterogeneity seeks to draw meaningful conclusions about results obtained in a meta-analysis by measuring between-studies variance (Higgins & Thompson, 2002). Between-studies variance refers to differences in effect sizes that may have arisen due to variability in study design (Deeks et al., 2020). It was necessary to assess heterogeneity for this meta-analysis, since studies differed in their location (US, Eurasian continent, Philippines, Australia), including the majors of students (commerce, medicine, sciences, social sciences) as well as outcome measures for achievement. Heterogeneity within each attitude component is indicated in Table 4.4.

Table 4.4

Heterogeneity statistics for effect sizes

	Affect	Cognitive Competence	Value	Difficulty	Overall
Q	121.48*	124.47*	79.55*	303.05	690.92*
df (*Q*)	20	19	20	20	21
p_Q	0.000	0.000	0.000	0.000	0.000
I^2	83.54%	84.74%	74.86%	93.40%	88.13%
Predictive interval	0.05-0.49	0.07-0.51	0.04-0.38	-0.21-0.52	-0.01-0.47

Note. * $p < 0.001$

Two primary measures are reported for Heterogeneity, namely the *Q*-statistic and I^2. The *Q*-statistic compares the observed weighted sum of squares to the expected sum of squares, in order to reveal excess variation which is attributed to differences in the true effects of the studies. The I^2 value is expressed as a percentage, indicating the degree to which variability in effect sizes is due to heterogeneity within the results. Simply stated, I^2 describes the relative measure for the proportion of observed variance within the studies.

Results indicated that the degrees of freedom were calculated as 20 for the components, *Affect*, *Value* and *Difficulty*. The degrees of freedom were calculated as 19 for *Cognitive Competence*. *Q*-statistic calculation indicted heterogeneity as follows: *Affect*, $Q\ (20) = 121.48$, *Cognitive Competence*, Q (19) = 124.47, *Value*, Q (20) = 121.48, and *Difficulty*, Q (20) = 303.05. The results indicate excess dispersion observed within all the components; indicating that the observed variation between studies is greater than what is expected for between-studies error. Simply stated, this means that differences observed in the study effect sizes, are likely due to differences in methodological or clinical heterogeneity.

The I^2 value for *Affect* indicates that 83.54% of the variability is attributable to between-study variation, and an exact true effect size is difficult to ascertain. *Cognitive Competence* indicated 84.74% variability. *Value* indicated, 74.86% variability. Lastly, there was 93.40% of variability for *Difficulty*. The overall I^2 heterogeneity was 88.13% indicating that studies had overall variation that was due to methodological or clinical heterogeneity.

In summary, according to meta-analysis guidelines (Higgins & Thompson, 2002), the above results represent notable heterogeneity in all attitude components (Affect, Cognitive Competence, Value, Difficulty), which is likely a result of methodological differences related to study location, the majors of student participants, and achievement (outcome) measures. This heterogeneity, however, does not mean that the effect sizes calculated are not significant – there is still a statistically significant relationship between students' attitudes and achievement, but there are differences in study characteristics that exist within the meta-analysis.

4.3 Meta-Analysis 2: Psychology Students' Attitudes towards Statistics

The second meta-analysis was performed on the ten retained studies involving Psychology students. A random effects model was applied to the data. The effect sizes were calculated using Fisher's r-to-z transformation, with Pearson's correlation coefficient (r) values and sample size (n) from each of the ten studies. The correlation coefficient represented the relationship between the SATS components (*Affect*, *Cognitive Competence*, *Value*, *Difficulty*,) and achievement. Similar to the first analysis, achievement was measured by statistics course grades, exam results, or compiled statistics tests. Results for the second analysis represent the relationship between Psychology students' attitudes towards statistics and achievement in statistics courses.

4.3.1 Forest plots

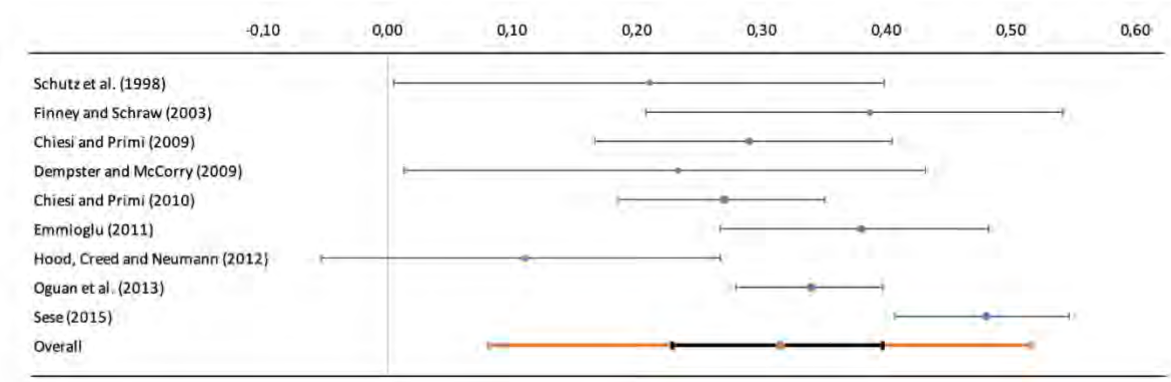
Forest plots for the meta-analysis obtained using Meta-Essentials for Excel (Suurmond et al., 2017). A random effects model estimator was used with a 95% confidence interval and no moderators. A statistically significant global correlation score was calculated with a moderate confidence interval, $r = 0.28$ (95% CI, 0.23 – 0.33, $p < 0.05$). The individual forest plots for each component and its correlation to achievement measures are shown in Figures 4.7-4.10.

Affect and achievement

In Figure 4.7 the effect size for *Affect* was calculated to be r = 0.32 (95% CI, 0.08 – 0.52, $p < 0.05$). This represents a significant, medium effect for *Affect* on achievement among Psychology students. This effect represents a higher effect than the above for university students, r = 0.28, and that reported in Emmioglu and Capa-Aydin (2012), r = 0.30.

Figure 4.7

Forest plot of Affect and achievement correlation at 95% confidence interval



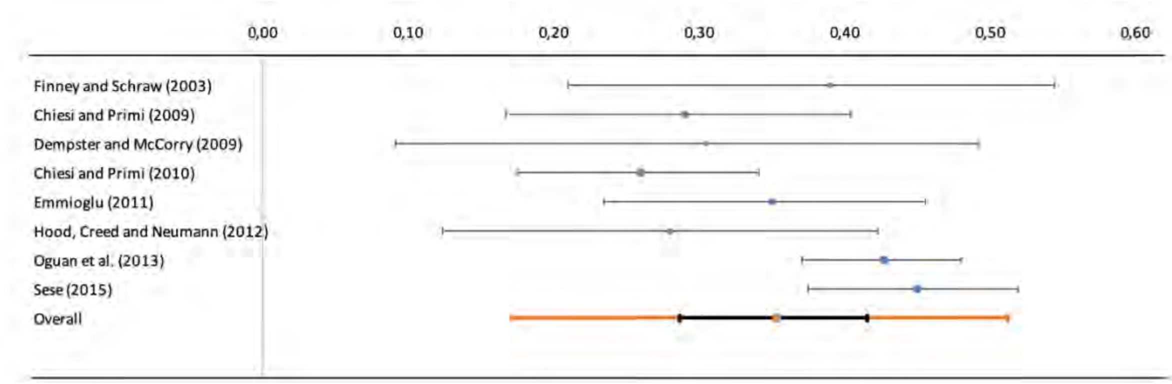
Note. Overall effect size and 95% CI shown as final chart value.

Cognitive Competence and achievement

Cognitive Competence also had the highest overall global correlation score among Psychology students, as seen in Figure 4.8. This was a medium, statistically significant relationship, r = 0.35 (95% CI, 0.29 – 0.42, $p < 0.05$). The effect size among university students, r = 0.31, and that reported by Emmioglu and Capa-Aydin (2012), r = 0.30, were also medium, but lower.

Figure 4.8

Forest plot of Cognitive Competence and achievement correlation at 95% confidence interval



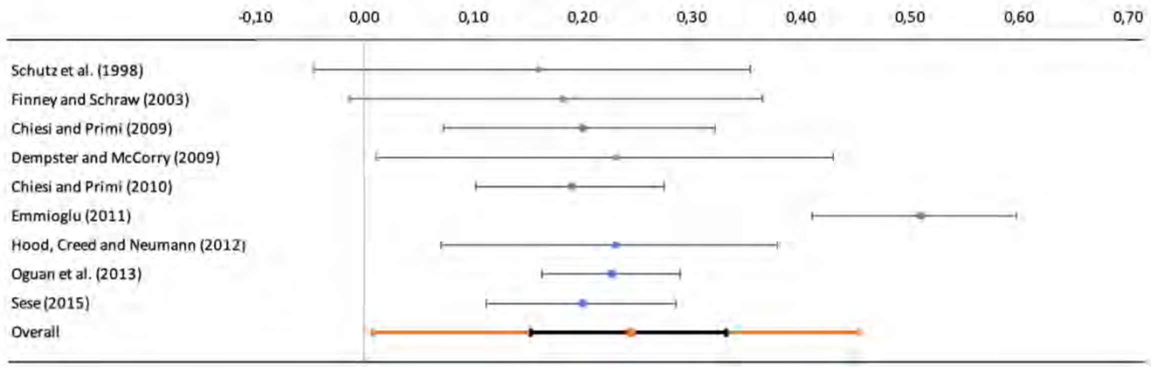
Note. Overall effect size and 95% CI shown as final chart value.

Value and achievement

For the *Value* component in studies including Psychology students, a small, statistically significant overall effect size was calculated, $r = 0.24$ (95% CI, 0.15 – 0.33, $p < 0.05$). This is seen in Figure 4.9 below. Emmioglu and Capa-Aydin (2012) also reported a similar small effect size for Value, $r = 0.21$, and the effect size calculated in this enquiry for university students was also small, $r = 0.22$.

Figure 4.9

Forest plot of Value and achievement correlation at 95% confidence interval



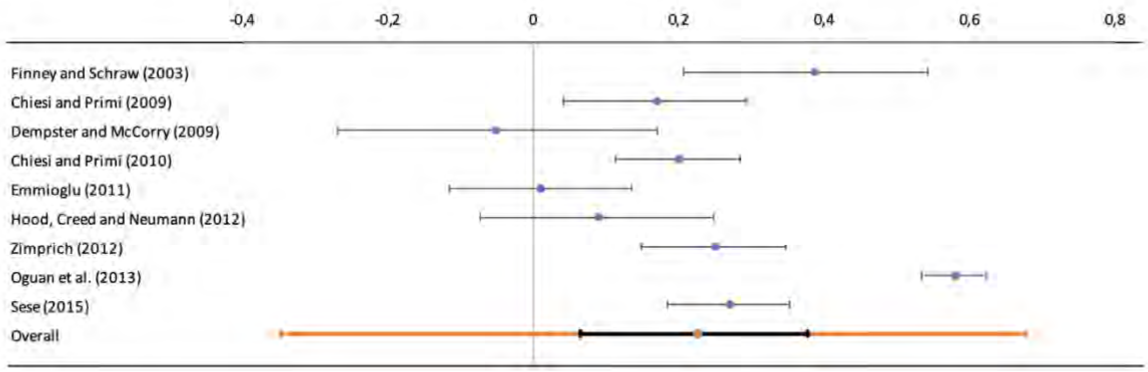
Note. Overall effect size and 95% CI shown as final chart value.

Difficulty and achievement

There was a small but statistically significant overall effect size for *Difficulty*, $r = 0.23$ (95% CI, 0.06 – 0.38, $p < 0.05$) seen in Figure 4.10. A small effect size was also calculated in the meta-analysis on university students, $r = 0.18$, and Emmioglu and Capa-Aydin (2012), $r = 0.20$.

Figure 4.10

Forest plot of Difficulty and achievement correlation at 95% confidence interval



Note. Overall effect size and 95% CI shown as final chart value.

4.3.2 Subgroup Analysis

Subgroup analysis was run on the data. Results are summarized in Table 4.5. Pearson correlation coefficients, sample sizes, and statistically significant studies at the 95% confidence level are indicated.

