Rhodes University – Department of Psychology

Research project cover sheet

To accompany a research project submitted for examination in partial fulfilment of the requirements for the Honours Degree in Psychology / Organisational Psychology

1. Information

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Type of thesis	Research Project
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2. Declaration by supervisor

Either:

This project has been prepared under my supervision. I have read it carefully and believe that it meets the standards set out in the appropriate guidelines booklet in terms of academic content, clarity of research question, description of methodology, quality of analysis and ethical standards, as well as in terms of format, length, structure and referencing. Signature and date:

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This project has been prepared under my supervision using the guidelines set out in the appropriate guidelines booklet in terms of format, structure and referencing. However, I am not convinced that it meets the required academic standards with regards to academic content, clarity of research question, details of the methodology, quality of analysis, or ethical aspects.

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STATISTICS FOR PSYCHOLOGY:

A Meta-Analysis of Psychology Students' Attitudes Towards Statistics

to Address Statistics Anxiety In The Social Sciences

Research submitted by

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Thesis submitted in partial fulfilment of the requirements for the degree of

Bachelor of Science with Honours in Psychology

Supervisor: Mr Sizwe Zondo

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ABSTRACT

Statistics anxiety is a well-documented phenomenon amongst students which is a result of negative attitudes towards Statistics. This is especially prevalent in the Social Sciences with Psychology students, where research indicates a relationship between attitudes and achievement in Statistics courses. This research project aimed to investigate this relationship. My study took the form of a meta-analysis comparing Psychology students' attitudes towards statistics using the SATS, to their achievement in statistics/quantitative research methods courses. Results indicated a statistically significant relationship between the attitudes of Psychology students (r = 0.226, p < 0.05), quantified by their reported *Affect*, self-perceived *Cognitive Competence*, measure of *Value* and degree of *Difficulty* of Statistics, and their subsequent achievement in Statistics. The strongest correlations were noted for *Affect* (r = 0.247, p < 0.005) and *Cognitive Competence* (r = 0.29, p < 0.005) SATS scores. Heterogeneity was noted in *Affect* (I^2 = 30.998%) and *Difficulty* (I^2 = 54.248%). The study possessed limitations in the integration of other factors into the meta-analysis, availability of studies, and understanding of meta-analysis. Future Statistics attitudes research should include achievement measurements for more investigation into this relationship. This research will hopefully lead to more support in both quantitative research design and statistical training for postgraduate Psychology students at Rhodes University.

Keywords: SATS-28, SATS-36, statistics anxiety, attitudes towards statistics, statistics education in Psychology

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1. LITERATURE REVIEW

1.1 Context & Rationale