Table 4.5

Pearson correlation coefficients (r) of SATS components and achievement for Psychology students

Study	n	Affect	Cognitive Competence	Value	Difficulty
Schutz et al. (1998)	94	0.21*	-	0.16	-
Finney and Schraw (2003)	103	0.387*	0.39*	0.182	0.387*
Chiesi and Primi (2009)	232	0.29*	0.29*	0.20*	0.17*
Dempster and McCorry (2009)	82	0.233*	0.305*	0.231*	-0.052
Chiesi and Primi (2010)	487	0.27*	0.26*	0.19*	0.20*
Emmioglu (2011)	247	0.38*	0.35*	0.51*	0.01
Hood, Creed and Neumann (2012)	149	0.11	0.28*	0.23*	0.09
Zimprich (2012)	346	-	-	-	0.25*
Oguan et al. (2013)	863	0.340*	0.427*	0.227*	0.580*
Sesé et al. (2015)	472	0.48*	0.45*	0.20*	0.27*
Overall		0.32*	0.35*	0.24*	0.23*

Note. * $p < 0.05$

Due to missing data, nine studies were included in the subgroup analysis for *Affect*, *Value* and *Difficulty*, while eight studies were included for *Cognitive Competence*. All eight studies for *Cognitive Competence* were found to be statistically significant at 95% confidence level (Chiesi & Primi, 2009, 2010; Dempster & McCorry, 2009; Emmioglu, 2011; Finney & Schraw, 2003; Hood et al., 2012; Oguan et al., 2013; Sesé et al., 2015b). Eight of nine studies were statistically significant for *Affect* (Chiesi & Primi, 2009, 2010; Dempster & McCorry, 2009; Emmioglu, 2011; Finney & Schraw, 2003; Oguan et al., 2013; Schutz et al., 1998; Sesé et al., 2015b), seven for *Value* (Chiesi & Primi, 2009, 2010; Dempster & McCorry, 2009; Emmioglu, 2011; Hood et al., 2012; Oguan et al., 2013; Sesé et al., 2015b), and six for *Difficulty* (Chiesi & Primi, 2009, 2010; Finney & Schraw, 2003; Oguan et al., 2013; Sesé et al., 2015b; Zimprich, 2012). A negative correlation was reported for *Difficulty* by Dempster and McCorry (2009). This correlation was found to be statistically insignificant. Sample size estimates ranged from 82 (Dempster and McCorry, 2009) to 863 (Oguan et al., 2013).

As per the above meta-analysis, *Affect* and *Cognitive Competence* had the largest overall effect sizes. The largest effect size for *Affect* and *Cognitive Competence* were reported by Sesé et al. (2015), $r = 0.48$ and $r = 0.45$ respectively. The largest effect size for *Value* was

$r = 0.51$ (Emmioglu, 2011). The largest effect size for Difficulty was $r = 0.58$ (Oguan et al., 2013).

4.3.3 Heterogeneity measures

The *Q*-statistic and I^2 value were used to investigate between-studies variance. In Table 4.6, heterogeneity among the studies involving psychology students is reported along with predictive intervals.

Table 4.6

Heterogeneity statistics for effect sizes

	Affect	Cognitive Competence	Value	Difficulty	Overall
Q	29.28	19,48	28.41	157.39	264.92
df (*Q*)	8	7	8	8	9
p_Q	0.000	0.000	0.000	0.000	0.000
I^2	72.68%	64.07%	71.84%	94.92%	87.17%
Predictive interval	0.08-0.52	0.17-0.51	0.04-0.38	-0.35-0.68	-0.02-0.53

Note. * $p < 0.001$

Degrees of freedom were calculated as 8 for *Affect*, *Value* and *Difficulty*, and 7 for *Cognitive Competence*. Smaller *Q*-statistics were observed for all components for Psychology students when compared to university students, The *Q*-statistic calculated for the components were: *Affect*, Q (8) = 29.28, *Cognitive Competence*, Q (7) = 19.48, *Value*, Q (8) = 28.41, and *Difficulty*, Q (8) = 157.39. The results represent that excess dispersion was observed in all components, but there was less excess variation between studies. Differences in study effect sizes are likely due to differences in methodological or clinical heterogeneity. However, this measure alone is not adequate for meta-analyses involving a small number of studies (Higgins & Thompson, 2002).

The I^2 values confirms the above assumptions and indicated a 72.68% variability in *Affect* due to between-study variation. Compared to the total university student population in the first meta-analysis, this means that there is more homogeneity in results among Psychology students. *Cognitive Competence* had the smallest I^2 value and was also lower than the first meta-analysis, representing 64.07% variability. *Value* indicated 71.84% variability, which was also lower than the first meta-analysis. *Difficulty* had the highest I^2 statistic, 94.92%. This was also observed in the meta-analysis on university students, although more between-studies variability was observed for the Psychology students. The overall I^2 heterogeneity was 87.17%

indicating that studies had overall variation that was due to methodological or clinical heterogeneity.

4.4 Summary of meta-analysis results: Meta-Analysis 1 and 2

Table 4.7 provides a summary of the effect sizes juxtaposed between all university students and Psychology students, including 95% confidence intervals and heterogeneity statistics.

Table 4.7

Meta-analysis results for university and Psychology students

		University students	Psychology students
Affect	r	0.28**	0.32**
	95% CI	0.24 – 0.33	0.23 – 0.40
	Q	*Q* (20) = 121.48*	*Q* (8) = 29.28*
	I^2	83.54%	72.68%
Cognitive Competence	r	0.31**	0.35**
	95% CI	0.27 – 0.34	0.29 – 0.42
	Q	*Q* (19) = 124.47*	*Q* (7) = 19.48*
	I^2	84.74%	64.07%
Value	r	0.22**	0.24**
	95% CI	0.17 – 0.26	0.15 – 0.33
	Q	*Q* (20) = 79.55*	*Q* (8) = 28.41*
	I^2	74.86%	71.84%
Difficulty	r	0.18**	0.23**
	95% CI	0.11 – 0.25	0.06 – 0.38
	Q	*Q* (20) = 303.05*	*Q* (8) = 157.39*
	I^2	93.40%	94.92%
Overall	r	0.25**	0.28**
	95% CI	0.22 – 0.27	0.23 – 0.33
	Q	*Q* (21) = 690.92*	*Q* (9) = 264.92*
	I^2	88.13%	87.17%

Note. $*p < 0.01$, $**p < 0.05$

When majors were isolated, a larger effect size was observed for studies involving Psychology students as opposed to university students on all four components (*Affect Cognitive Competence Value*, *Difficulty*). A medium effect size was reported for *Cognitive Competence* in both groups, while *Affect* measures ranged from small to medium effect in Psychology studies. It is however worth noting that a wider 95% confidence interval (CI) was observed amongst Psychology studies for all four components, indicating that there is more uncertainty surrounding the true effect size. Heterogeneity was lower in studies with Psychology students for *Affect*, *Cognitive Competence* and *Value,* which showed more homogeneity between studies.

In summary, results from the meta-analysis indicated that there is a *small but significant* relationship between university students' *Affect*, *Value* and *Difficulty* and subsequent achievement in statistics. The meta-analysis also indicated that that there is a *medium, significant* relationship between university students' *Cognitive Competence* and their level of achievement. Within the Psychology meta-analysis, data indicated a *medium, significant* relationship between *Affect* and *Cognitive Competence* on achievement. Similarly, the meta-analysis indicated, a *small, significant* relationship between *Value* and *Difficulty* and achievement. Significant heterogeneity was noted in both meta-analyses. The next chapter provides case study results on the cortical neuroimaging of statistical stimuli amongst Psychology students.

CHAPTER 5
RESULTS: FUNCTIONAL NEAR-INFRARED SPECTROSCOPY

This chapter details findings from the cortical activation of the dorsolateral prefrontal cortex as participants completed the statistical reasoning tasks. Seed-based correlation was performed to assess cortical activation whilst participants completed the tasks. All analyses were processed using Satori Software (Lührs & Goebel, 2017). The case study approach was undertaken to analyse each participant's brain responses, correlated to individual performance on the SATS.

5.1. Participant information

5.1.1 Cranial Measurement

Participant cranial measurement were collected based on suggestions by Yücel et al., (2021). Artemenko et al. (2018) further suggest developmental changes to the bilateral fronto-parietal network, due to age, and how developmental changes influence neuronal activation in fronto-parietal network, in the processing of arithmetic tasks. Given these findings, participant's ages were coupled with cranial measurements, in accordance with best practices for fNIRS research. To protect participant confidentiality, pseudonyms were used for all participant data for the case analysis. Table 5.1 summarizes cranial measurements and the ages of all participants for the fNIRS segment of the study.

Table 5.1

Cranial measurements of participants

Participant pseudonym	Sex	Ear-to-ear across top of head (cm)	Mid-forehead to nape of neck (cm)	Age at start of year	Date of data collection
AL	F	32	33	23	1/6/2022
BN	F	33	33	21	2/6/2022
CH	F	32	33	22	2/6/2022
DT	F	34	34	22	2/6/2022
EV	M	33	31	21	2/6/2022
FN	F	34	34	22	3/8/2022
GH	F	34	31	23	4/8/2022
HN	F	35	31	22	16/8/2022
TI	M	35	32	21	18/8/2022
JT	F	--	--	27	31/8/2022

Note. EV, GH and TI had fair skin while the rest of the participants had pigmented skin. The first four participants had thick, braided hairstyles that resulted in the photon cap not sitting flush against the skull. DT was wearing a hairband. fNIRS data for participant FN and TI were not analysed due to a large number of bad channels. Cranial measurements of JT were not collected.

5.1.2 Overall SATS Responses

Participants' attitudes towards statistics were assessed using the SATS. Based on qualitative data, descriptive statistics indicated that five participants expected to achieve 75% and above for their statistics course grade, three participants expected 66-75%, and two participants expected 56-65%. Participants spent an average of 8.8 hours per week studying for statistics and this varied between participants (SD = 6.86). Overall, participants had positive responses to the *Effort* component, M = 6.68 (SD = 0.57), indicating that participants put a great deal of effort into their statistics coursework. All participants responded "Strongly Agree" to Item 1 ("I tried to complete all of my statistics assignments"), indicating they were diligent in submitting required coursework.

Neutral responses were noted for *Affect*, M = 4.28 (SD = 1.77), *Cognitive Competence*, M = 4.72 (SD = 1.60), *Value*, M = 4.26 (SD = 0.90), and *Interest*, M = 4.45 (SD = 1.58). Negative responses were noted for *Difficulty*, M = 3.06 (SD = 1.02). Most participants believed that statistics took time and discipline to learn ("Statistics is a subject not quickly learned by most people"). For the case study analysis, individual SATS responses are analysed for each participant, in relation to their cortical mapping data.

5.1.3 Signal Quality

The scalp coupling index (SCI) data indicated varied signal quality for all participants. Signal quality ranged from low quality (e.g., C5, C6 for participant DT) to high quality (e.g., C2, C3 for participant AL), as indicated on Table 5.2 (*Channel signal quality ratings*). Since this is the first study on fNIRS in South Africa, we did not have a baseline against which to compare signal quality due to SCI. Nonetheless, as indicated on Table 5.2, for the most part, the experiment indicated good signal quality to allow for further analysis of the data.

Table 5.2

Channel signal quality ratings based on SCI threshold

	AL	BN	CH	DT	EV	FN	GH	HN	TI	JT
C1	M	B	L	B	H	--	B	B	--	B
C2	H	L	M	H	M	--	B	B	--	B
C3	H	H	M	B	M	--	B	B	--	L
C4	H	H	L	L	L	--	H	B	--	H
C5	L	H	H	L	M	--	L	H	--	M
C6	H	L	H	L	L	--	L	H	--	H
C7	H	L	H	L	H	--	L	H	--	H
C8	L	H	H	L	L	--	L	H	--	H
C9	L	M	H	L	M	--	L	L	--	L
C10	H	H	H	L	L	--	L	H	--	H
C11	M	H	H	L	M	--	L	L	--	M
C12	H	H	H	H	M	--	L	M	--	H

Note. H = high quality, M = medium quality, L = low quality, B = bad channel

Loss of signal on a channel may be due to hardware failure. As a result, data for these channels were automatically replaced with data before the enhancement process and were marked "bad channels". Bad channels were seen in C1-C4, on the prefrontal cortex area. C1 was a bad channel in BN, DT, GH, HN and JT. C2 was a bad channel in GH, HN and JT. C3 was a bad channel for DT, GH and HN. C4 was a bad channel in HN.

5.2 Case study analysis

Seed-based correlations were performed on channels with high signal quality that were surrounded by channels with SCI values above 0.80. Sampling rates for participants varied in a range of 10.753 – 15.873 Hz. fNIRS data could not be processed for two participants, (FN and TI) due to incomplete and missing data.

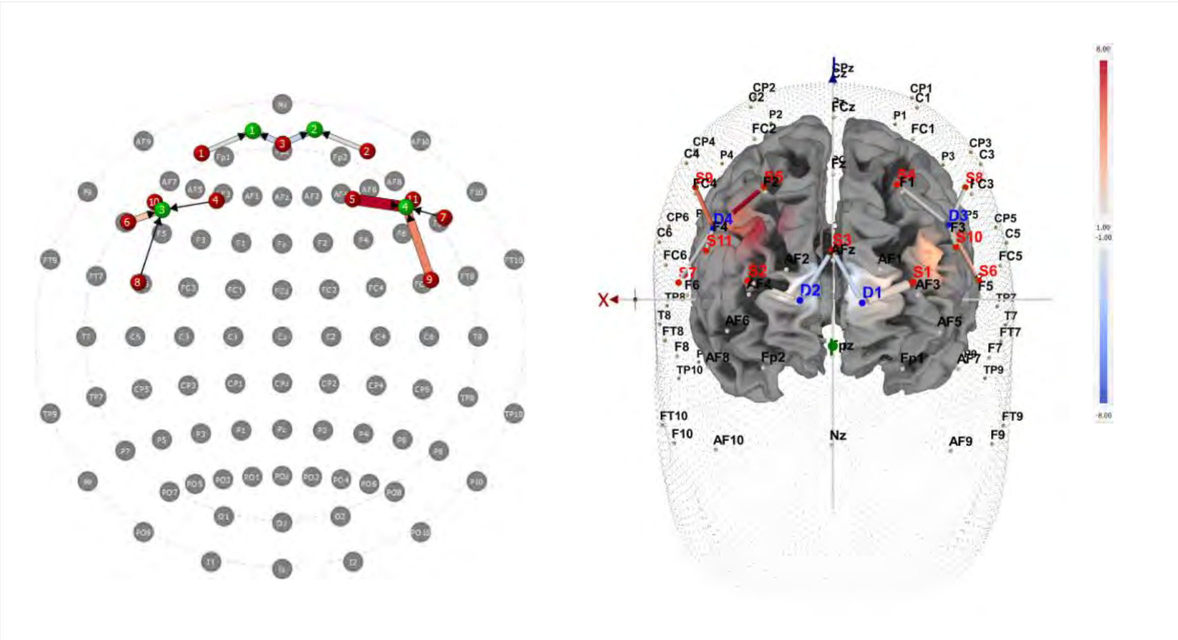
5.2.1 Participant AL

AL was a General Psychology Honours student with a long, braided hairstyle that had to be adjusted to improve scalp coupling index (SCI) readings. AL indicated she expected to receive 75% or above for her quantitative research assessments. She estimated that she spent approximately 14 hours per week studying for statistics. She rated her overall stress levels as high within a typical university week. On the SATS, AL reported a positive *Affect*, $M = 5.17$ ($SD = 1.77$), high *Cognitive Competence,* $M = 5.83$ ($SD = 1.47$), a high *Interest* in statistics, $M = 6.50$ ($SD = 1.00$) and high *Effort* to master the subject, $M = 6.75$ ($SD = 0.50$). She responded neutrally to *Difficulty*, $M = 3.86$ ($SD = 1.77$) and the *Value* of statistics, $M = 4.78$ (SD = 2.44). Nonetheless, she acknowledged the value and use of statistics in her professional life ("Statistics is not worthless", "I will have applications for statistics in my profession". She did however, indicate, she did not believe statistics was valuable in everyday life ("I do not use statistics in my everyday life"). Overall, AL indicated a positive attitude towards statistics.

Signal quality values for C1 and C11 showed SCI values between 0.80 - 0.89, and all other channels had SCI values above 0.90, which indicated acceptable signal quality values according to typical SCI values (Lührs & Goebel, 2017). Nonetheless, Channels C5, C8 and C9 had low SCI values below 0.80. Seed-based correlations were performed on channel C6 (S5-D4) on the right hemisphere. Cortical activation was viewed in the DLPFC region. Figure 5.1 indicates 2D and 3D modelling of cortical activation whilst AL conducted the statistical reasoning task. From the 3D seed-based correlation, we can note that the highest seed correlation was with F4, and AF3, which correspond with the dorsolateral prefrontal cortex (F4) and Brodmann Area 9 (AF3) respectively. In conclusion, positive attitudes to statistics (*Affect*, $M = 5.17$; *Cognitive Competence,* $M = 5.83$; *Interest,* $M = 6.50$; *Effort,* $M = 6.57$) were correlated with activation of the dorsolateral prefrontal cortex and Brodmann Area 9. All data was processed at a sampling frequency rate of 11.364 Hz.

Figure 5.1

2D and 3D modelling of cortical activation in Participant AL.



Note. 2D and 3D models are inverse, i.e., the seed-based correlation on C6 (S5-D4) is viewed on the right side of the 2D model, representing the right hemisphere. In the 3D model, the right hemisphere is on the left.

5.2.2 Participant BN

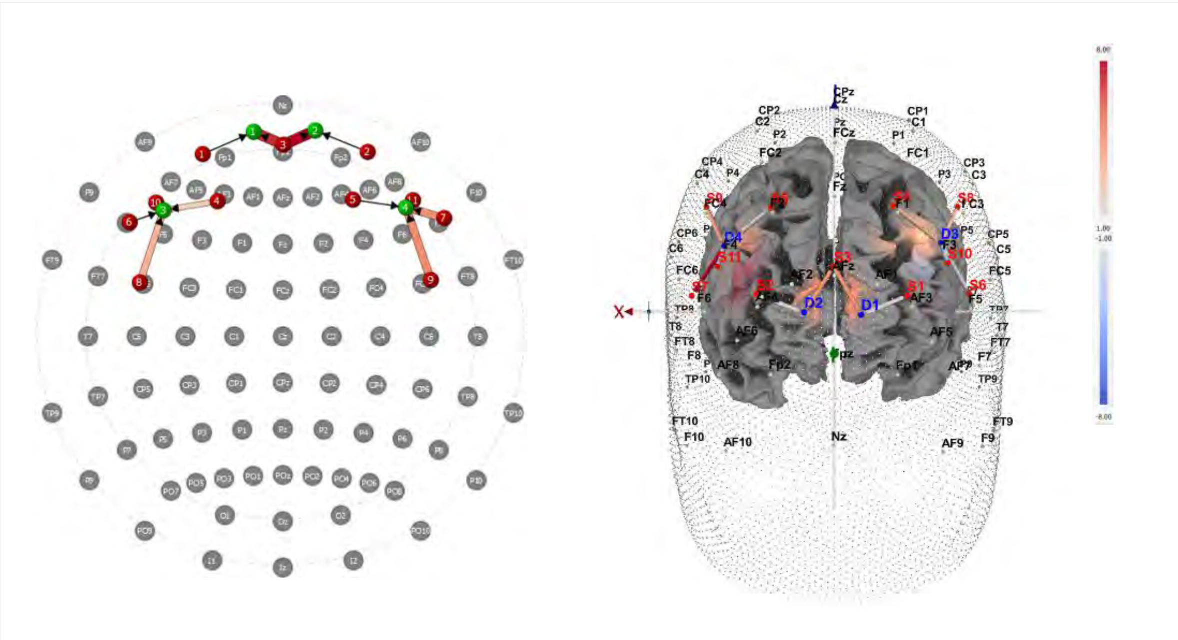
BN was a General Psychology Honours student, also with a long, braided hairstyle that needed adjustment to improve SCI readings. BN expected to receive 75% and above for her quantitative research assessments. She estimated that she spent 4 hours in a usual week studying for statistics. She rated her overall stress levels as very high in a usual university week. On the SATS, BN reported a positive *Affect*, $M = 6.33$ ($SD = 0.52$) and reported that she is not under stress during statistics classes. She also reported high *Cognitive Competence*, $M = 6.33$ ($SD = 0.52$), *Interest* in statistics, $M = 5.75$ ($SD = 0.96$) and *Effort* in statistics coursework and class attendance, $M = 6.50$ ($SD = 0.58$). She responded neutrally to *Value* of statistics, $M = 4.56$ ($SD = 1.88$) and *Difficulty*, $M = 4.29$ ($SD = 2.36$), and felt that statistics was “quickly learned by most people”, technical and not complicated, but “requires a great deal of discipline” and massive computations. Overall, BN had a positive attitude towards statistics.

Channel C1 was a bad channel, with SCI values below 0.75, and was removed. Channels C2, C6 and C7 had SCI values of below 0.80, C9 had an SCI value between 0.80-

0.89, and all other channels had SCI values above 0.90. Overall signal quality was acceptable according to SCI values (Lührs & Goebel, 2017). Seed-based correlations were performed on channel C8 (S7-D4) on the right hemisphere. Cortical activation was viewed in the DLPFC and prefrontal cortex region. Figure 5.2 indicates 2D and 3D modelling of cortical activation in BN during the statistics task. The 3D seed-based correlation notes highest seed correlation with F3 and F4, corresponding to the DLPFC. In conclusion, positive attitudes to statistics (*Affect*, M = 6.33; *Cognitive Competence,* M = 6.33; *Interest*, M = 5.75; *Effort*, M = 6.50) were correlated with activation of the dorsolateral prefrontal cortex. The sampling frequency rate was 15.873 Hz.

Figure 5.2

2D and 3D modelling of cortical activation in Participant BN



Note. Seed-based correlation performed on C8, right hemisphere.

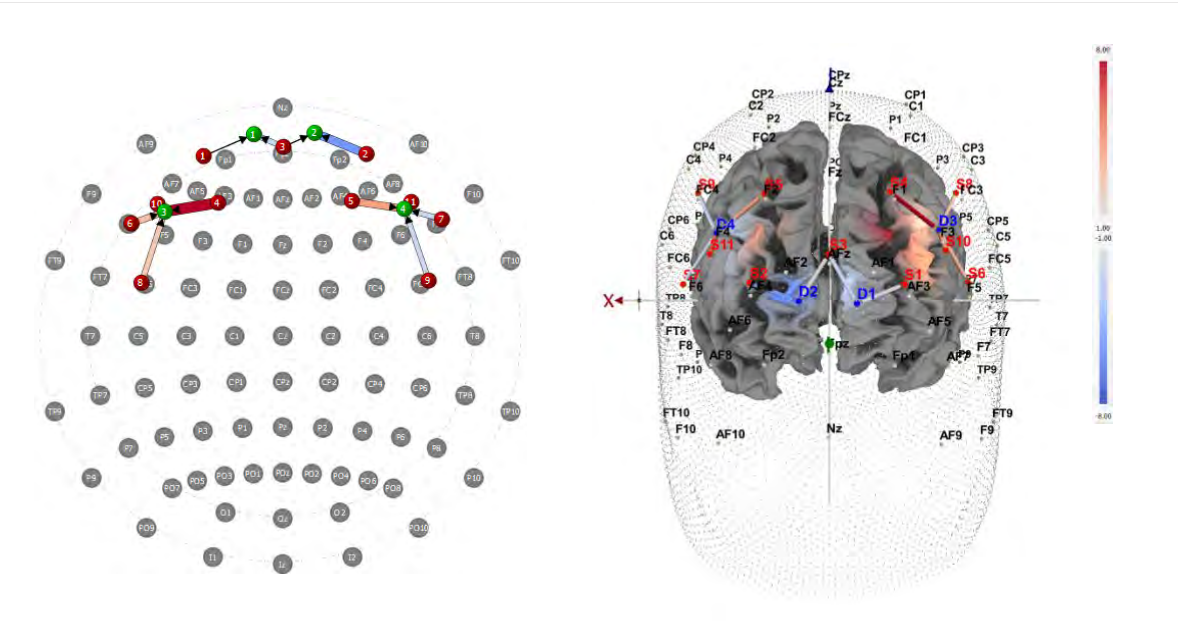
5.2.3 Participant CH

CH was a General Psychology Honours student with short, cropped hair that did not require readjusting for SCI readings. CH indicated that she expected to receive 75% and above for her quantitative research assessments and estimated that she would spend 25 hours in a usual week studying for statistics. She rated her overall stress levels in a usual university week as average. On the SATS, CH responded positively to *Value*, M = 5.56 (SD = 0.88) and very high *Effort*, M = 7.00 (SD = 0.00), indicating that she attended every class, completed all statistics assignments, and worked hard in coursework and tests. She responded negatively to *Affect*, M = 3.33 (SD = 1.03) and *Difficulty*, M = 1.86 (SD = 0.38) and believed that a great deal of training, discipline and computations are required. She responded neutrally to *Cognitive Competence*, *M* = 4.17 (SD = 0.52) and *Interest*, *M* = 4.00 (SD = 0.82), and overall, participant CH had a neutral attitude towards statistics.

Signal quality was acceptable according to SCI values (Lührs & Goebel, 2017), with no bad channels excluded. Channels C1 and C4 had SCI values between 0.75-0.79, C2 and C3 had SCI values between 0.80-0.89, and all other channels had SCI values above 0.90. Seed-based correlations were performed on channel C5 (S4-D3) on the left hemisphere. Cortical activation was viewed in the DLPFC region. Figure 5.3 shows the 2D and 3D modelling of cortical activation in CH during the statistical reasoning task. The 3D seed-based correlation shows highest seed correlation with F3 which corresponds with the DLPFC; hence, positive attitudes towards statistics (*Value*, *M* = 5.56; *Effort*, *M* = 7.00) was correlated to dorsolateral prefrontal cortex activation. Data was processed at 11.494 Hz sampling frequency rate.

Figure 5.3

2D and 3D modelling of cortical activation in Participant CH.



Note. Seed-based correlation performed on C5, left hemisphere.

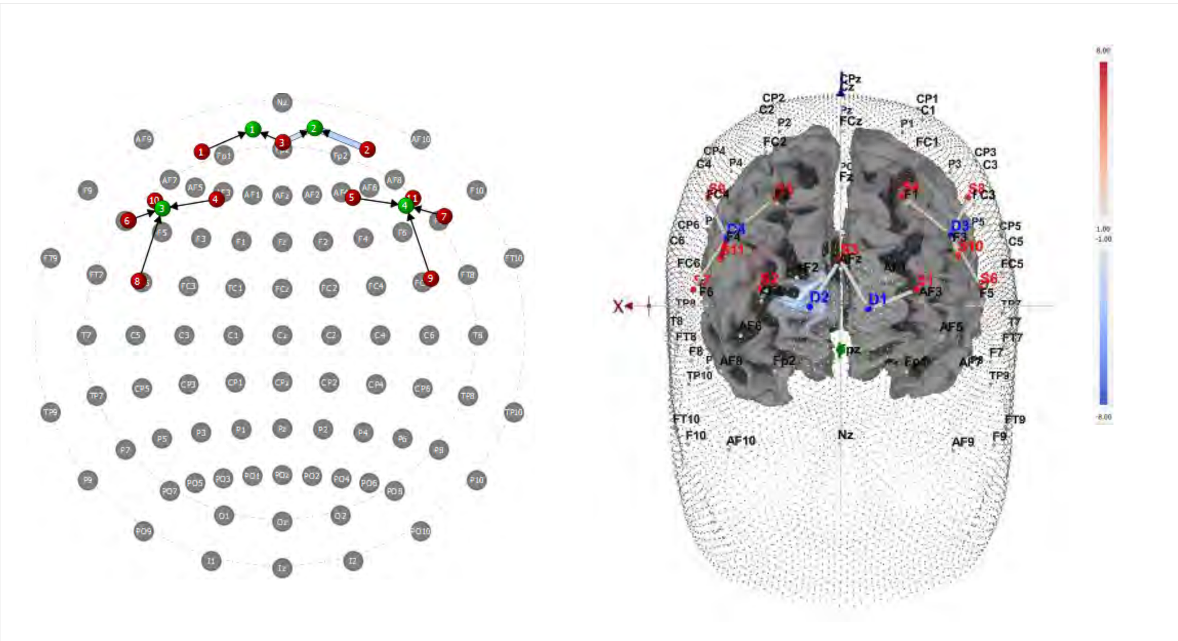
5.2.4 Participant DT

DT was a General Psychology Honours student with thick hair that required some adjusting to improve scalp coupling index (SCI) readings. DT believed she would receive 56-65% for her quantitative research assessments. She estimated that she would spend 10 hours in a usual week studying for statistics. DT rated her overall stress levels in a usual university week as very high. On the SATS, DT responded positively to *Effort*, *M* = 6.50 (*SD* = 0.58) like their peers. She responded neutrally to *Cognitive Competence*, *M* = 4.83 (*SD* = 1.17) and *Value*, *M* = 5.22 (*SD* = 1.72). DT reported slightly negative *Affect*, *M* = 3.67 (*SD* = 1.21) and *Interest*, *M* = 3.25 (*SD* = 0.50), expressing that she is not interested in learning and using statistics, and negative *Difficulty*, *M* = 2.86 (*SD* = 1.77), indicating that statistics is "not easy to understand", "highly technical", and "not quickly learned by most people". Overall, DT had a neutral attitude towards statistics.

Low signal quality was noted for DT according to typical SCI values (Lührs & Goebel, 2017), with Channel C1 and C3 being excluded as bad channels (SCI<0.75). Channels C2 and C12 were the only channels with SCI values above 0.90, and all other channels had SCI values between 0.75-0.79. Seed-based correlations were performed on channel C12 (S14-D4) on the right hemisphere. Cortical activation could not be observed. Figure 5.4 shows 2D and 3D modelling imagery obtained with no activation in the DLPFC or Brodmann areas during the statistical reasoning task. The sampling frequency rate was 10.989 Hz.

Figure 5.4

2D and 3D modelling of cortical activation in Participant DT.



Note. Seed-based correlations performed on C12, right hemisphere.

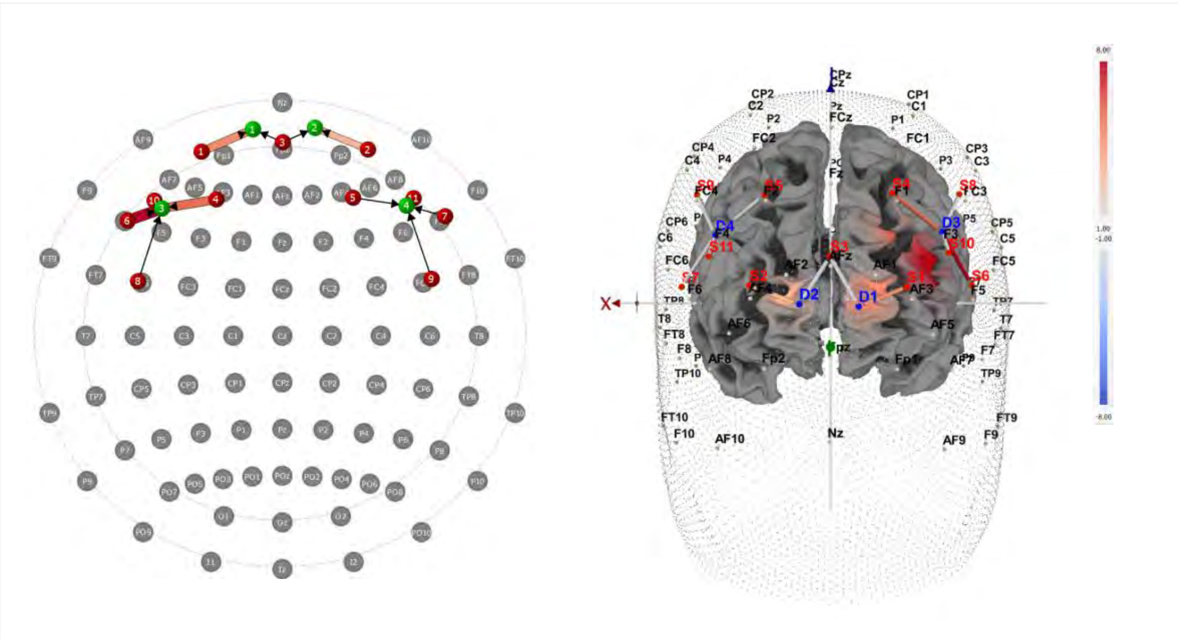
5.2.5 Participant EV

EV was a General Psychology Honours student, with fine brown hair that required slight adjustment to improve scalp coupling index (SCI) readings. EV indicated that he expected to receive above 75% for his quantitative research assessments and estimated that he spent 6 hours in a usual week studying for statistics. He rated his overall stress levels in a usual university week as very low. On the SATS, EV responded positively to *Affect*, M = 6.33 (SD = 0.82), *Cognitive Competence, M* = 5.83 (SD = 0.98), *Interest*, M = 5.00 (SD = 0.82) and *Effort*, M = 6.75 (SD = 0.50). He responded neutrally *Value*, M = 4.89 (SD = 1.76) and negatively to *Difficulty*, M = 3.14 (*SD* = 0.90). EV did not believe statistics was useful in his life ("Statistical thinking is not applicability in my life outside my job", "I do not use statistics in my everyday life"). Overall, EV had a positive attitude towards statistics.

Channels C4, C6, C8 and C10 had SCI values between 0.75-0.79, with SCI values of 0.80-0.89 for C2, C3, C5, C9, C11 and C12. Medium signal quality was noted for EV according to typical SCI values (Lührs & Goebel, 2017). Two channels (C1 and C7) had SCI values above 0.90. Seed-based correlations were performed on channel C7 (S5-D4) on the left hemisphere. Figure 5.5 indicates the 2D and 3D modelling of cortical activation observed while EV completed the statistical reasoning task. The 3D seed-based correlation exhibits the highest seed correlation with F3, and AF3, which correspond to the DLPFC (F3) and Brodmann Area 9 (AF3). In conclusion, positive attitudes (*Affect*, M = 6.33; *Cognitive Competence, M* = 5.83; *Interest*, M = 5.00; *Effort*, M = 6.75) were correlated to activation of the dorsolateral prefrontal cortex and Brodmann Area 9. Data was processed at a sampling frequency rate of 11.905 Hz.

Figure 5.5

2D and 3D modelling of cortical activation in Participant EV.



Note. Seed-based correlation performed on C7, left hemisphere

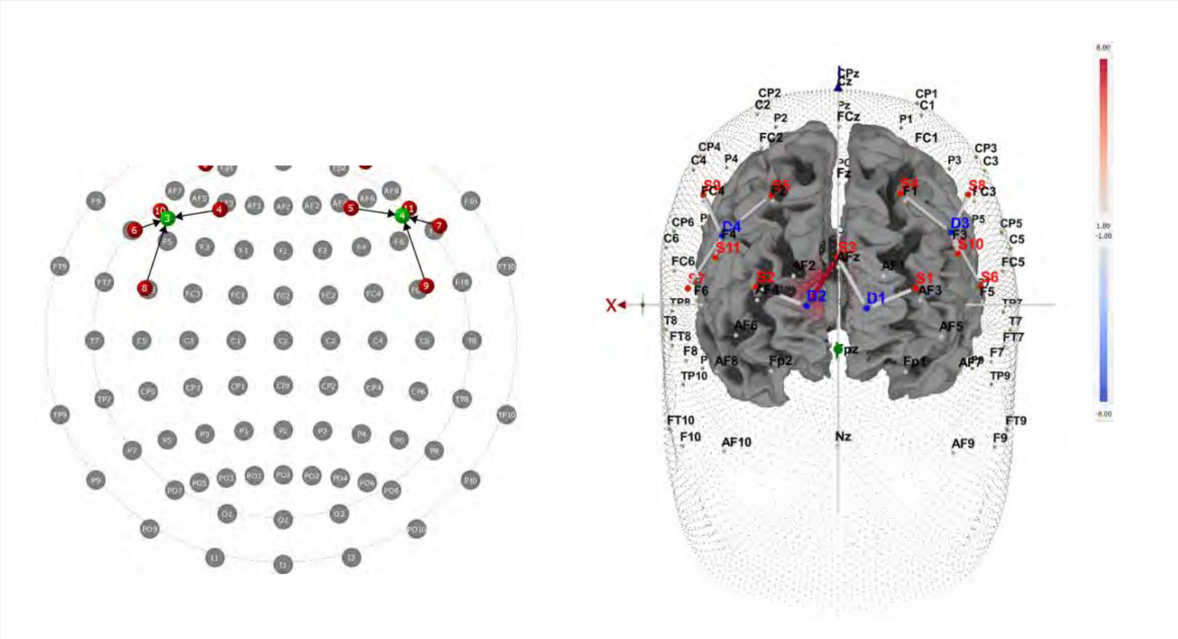
5.2.6 Participant GH

GH was a General Psychology Honours student with dark hair that required some adjustment to improve scalp coupling index (SCI) readings. GH estimated that she would receive 66-75% for her quantitative research assessments, and that she spent 6 hours in a usual week studying for statistics. In a usual university week GH rated her overall stress levels as high. GH responded positively on the SATS to *Effort*, $M = 6.75$ ($SD = 0.50$). She responded neutrally to all other components, *Affect*, $M = 2.83$ ($SD = 2.04$), *Cognitive Competence,* $M = 4.83$ ($SD = 1.17$), *Value*, $M = 3.56$ ($SD = 1.24$), *Difficulty*, $M = 3.29$ ($SD = 1.60$) and *Interest*, $M = 4.50$ ($SD = 1.00$). She expressed that statistics is not important in her life ("I do not use statistics in my everyday life", "Statistical thinking is not applicable in my life outside my job") and while statistics can be learned relatively easily by most people, it is a technical and difficult subject. Overall, GH had a neutral attitude towards statistics.

Signal quality was low according to SCI values (Lührs & Goebel, 2017). Three channels were excluded as bad channels, C1, C2, C3, for SCI values below 0.75. Channel C4 was the only channel with high SCI of above 0.90. Seed-based correlations were performed on channel C4 (S3-D2) in the prefrontal cortex in the right hemisphere. Cortical activation was viewed in the prefrontal cortex. Figure 5.6 indicates the 2D and 3D modelling of cortical activation whilst GH was completing the statistical reasoning task. From the 3D seed-based correlation it was noted that the highest seed correlation was with AF2, which correspond to prefrontal cortex. In conclusion, positive attitudes (*Effort*, $M = 6.75$) were correlated to activation of the prefrontal cortex. The sampling frequency rate for data processing was 10.870 Hz.

Figure 5.6

2D and 3D modelling of cortical activation in Participant GH.



Note. Incomplete 2D modelling was obtained for this participant, but 3D modelling demonstrates cortical activation did occur. Seed-based correlations were performed on C4.

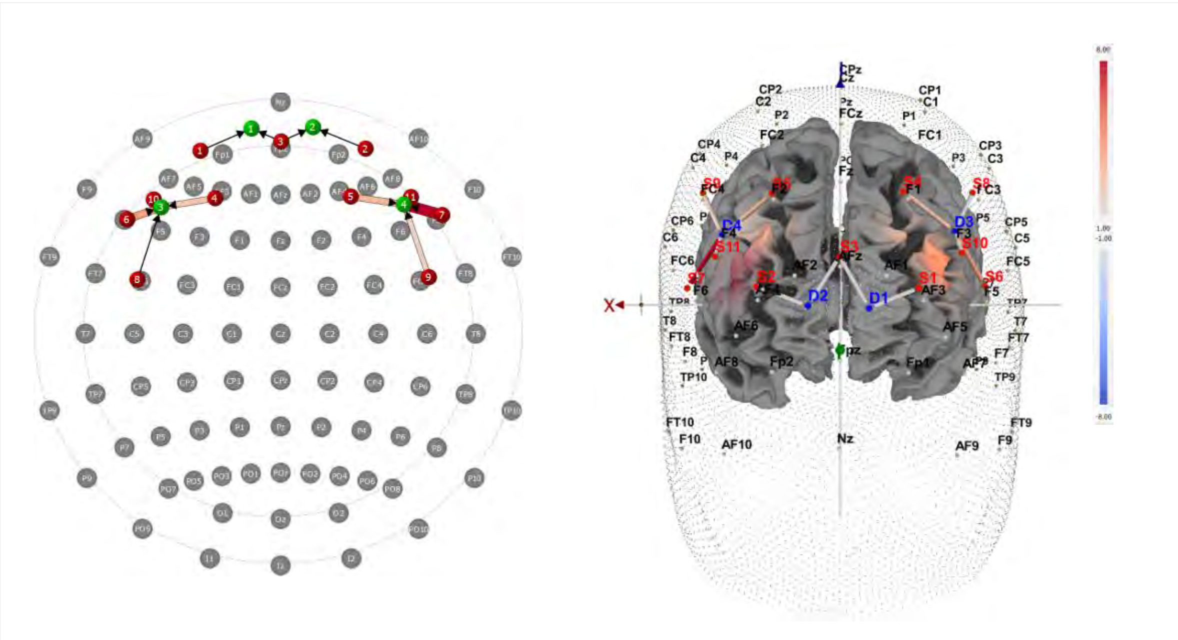
5.2.7 Participant HN

HN was an Organisational Psychology Honours student with shaved hair that did not warrant adjustment to improve scalp coupling index (SCI) readings. HN estimated a result of 56-65% for her quantitative research coursework and she spent 4 hours in a usual week studying for statistics. She rated her overall stress levels as high in a usual university week. On the SATS, HN responded positively to *Effort*, $M = 7.00$ ($SD = 0.00$). She responded neutrally to *Value*, $M = 3.44$ ($SD = 1.33$). HN indicated negative attitudes in terms of *Affect*, $M = 1.00$ ($SD = 0.00$), *Cognitive Competence*, $M = 1.50$ ($SD = 0.55$), *Difficulty*, $M = 2.43$ ($SD = 1.60$) and *Interest*, $M = 1.00$ ($SD = 0.00$). The scores for *Affect* and *Interest* indicate negative feelings around statistics and no interest in learning and using statistics. HN expressed low self-concept of statistics abilities ("I have trouble understanding statistics", "I cannot learn statistics", "I find it difficult to understand statistical concepts") and accredited this to the subject itself ("Statistics is a complicated subject", "Statistics formulas are not easy to understand", "Statistics is a subject not quickly learned by most people"). Overall, HN had a negative attitude towards statistics.

Channels C1-C4 had SCI values below 0.75 and were excluded as bad channels. Channels C9 and C11 had SCI values between 0.75 and 0.79, with C12 having medium signal quality with SCI values 0.80-0.89. All other channels had high signal quality according to typical SCI values (Lührs & Goebel, 2017). Technical difficulties resulted in temporary signal loss at t = 850s, when the participant was on question 17. Seed-based correlations were performed on channel C8 (S7-D4) in the right hemisphere. Cortical activation was viewed in the DLPFC. Figure 5.7 shows the 2D and 3D modelling of cortical activation in HN while engaging in the statistical reasoning task. The 3D seed-based correlation showed highest seed correlation for F3, which corresponds to the DLPFC. Hence, positive attitudes towards statistics (*Effort*, M = 7.00) are correlated with activation of the dorsolateral prefrontal cortex. Data was processed at a sampling frequency rate of 10.753 Hz.

Figure 5.7

2D and 3D modelling of cortical activation in Participant HN



Note. Seed-based correlation performed on C8, right hemisphere.

5.2.8 Participant JT

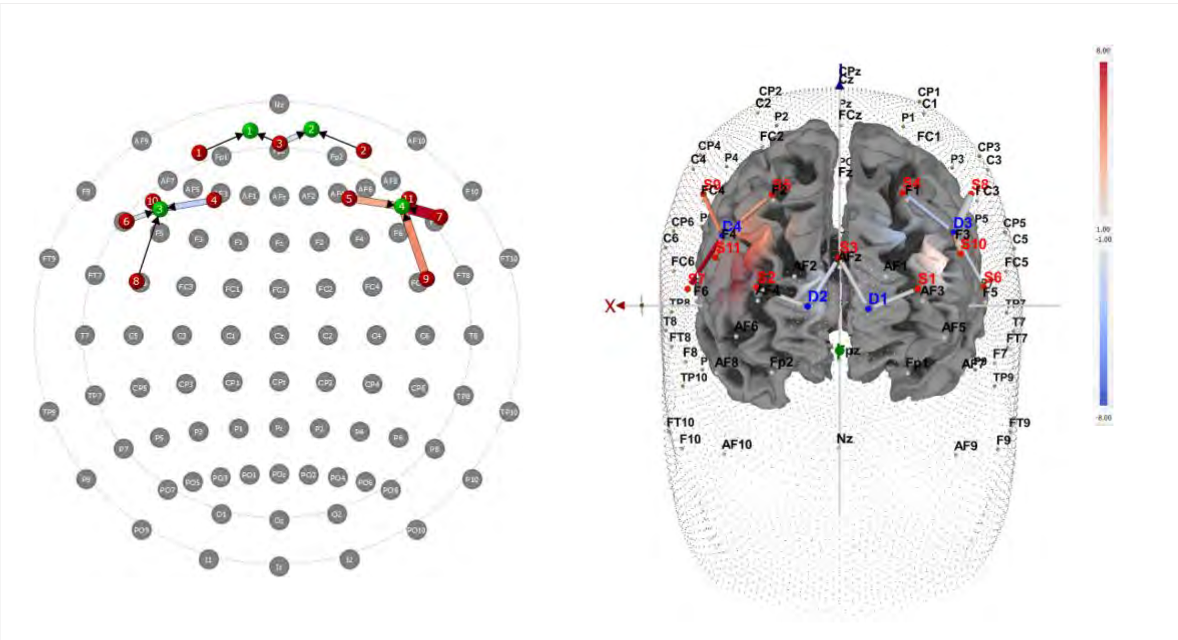
JT was a General Psychology Honours student and her hair was adjusted to improve scalp coupling index (SCI) readings. JT estimated a result of 66-75% for her quantitative research assessments and spent 5 hours in a usual week studying for statistics. She rated her overall stress levels in a usual university week as very high. On the SATS, JT responded positively to *Cognitive Competence, M* = 5.17 (*SD* = 1.47), *Interest*, M = 6.00 (*SD* = 0.82) and *Effort*, M = 6.00 (*SD* = 2.00). JT responded neutrally to *Affect*, M = 3.50 (*SD* = 1.52) and *Value*, M = 4.33 (*SD* = 2.12). She reported negative attitudes towards *Difficulty*, M = 2.57 (*SD* = 1.62). JT believed in her ability to learn statistics but reported being scared by statistics. Further, while

JT viewed statistics as useful to professionals, she did not see its value in her own career ("I will have no application for statistics in my profession"). Overall, JT had a neutral attitude towards statistics.

Varied signal quality for JT was noted, with channels C1 and C2 being excluded as bad channels with SCI values below 0.75. SCI values for C3 and C9 were 0.75-0.79. C5 and C11 had SCI values 0.80-0.89. All other channels had high signal quality according to SCI values (Lührs & Goebel, 2017). The sampling frequency rate at which data was processed was not recorded. Seed-based correlations were performed on channel C8 (S7-D4) in the right hemisphere. Cortical activation was viewed in the DLPFC. Figure 5.8 presents 2D and 3D modelling indicating cortical activation in Participant K during the statistical reasoning task. The 3D seed-based correlation shows the highest seed correlation was with F4 which corresponds to the DLPFC. In conclusion, positive attitudes towards statistics (*Cognitive Competence, M* = 5.17, *Interest*, *M* = 6.00, *Effort*, *M* = 6.00) were correlated with activation of the dorsolateral prefrontal cortex.

Figure 5.8

2D and 3D modelling of cortical activation in Participant JT



Note. Seed-based correlation performed on C8, right hemisphere.

5.3 Chapter summary

This chapter presented data from eight cases, depicting cortical activation due to handling statistical content. In the majority, participants had neutral attitudes towards statistics and put in a great deal of effort to complete statistics related coursework. fNIRS signal quality varied across participants with seed-based correlation indicating, for the most part, cortical activation in the DLPFC, in six participants. Chapter 6 discusses the results and implications of the findings related to my research study.

CHAPTER 6
DISCUSSION

6.1 Context for the Research Problem

The application of statistics is ubiquitous in tertiary level studies, both as a field of study, and for research purposes. Many students will encounter statistical training or research methodology courses as part of their degree requirements, particularly students in the biological and mathematical sciences, commerce subjects, education and social sciences. Social science research relies on descriptive and inferential statistics to inform and analyse important observations of human behaviour. In Psychology, the use of statistics often transfers into clinical assessment and therapeutic practice. Despite the clear applications of statistics in Psychology, students studying Psychology at tertiary level often fail to understand its inclusion in their curriculum (Bose, 2017). To this end, misguided feelings or attitudes towards statistics as a subject of study, especially in the Social Sciences, has often resulted in students experiencing statistics anxiety. Importantly, feeling statistics anxiety, and negative perceptions of both abilities in statistics, and the usefulness of statistics, have been found to impact course performance, and course outcomes in statistics courses (Onwuegbuzie, 2000).

Given the above relationship between statistics anxiety, and performance in statistics courses, this study sought to collate research investigating the relationship between attitudes towards statistics and achievement in the subject. The objectives of the study were investigated using two meta-analytic studies: one on university students across various fields of study; and another, specifically on Psychology students. In its general application, my study sought to expand on the initials finding by Emmioğlu and Capa-Aydin (2012), who conducted a meta-analysis on attitudes towards statistics and achievement in statistics.

In addition to updating conducting a meta-analysis on the relationship between the variables identified above, my study sort to map out the neural correlates of statistics education. The objectives of the second study were based on suggestions that the use of neuroimaging (e.g., fNIRS), provides educators with the potential to better understand intervention effectiveness in classrooms (Barreto & Soltanlou, 2022), and this may help mitigate negative experiences, in subjects such as Mathematics and Statistics, that are often associated with anxiety. Given the above, the primary objective of the applying fNIRS neuroimaging technology, was to explore the cortical mapping of statistical reasoning, and to confirm the activation of the DLPFC in statistical reasoning.

6.2 Reiteration of Research Questions and Summary of Results

The primary research questions for the two meta-analysis studies were derived from Emmioğlu and Capa-Aydin (2012). These were namely:

1. What is the relationship between university students' attitudes towards statistics and achievement in statistics?
2. What is the relationship between Psychology students' attitudes towards statistics and achievement in statistics?

The last research question based on cortical brain mapping whilst completing a statistical education task was:

3. Can the neural correlates of Statistical Reasoning be defined using Functional Near-Infrared Spectroscopy?

6.3 Summary of Results

Findings from the *first* meta-analysis investigating students' attitudes towards statistics (*Affect*, *Cognitive Competence, Value*, *Difficulty*) and achievement, can be summarized as follows. There was a small statistically significant relationship between *Affect* and achievement in statistics courses, ($r = 0.28$ (95% CI, 0.24 – 0.33, $p < 0.05$). This indicates that the feelings that students have towards statistics, can affect university students' performance and achievement in the subject. Particularly, negative attitudes could result in lower achievement. The study also found a medium statistically significant relationship between *Cognitive Competence* and achievement in statistics course, ($r = 0.31$ (95% CI, 0.27 – 0.34, $p < 0.05$). This finding indicates that students' beliefs about their own capabilities in performing statistics tasks, are likely to affect their abilities to achieve in statistics. Moreover, the study found a small but statistically significant relationship between *Value* and achievement, in statistics courses ($r = 0.22$, (95% CI, 0.17 - 0.26, $p < 0.05$). This finding indicates that the value students place on statistics in their personal and professional lives could affect their achievement. Finally, the study found a small but significant relationship between *Difficulty* and achievement, ($r = 0.18$ (95% CI, 0.11 – 0.25, $p < 0.05$). This finding indicates that the level of difficulty of statistics as discerned by students will also impact achievement in statistics.

The meta-analysis investigating attitudes towards statistics (*Affect*, *Value*, Difficulty, *Cognitive Competence*), amongst Psychology students, and subsequent achievement in the course can be summarized as follows: There was a small statistically significant relationship between *Affect* and achievement in statistics courses, ($r = 0.32$ (95% CI, 0.08 – 0.52, $p < 0.05$). As above, this finding indicates that emotions surrounding statistics tasks are likely to influence Psychology students' abilities to achieve in statistics courses and assessments. There was a medium statistically significant relationship between *Cognitive Competence* and achievement in statistics courses, (r = 0.35; 95% CI 0.29 – 0.42, p< 0.05). This finding indicates that self-perceived abilities in statistics that Psychology students may possess can influence their statistics achievement. The study also found a small but statistically significant relationship between *Value* and achievement, in statistics courses (r = 0.24; 95% CI, 0.15 – 0.33, p < 0.05). This finding indicates that the discerned worth of statistics in a Psychology students' every day and future working life could have an impact on their achievement in statistics courses while studying or training. Additionally, the study found a small but significant relationship between *Difficulty* and achievement, (r = 0.23; 95% CI, 0.06 – 0.38, p < 0.05). This indicates that Psychology students' judgement of the difficulty of statistics courses can affect their achievement in these courses.

Regarding cortical activation of the Dorsolateral Prefrontal Cortex (DLPFC), interpreted using seed-based correlation analysis, results indicated that the DLPFC was activated in six of the participants, as they completed the statistical reasoning task. Nonetheless, signal quality as measured by Scalp Coupling Index (SCI) varied among participants. This finding indicates evidence that fNIRS technology has the potential to measure statistical reasoning and may carry potential to be used to study statistics anxiety, when paired with the DLPFC cortex.

6.4 Discussion of Findings in Relation to the Literature

Like the prior meta-analysis by Emmioğlu and Capa-Aydin (2012), a medium significant relationship was reported between *Cognitive Competence* and achievement for both meta-analysis studies. Additionally, a small significant relationship between *Difficulty* and *Value* and achievement was reported by Emmioğlu and Capa-Aydin (2012) and computed in both studies. The relationship between Psychology students' *Affect* and achievement was medium and significant, like the relationship between *Affect* and achievement reported by Emmioğlu and Capa-Aydin (2012). Statistically significant heterogeneity between studies for all components were found in the first and second meta-analysis, and this was also true for the studies in the prior meta-analysis by Emmioğlu and Capa-Aydin (2012).

There are also some differences in the findings to those reported by Emmioğlu and Capa-Aydin (2012). The *Affect* and achievement relationship for university students was small and significant, while Emmioğlu and Capa-Aydin (2012) reported a medium significant relationship as above. Confidence intervals for effect sizes in Emmioğlu and Capa-Aydin (2012) were smaller than the confidence intervals in the first and second meta-analysis studies here. These findings also include I^2 statistic measures for heterogeneity.

These findings confirm assertions made by early statistics anxiety researchers that a relationship exists between achievement and attitudes, in that negative attitudes towards statistics can lead to negative achievement outcomes (Onwuegbuzie, 2000). Conversely, poor prior achievement can lead to statistics anxiety and negative attitudes (Onwuegbuzie & Wilson, 2003). This relationship is statistically significant and small to medium in size, meaning that the effects of negative attitudes may result in poor performance in statistics coursework and assessments, and hence attitudes can be a predictor of achievement. Modelling by Zimprich (2012) also found attitudes to be a predictor of achievement.

Cortical activation was seen in the dorsolateral prefrontal cortex (DLPFC) during statistical reasoning tasks in six participants. Similar activation was reported by Artemenko et al. (2018), where activation was viewed in the bilateral fronto-parietal network, which includes the DLPFC, during arithmetic processing. Artemenko et al. (2018) also report activation in the angular and middle temporal gyri, which was not a region of interest in this study. The findings are also similar to Pfurtscheller et al. (2010) who found activation of the DLPFC in eight out of 10 participants during an arithmetic task.

The findings also help to confirm the use of fNIRS for education research. Questions posed by Barreto and Soltanlou (2022) regarding how students learn and what biological mechanisms can cause individual differences in learning are able to be answered through fNIRS. The varied findings in the case study analysis show that fNIRS can show these individual differences in learning between student participants, and these can be corresponded to attitudes. As above, attitudes affect how students learn and how successful students are in learning according to achievement measures.

6.5 Threats to Internal Validity

Findings from my meta-analysis should be interpreted with caution due to large variation in heterogeneity measures. This heterogeneity indicates large excess dispersion and large between-studies variance for most of the attitudinal components measuring attitudes towards statistics. For example, there was a considerable variance in effect size measures for *Difficulty* due to a negative correlation between achievement and *Difficulty* having been reported by Dempster and McCorry (2009) and Melad (2022). It was hypothesized by Zimprich (2012) that a reported negative relationship between attitudes and achievement could be due to suppression in students, meaning students incorrectly believe statistics is easier than it is and do not devote sufficient time to study. Hence, students who judged statistics as being easy may have prepared less for the assessment and subsequently performed worse, which would result in a positive response for *Difficulty* but low achievement (Zimprich, 2012). In considering the implications for this research in statistics education for university students, this phenomenon of suppression should be addressed. Emmioglu and Capa-Aydin (2012) and Schau (2019) reported internal consistency values for SATS components as Cronbach's alpha values. This is the measure of the reliability of the items, i.e., if they measure what they intended to measure. The range for *Difficulty*, 0.64 to 0.81 (Schau, 2019), straddles on what is deemed an acceptable level of Cronbach's alpha There is thus concern, that poor interrelatedness in *Difficulty* items, could result in different interpretations of the value of this scale amongst participants.

Another threat to the internal validity of the study is that the fNIRS research was conducted as a case study approach and cannot be easily extrapolated to larger studies without some considerations. Although the aim of the case studies was to demonstrate the neural correlates of statistical reasoning, using seed-based correlation methods. A pure general linear analysis could not be conducted on the data to extrapolate the finding of the data to the general population. Further limitation, other that threat to internal validity will be discussed in the next section.

6.5.1 Meta-analysis

While a meta-analysis can theoretically be performed on as few as two studies, it is noted that some heterogeneity measures, such as the *Q*-statistic, are not sufficiently robust for smaller meta-analyses. Ideally, a meta-regression would accompany a meta-analysis to show the effects of study characteristics on the results obtained. In this meta-analysis, it would have been ideal to also carry out a meta-regression analysis on the countries that the studies originated from. Emmioglu and Capa-Aydin (2012) found it insightful to compare effect sizes of studies conducted in the United States to those carried out in other countries. Regression analyses in the first meta-analysis could be used to tie the two meta-analyses together, by showing insight into how Psychology students' results differed from the general group. While the statistics achievement limitation of the meta-analysis by Emmioglu and Capa-Aydin (2012) was addressed, regression analysis could reveal which of these measures is a more accurate representation of achievement.

As highlighted in the comparison to the meta-analysis performed by Emmioglu and Capa-Aydin (2012), there are sample differences in studies that were not reported by authors which could be the reason why relationships between attitudes and achievements differ between studies. Hence, not all possible causes for heterogeneity could be explored. Level of education was not an exclusion criterion, and studies using undergraduate or postgraduate students were used. Not enough literature existed to discriminate between regional differences, but Emmioğlu and Capa-Aydin (2012) did note considerable differences in effect sizes when using this as a factor.

6.5.2 fNIRS Research

My research could have benefitted from a through enquiry into differences between oxyhaemoglobin and deoxyhemoglobin changes using General Linear Modelling (GLM), instead of only running a seed-based correlation. GLM requires extensive prefiltering of data to remove confounding signals, such as physiological components like cardiac and respiration signal noise and blood pressure variations (Yücel et al., 2021). This pre-processing is followed by a regression analysis based on task-related regressors (in response to stimuli) compared to non-task regressors (interblock intervals) (Tak & Ye, 2014). Undertaking this advanced approach could have led to group analysis of statistical reasoning, using multi-level analysis for more robust statistical conclusions (Tak & Ye, 2014). It was this a major limitation to conduct a case study analysis, without group level GLM.

6.6 Implications of Research

6.6.1 Recommendations for Statistics Education

In the literature review, goals of statistics education were discussed while defining statistical literacy's positioning in higher education. Gal et al. (1997) asserts that the understanding of statistics attitudes and its effect on achievement is vital in making statistics learning less frustrating and fearful. One such recommendation that was seen throughout the research, and is confirmed by the second meta-analysis, was having separate statistics courses for Science Technology Engineering Mathematics (STEM) and non-STEM majors (Malik, 2014).

In relation to the above, especially as it relates to the social sciences, if statistics is positioned as a *language of research* educators can help student connect statistics education to research methodology courses (Berens, 2018). This positioning implies that statistics can be treated as a means of exploring, explaining and interpreting questions in research methodology courses. As such, if educators' position statistics as another "language" to communicate results, this may help break down the apprehension that surrounds knowledge acquisition related to "math side" that may intimidate students in the social sciences. of research.

6.6.2 Statistics Education in South African Schools and Universities

In addition to the above, the current South African curriculum for Mathematics and Mathematical Literacy at the Further Education and Training phase does not promote the acquisition of statistical knowledge that incoming university students require, such as learning statistics concepts beyond descriptive statistics. While the current CAPS Mathematics curriculum can be seen to adhere to some guidelines set by Malik (2014), some students opt to instead enrol in Mathematical Literacy. Ncube and Moroke (2015) note the absence of support for Mathematical Literacy students entering university – this, combined with the absence of statistics in their curriculum, has been thought to lead to negative attitudes towards statistics. It is recommended that more awareness is made of statistics requirements and prerequisites for university programmes, in order to prepare future South African university students for engagement with this important subject.

6.6.3 The Use of fNIRS in Africa

Findings from my study indicated that fNIRS was a more user-friendly alternative to other neuroimaging techniques, and results could be obtained in non-clinical settings such as a university department. The use of fNIRS in classrooms is also noted by other studies (Artemenko et al., 2018; Barreto & Soltanlou, 2022). These findings are supported by other studies, that have, for example, undertaken cortical mapping of cognitive function in infancy in Gambia, using fNIRS (Lloyd-Fox et al., 2014). fNIRS technology due to its portability offers transportability and easier objective measures to study cognition where neuroscientific interventions and screening practices are inaccessible. Seed-based correlation was used to obtain succinct neural correlates in this study, using a simple stimulus design with high reproducibility. The equipment was also easy to use, yet results in high-resolution images that are coupled with well-established cortical mapping techniques to result in definitive activation responses. This is important to future neuroscience research in Africa in rural settings without access to medical facilities, hence the suitability of the portable fNIRS technology that still results in state-of-the-art research outputs.

6.7 Conclusion

Findings from my meta-analysis found a statistically significant relationship between the attitudes that university students possess towards statistics and their achievement in the subject. However, heterogeneity was noted for all components and was hypothesised to be due to methodological factors, namely sample differences, such as education level, region, and statistics course structures, as well as achievement measures used. Findings from my study aligned with those found in the meta-analysis by Emmioğlu and Capa-Aydin (2012) who found small to medium significant relationships between components of statistics attitudes and achievement in statistics. Future research can investigate the relationship between statistics attitudes, statistics anxiety and achievement of Psychology students using additional scales such as the Statistical Anxiety Rating Scale (STARS) or the Composite Survey of Statistics Anxiety and Attitudes (COSSAA) that combines the STARS and SATS (McGrath et al., 2015; Ruggeri et al., 2008).

In addition to the above findings, fNIRS revealed that the neural correlates of statistical reasoning are likely located in the DLPFC, and recommendations for replications of this study are made for definitive research in statistic anxiety. The transportability and methodology of fNIRS lends itself to use in developing countries, where access to neuroscience knowledge and screening tools is not possible. This research has been an insightful look into quantitative and statistical methods within the field of Psychology, and this was a cathartic process of researching both the subjective and objective. The research concludes by stating that more support is need for Psychology students in studying Statistics, due to the noted anxiety they present when undertaking this course, in order to improve their achievement in statistics.

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Appendix A

Recruitment emails

Permission to post to the Psychology Honours class mailing list was granted by the course co-ordinator, Mr Werner Böhmke, on 13 May 2022. Subsequent emails to the mailing list are also attached, dated 13 May 2022, 17 May 2022 and 27 July 2022.

From: **Werner Böhmke** w.r.bohmke@ru.ac.za
Subject: Re: Psych Honours Students: Research Participants
Date: 13 May 2022 at 09:58
To: Emma Wagenaar emmakatewagenaar@gmail.com

WB

Hi Emma,

I am perfectly happy for you to approach the honours class for participant recruitment. The easiest way would be to send an email to the mailing list: psyhon@lists.ru.ac.za

All the best for the data collection.

RHODES UNIVERSITY
Where leaders learn

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On Fri, 13 May 2022 at 09:53, Emma Wagenaar <emmakatewagenaar@gmail.com> wrote:

> Hi Werner!
>
> I hope you have been keeping well. I am not sure if Sizwe has approached you about this already, but I am needing research participants for my fNIRS study on Statistics Anxiety. We were hoping to use Psychology Honours students.
>
> Please let me know what information you would need in order for me to have permission to contact them. We have ethical approval, and all that would be required of them would be filling out a survey and then coming in at some point during SWOT week for the fNIRS, which would just be equipment measuring their response to some statistics stimuli.
>
> Kind regards
> Emma Wagenaar

From: **Emma Wagenaar** emmakatewagenaar@gmail.com
Subject: Participate in Research: Statistics Anxiety
Date: 13 May 2022 at 14:58
To: psyhon@lists.ru.ac.za

EW

Dear Psychology / Organisational Psychology Honours students,

I am Emma Wagenaar, a MA by Thesis student in Psychology. You may know me from working with me as a tutor. I hope studies are going well.

I am conducting research exploring Psychology students' experiences of Statistics Anxiety and I would like to call on you to participate in the study. It will simply involve you completing a survey about your feelings towards Statistics, and then letting me measure your reaction to Statistics using fNIRS software.

My own Honours meta-analysis research found a relationship existed between Psychology students reporting negative attitudes towards Statistics as a subject, and their achievement in Statistics. I am hoping this research could change the way we approach teaching Statistics to make it less stressful, so this can have a direct impact on future Honours students who will be in your shoes in subsequent years!

As stated above, if you are keen I will send you a survey to complete. It is quick and does not require you to flex your Stats skills. I will then make an appointment with you sometime in SWOT week to sit you down and run some fNIRS on you. It is basically brain-scanning equipment that works like an MRI but without magnets, and it is just a little cap that we place on your head to measure blood flow to indicate brain activity. I will show you some Statistics and measure how you react - you don't need to study and get answers right!

If you are keen, you can email me emmakatewagenaar@gmail.com so I can send you the Survey and we can set up a time that suits you. I have been granted permission to contact you and this research has been cleared by Rhodes University Ethical Standards Committee. My Project Supervisor is your lecturer Mr Sizwe Zondo. Also feel free to email me if you have any other questions.

Kind regards
Emma Wagenaar
MA by Thesis (Psychology)
Contract Lecturer
Psychology 1 Graduate Assistant

From: **Emma Wagenaar** emmakatewagenaar@gmail.com
Subject: Participate in Research: Statistics Anxiety
Date: 17 May 2022 at 21:49
To: psyhon@lists.ru.ac.za

Good day all!

Thank you for your responses so far. I am so grateful for everyone who is happy to participate - I'm sure you are all facing similar challenges with your own research.

It is not too late to join the research. You can fill in the survey below and get involved.

https://forms.gle/rvzjjKutSDv2ZF4YA

Thank you again!
Emma Wagenaar
MA by Thesis (Psychology)
Contract Lecturer
Psychology 1 Graduate Assistant

From: **Emma Wagenaar** emmakatewagenaar@gmail.com
Subject: Call for participants: Statistics study
Date: 27 July 2022 at 14:49
To: psyhon@lists.ru.ac.za

EW

Good day Honours students,

I am Emma Wagenaar, a MA by Thesis student in Psychology. You may know me from working with me as a tutor. I hope studies are going well.

I am conducting research exploring Psychology students' experiences of Statistics Anxiety and I would like to call on you to participate in the study. It will simply involve you completing a survey about your feelings towards Statistics, and then letting me measure your reaction to Statistics using fNIRS software.

If you are able to participate in this research (I will be using the fNIRS equipment to scan brain activity) then please fill out the following form: https://forms.gle/wpiUFLEwsghMMMjR8

I will then contact you if you are able to meet with me next Monday or Tuesday (1 or 2 August) to set a time. I will only ask for 30 mins of your time. Please do not hesitate to reach out to me at emmakatewagenaar@gmail.com

I have been granted permission to contact you and this research has been cleared by Rhodes University Ethical Standards Committee. My Project Supervisor is your lecturer Mr Sizwe Zondo. Also feel free to email me if you have any other questions. Five of your classmates have participated so far and the results were verified at an overseas conference, so it is looking very promising!

Thank you
Emma Wagenaar
MA by Thesis (Psychology)
Contract Lecturer
Psychology 1 Graduate Assistant

Appendix B

Demographic Questionnaire and SATS

Participants were supplied with a link to the questionnaire with the recruitment emails. Consent forms are also attached.

Survey of Attitudes Toward Statistics (SATS)

Thank you for agreeing to participate in my research. Please fill out this Survey.

It will begin with a demographic questionnaire, and then 6 different sections with statements pertaining to statistics.

It will take you less than 20 minutes to complete. The results will ONLY be used by me!

* Required

1. By writing my name and surname below, I consent to being contacted about participating in the second half of this study.

2. Rhodes University student number: *

3. Age at the start of your Honours year (1 January 2022): *

4. Are you an Organisational Psychology or General Psychology Honours student? *

   Mark only one oval.

   ◯ Organisational Psychology Honours

   ◯ General Psychology Honours

Instructions:
The questions specifically ask you about your experience studying statistics in your Research Methodology course. Try not to think too deeply about each response. Record your answer and move quickly to the next item.

Skip to question 5

Statements 1-9

The statements below are designed to identify your attitudes about statistics. Each item has 7 possible responses. The responses range from 1 (strongly disagree) through 4 (neither disagree nor agree) to 7 (strongly agree). If you have no opinion, choose response 4.

5. I tried to complete all of my statistics assignments. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

6. I worked hard in my statistics course. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

7. I like statistics. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

8. I feel insecure when I have to do statistics problems. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

9. I have trouble understanding statistics because of how I think. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

10. Statistics formulas are easy to understand. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

11. Statistics is worthless. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

12. Statistics is a complicated subject. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

13. Statistics should be a required part of my professional training. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

Skip to question 14

Statements 10-18

14. Statistical skills will make me more employable. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

15. I have no idea of what's going on in this statistics course. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

16. I am interested in being able to communicate statistical information to others. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

17. Statistics is not useful to the typical professional. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

18. I tried to study hard for every statistics test. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

19. I get frustrated going over statistics tests in class. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

20. Statistical thinking is not applicable in my life outside my job. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

21. I use statistics in my everyday life. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

22. I am under stress during statistics class. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

Skip to question 23

Statements 19-27

23. I enjoy taking statistics courses. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

24. I am interested in using statistics. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

25. Statistics conclusions are rarely presented in everyday life. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

26. Statistics is a subject quickly learned by most people. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

27. I am interested in understanding statistical information. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

28. Learning statistics requires a great deal of discipline. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

29. I will have no application for statistics in my profession. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

30. I make a lot of math errors in statistics. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

31. I tried to attend every statistics class session. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

Skip to question 32

Statements 28-36

32. I am scared by statistics. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

33. I am interested in learning statistics. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

34. Statistics involves massive computations. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

35. I can learn statistics. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

36. I understand statistics equations. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

37. Statistics is irrelevant in my life. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

38. Statistics is highly technical. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

39. I find it difficult to understand statistical concepts. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

40. Most people have to learn a new way of thinking to do statistics. *

Mark only one oval.

	1	2	3	4	5	6	7	
Stro	◯	◯	◯	◯	◯	◯	◯	Strongly agree

Skip to question 41

Final Questions

Note that these are questions, not statements! Please answer them below

41. How good at mathematics are you? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very	◯	◯	◯	◯	◯	◯	◯	Very good

42. In the field in which you hope to be employed when you finish school, how much will you use statistics?

Mark only one oval.

	1	2	3	4	5	6	7	
Not	◯	◯	◯	◯	◯	◯	◯	Great deal

43. How confident are you that you have mastered introductory statistics material? *

Mark only one oval.

	1	2	3	4	5	6	7	
Not	◯	◯	◯	◯	◯	◯	◯	Very confident

44. As you complete the remainder of your degree program, how much will you use statistics?

Mark only one oval.

	1	2	3	4	5	6	7	
Not	◯	◯	◯	◯	◯	◯	◯	Great deal

45. If you could, how likely is it that you would choose to take another course in statistics? *

Mark only one oval.

	1	2	3	4	5	6	7	
Not	◯	◯	◯	◯	◯	◯	◯	Very likely

46. How difficult for you is the material currently being covered in this course? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very	◯	◯	◯	◯	◯	◯	◯	Very difficult

47. What grade are you expecting to receive in this course for the statistics component? *

Mark only one oval.

- 45% or below
- 46-55%
- 56-65%
- 66-75%
- 75% and above

48. In a usual week, how many hours did you spend outside of class studying statistics? Give a whole number as a response.

49. In a usual university week, how would you describe your overall stress level? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very								Very high

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Participant Consent Form

Psychology Department
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Study Title: Investigating the Neural Correlates of Statistics Anxiety: An fNIRS study

I, _________________________ give consent to participate in the research project titled **Investigating the Neural Correlates of Statistics Anxiety: An fNIRS study**

I understand that:

- The nature of the research and the nature of my participation have been explained to me verbally.
- There is no risk or harm that could come to me from participating in the research study.
- Participation in the research study is voluntary and I am free to withdraw from the study at any point.
- My details will remain confidential.

By agreeing to participate in the study, I further state that:

- I have previously taken a Statistics or Quantitative Research Methods Course offered in Psychology.
- I understand that functional near-infrared spectrometry imaging techniques will be used in the study to gain information about my cognitive performance on various neuropsychological.
- The fNIRS technique is a neuroimaging technique used to collect data on brain function.
- I will be assessed on an instrument that measures statistics anxiety. The data will be collected whilst I wear the fNIRS cap.

I agree to participate in the study (Tick one box)?

□ Yes, I provide consent.

□ No, I do not provide consent.

Signing at the bottom of this form means that you agree to participant in the study.

Thank you very much,

Name of Participant: ______________________________________
Date ______________________________________
Place ______________________________________
Signature ______________________________________

Witnessed By

Name of Witness ______________________________________
Date ______________________________________
Place ______________________________________
Signature ______________________________________

Assigned Participant Number: ______________________________________

Appendix C

Statistical reasoning test

The stimuli for the fNIRS procedure was a statistical reasoning test. The stimuli was presented on Microsoft PowerPoint. Slide numbers are indicated on the left with slide contents.

1

You will be shown multiple-choice statistics questions with four possible answers (A-D).

Please read the question and mark your answer on the answer sheet provided.

You will have 40 seconds for each question, followed by a 7 second break.

Do not finish calculating or writing answers during your designated breaks.

The questions will appear automatically.

2

REST

3

1. A researcher conducts an experiment where participants are exposed to dose X of a drug (group 1) or dose Y of the same drug (group 2). Both groups are then shown a list of 20 words and then asked to recall the words two days later. What type of data is the dependent measure (number of words recalled)?

a. Nominal.
b. Ordinal.
c. Interval.
d. Ratio.

4

REST

5

2. 5 people were asked how many times they visited a Covid-19 testing site in the year of 2021. The reported amounts were 2, 5, 7, 4, 2. What statement is true?

a. The mean number of visits is 5.

b. The median number of visits is 2.
c. The median number of visits is 4.
d. The modal number of visits is 4.

6

REST

7

3. If a variable's distribution is normally distributed, what is most likely to also be true about the distribution?

a. Its mean will be greater than its median and mode.
b. Its median will be greater than its mean and mode.
c. Its mean will be similar to its median and mode.
d. Its mean will be greater than its median but less than its mode.

8

REST

9

4. What is the name for scores that are found to be very different from the central tendency of a distribution, leading to large dispersion in the distribution?

a. Outliers.
b. Deviates.
c. Mean deviates.
d. Non-respondents.

10

REST

11

5. What is NOT true about normal distribution?

a. The distribution of scores is symmetrical about the mean.
b. All scores on the variable will have been observed with equal

frequency.
c. Similar distributions are commonly observed in data obtained from psychological research.
d. There will be relatively few extreme scores.

12 ☐
REST

13 ☐
6. Which statement is true in regards to correlations?

a. A negative correlation is the same as no correlation.
b. Scatterplots are a very poor way to show correlations.
c. Negative correlations are of no use for predictive purposes.
d. None of the above.

14 ☐
REST

15 ☐
7. A study produces a Pearson's r value of -0.96. Which statement is false?

a. The observed correlation between variables is negative.
b. There is a small amount of negative covariance between variables relative to random error.
c. A high score on one variable is associated with a low score on the other.
d. Points on a scatterplot would resemble a straight line.

16 ☐
REST

17 ☐
8. Pearson's r is calculated as 0.2 when measuring strength of association between two variables. If this is found to be significant at alpha = 0.05, what would you conclude?

a. There is a significant but small relationship between the two

variables.
b. There is a non-significant but large relationship between the variables.
c. There is a significant and moderate relationship between the variables.
d. The two variables are unrelated.

18

REST

19

9. 221 participants complete 24 measures designed to assess the impact of social and psychological factors on stress in the workplace. Correlations between pairs of these variables are conducted. How many degrees of freedom will the analysis have?

a. 220
b. 219
c. 24
d. 23

20

REST

21

10. Research identified a significant positive correlation (r = .42) between the number of children people have and their life satisfaction. Which of the following is it inappropriate to conclude from this research?

a. That having children makes people more satisfied with their life.
b. That someone who has children is likely to be happier than someone who does not.
c. That the causes of life satisfaction are unclear.
d. That it is possible to predict someone's life happiness partly on the basis of the number of children they have.

22

REST

23

11. A regression analysis is performed to predict excitability of participants based on the amount of cups of coffee consumed. The straight line equation generated was $y = 0.46x + 68.20$. What predicted excitability will be seen if a person consumes 8 cups of coffee?

a. -148.26
b. 71.88
c. 68.20
d. 31.37

24

REST

25

12. Attention spans over amount of hours reading was investigated for a study. According to the coefficient table showing regression analysis, what is the standard error for the hours spent reading?

a. 49.218
b. 0.460
c. 0.764
d. 0.221

26

REST

27

13. What would a regression variation = 421 and residual variation = 69413 in a regression model, p-value = 0.038 lead you to conclude?

a. The regression model is insignificant due to regression variation being much smaller than the residual variation.
b. The regression model is significant due to regression variation

being much smaller than the residual variation.

c. The regression model is expected to be insignificant but will in fact be significant.

d. The regression model is expected to be significant but will in fact be insignificant.

28

REST

29

14. Given the table below, calculate the F-value obtained at x.

a. 3.53
b. 0.06
c. 17.00
d. 1.06

30

REST

31

15. A straight line equation generated from regression analysis was y = -0.87x + 27.34. If the outcome variable was found to be 19.65, what was the value for the predictor variable?

a. 10.24
b. 8.84
c. 49.93
d. 8.56

32

REST

33

16. The mean height of a sample of 100 men in 2022 is 180 cm, with a standard deviation of 10 cm. The mean for the same population in 1922 was 170 cm. If we were to use the 2022 sample to test if the height of men has changed over 100 years since 1922, what will be our t-value?

a. 1
b. 0.1
c. 10
d. -10

34

REST

35

17. You conducted a t¬-test to compare two groups, but find that in group 1 the standard deviation is much larger than in group 2. What is the reason for this?

a. The variances are robust.
b. The assumption of equal variance may have been violated.
c. The researchers should make sure that their distributions are free of parameters.
d. The standard deviations are not normal.

36

REST

37

18. In hypothesis testing with alpha value =0.05, you examine a difference between two means. You obtain a t-value of 3.46, and discover that the critical t-value with alpha=0.05 is 2.056. What will you conclude?

a. There is a statistically significant difference between the means.
b. The difference between the means is not statistically significant.
c. The alpha value must be lowered to 0.01.
d. A conclusion cannot be drawn from this information alone.

38

REST

39 ☐

19. In an experiment, participants were randomly assigned to a control or experimental condition. What statement(s) would be true?

a. A between-subjects t-test can be used to analyse results.
b. The experiment involves two related samples.
c. In a t-test here, there will be n-1 degrees of freedom.
d. Both a and c

40 ☐

REST

41 ☐

20. When will assumptions for a between-subjects t-test be violated?

a. Evidence that the dependent variable is normally distributed.
b. Evidence that the samples being compared have unequal variances.
c. Evidence that the manipulation of the independent variable had no effect.
d. Evidence that sampling was random, and that scores were independent.

42 ☐

REST

43 ☐

21. In a one-way ANOVA, the total sum of squares comprises what sources of variance?

a. Within-groups variance.
b. Information variance.
c. Between-groups-variance.
d. Both a and c.

44 ☐

REST

45

22. What is not a difference between ANOVA and a t-test?

a. ANOVA can compare responses of more than two groups.
b. ANOVA does not make assumptions of homogeneity, normality and independence.
c. ANOVA can examine the impact of more than one variable.
d. ANOVA is concerned with analysis of ratios of variances.

46

REST

47

23. Which of the following statements about the F-distribution is false?

a. The distribution is asymmetrical.
b. The distribution is one-tailed.
c. Higher values of F are associated with a higher probability value.
d. The distribution is positively skewed.

48

REST

49

24. A Levene's test reveals an F-value of 1.51 and a p-value of 0.225. Have assumptions of ANOVA been met?

a. Yes, Homogeneity of Variance has not been violated ($p>0.05$)
b. No, Homogeneity of Variance has been violated ($p>0.05$)
c. No, as the F-value is greater than 1.
d. Yes, as the F-value is greater than 1.

50

REST

51

25. If you are to analyse the differences between 3 independent groups, where the data is found to be continuous and not normally distributed, what test would be most appropriate to use?

a. t-test
b. One-way ANOVA
c. Chi-squared test
d. Kruskall-Wallis test

52

REST

53

END OF TEST.

Thank you for your participation!

Appendix D

Published Protocol

The fNIRS protocol was published (dx.doi.org/10.17504/protocols.io.14egn24e6g5d/v1).

protocols.io

fNIRS Statistical Reasoning

Emma Wagenaar[1], Sizwe Zondo[1]

[1]Rhodes University

E Emma Wagenaar

ABSTRACT

fNIRS and fMRI techniques have been utilised in the exploration and confirmation of the region of interest for mathematical reasoning, i.e. neural correlates involved when statistics tasks are performed. A block design protocol was created for statistical reasoning.

Protocol Info: Emma Wagenaar, Sizwe Zondo . fNIRS Statistical Reasoning. **protocols.io** https://protocols.io/view/fnirs-statistical-reasoning-ck4fuytn

Created: Dec 30, 2022

Last Modified: Dec 30, 2022

PROTOCOL integer ID: 74599

Introducing participants to procedure

1 Obtain consent from participant for procedure

Positioning Photon Cap on participant

1 Place Cortivision Photon Spectroscope Cap on participant's head, by first positioning it on the forehead and then gently pulling over the rest of the cranium to fit snugly on head.

1.1 Ensure that "AFz" optode position is squarely in the middle of the forehead. The edge of the cap should hence rest just above the participant's eyebrows.

1.2 Check that ear loops are in the same position on either side of the head and will allow ears to stick through.

1.3 Secure the cap by using velcro chin strap, pulling on the end of the ear loops so that the cap is snug.

2 Use measuring tape to take cranial measurements of the participant

2.1 Measure across the top of the head, ear-to-ear (width in cm)

2.2 Measure forehead (AFz) to nape of neck (where gyroscope/power source is attached) (length in cm)

3 Cover Photon Cap with blackout fabric cap (velcro strap meets at nape of neck)

4 Attach power supply device to participant's left upper arm

Preparing the fNIRS software for use

2m

5 Open Cortivision Cortiview software on computer device

2m

6 Switch on Cortivision Photon Spectroscope cap on power supply pack

6.1 Select "CONNECT" on Cortiview programme. If the device has not been paired, access computer's Bluetooth setting and pair Cortivision device to the computer.

7 Load dorsolateral prefrontal cortex montage from library

Calibration of signals

1m 30s

8 Dim room lights as much as possible to mitigate light interference

9 Select "START NIRS" on right hand panel on Cortiview and allow signal to run for 30s 30s

9.1 Check signal quality at the bottom of the screen.
Low = Red, Medium = Orange, High = Green

9.2 Identify low-quality signals and adjust areas accordingly: this may mean gently pulling the cap downwards by its edge so that the optodes are closer to the skull. It may require moving the participant's hair out the way if this is deemed to be blocking the signal.

10 Once the signals are acceptable quality (mostly green), begin calibration.

10.1 Ask the participant to sit comfortably in a natural position and remain still. They should be positioned how they will be during the testing procedure.

10.2 Select "CALIBRATE NIRS" on right-hand panel. Allow the software to calibrate. 30s

10.3 Select "CALIBRATE IMU" on right-hand panel. Allow gyroscope to calibrate on software. A flatline should be noted when participants are still once properly calibrated. 30s

Data Collection

11 Select "RECORD" and enter participant's details. Device begins recording data once this step is complete.

12 Open testing procedure software and allow to run.

Testing procedure

20m 42s

13 Instructions page (Slide 1) 1m

14 REST 7s

15 Descriptive Statistics (Question 1-5)

15.1 Question 1 40s

15.2 REST 7s

15.3	Question 2	40s
15.4	REST	7s
15.5	Question 3	40s
15.6	REST	7s
15.7	Question 4	40s
15.8	REST	7s
15.9	Question 5	40s
15.10	REST	7s

16 Correlation (Question 6-10)

16.1	Question 6	40s
16.2	REST	7s
16.3	Question 7	40s
16.4	REST	7s
16.5	Question 8	40s
16.6	REST	7s
16.7	Question 9	40s
16.8	REST	7s

16.9	Question 10	40s
16.10	REST	7s
17	Regression (Question 11-15)	
17.1	Question 11	40s
17.2	REST	7s
17.3	Question 12	40s
17.4	REST	7s
17.5	Question 13	40s
17.6	REST	7s

17.7	Question 14	40s
17.8	REST	7s
17.9	Question 15	40s
17.10	Rest	7s
18	T-tests (Question 16-20)	
18.1	Question 16	40s
18.2	REST	7s
18.3	Question 17	40s
18.4	REST	7s

18.5	Question 18	40s
18.6	REST	7s
18.7	Question 19	40s
18.8	REST	7s
18.9	Question 20	40s
18.10	REST	7s
19	Analysis of Variance (Question 21-25)	
19.1	Question 21	40s
19.2	REST	7s

19.3	Question 22	40s
19.4	REST	7s
19.5	Question 23	40s
19.6	REST	7s
19.7	Question 24	40s
19.8	REST	7s
19.9	Question 25	40s
19.10	REST	7s

20 END OF TEST

Appendix E

Ethics clearance letters

Ethical clearance was granted for the meta-analysis and fNIRS study.

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NHREC Registration number: RC-241114-045

https://www.ru.ac.za/researchgateway/ethics/

21/09/2021

Emma Wagenaar

Email: g17w3806@campus.ru.ac.za

Review Reference: 2021-5148-6211

Dear Mr Sizwe Zondo

Title: Psychology Students' Attitudes and Achievement in Statistics: A Meta-Analysis

Principal Investigator: Mr Sizwe Zondo

Collaborators: Ms Emma Wagenaar

This letter confirms that the above research proposal has been reviewed and **APPROVED** by the Rhodes University Human Ethics Committee (RU-HEC). Your Approval number is: 2021-5148-6211

Approval has been granted for 1 year. An annual progress report will be required in order to renew approval for an additional period. You will receive an email notifying when the annual report is due.

Please ensure that the ethical standards committee is notified should any substantive change(s) be made, for whatever reason, during the research process. This includes changes in investigators. Please also ensure that a brief report is submitted to the ethics committee on the completion of the research. The purpose of this report is to indicate whether the research was conducted successfully, if any aspects could not be completed, or if any problems arose that the ethical standards committee should be aware of. If a thesis or dissertation arising from this research is submitted to the library's electronic theses and dissertations (ETD) repository, please notify the committee of the date of submission and/or any reference or cataloging number allocated.

Sincerely,

Prof Arthur Webb

Chair: Rhodes University Human Ethics Committee, RU-HEC

cc: Mr. Siyanda Manqele - Ethics Coordinator

Page 1 of 1

Rhodes University Human Ethics Committee
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25 November 2021

Mr Sizwe Zondo

Email: S.Zondo@ru.ac.za

Review Reference: 2021-5308-6453

Dear Mr Sizwe Zondo

Re: Investigating Executive Functions in a Healthy Student Population: An fNIRS Study

Principal Investigator: Mr Sizwe Zondo

Collaborators: Prof Philani Mashazi, Dr Nicola Wannenburg

This letter confirms that the above research proposal has been reviewed by the Rhodes University Human Ethics Committee (RU-HEC) and **PROVISIONALLY APPROVED PENDING PERMISSION/GATEKEEPER LETTER(S)**.

Gatekeeper permission is required from:

Prof Adele Moodly, Registrar: Rhodes University (registrar@ru.ac.za)

Once the Gatekeeper permission letter/s has been received please forward it to the Ethics Coordinator, in order to finalize your ethics approval.

Sincerely,

Prof. Arthur Webb

Chair: Rhodes University Human Ethics Committee, RU-HEC

cc: Ms Danielle de Vos - Ethics Coordinator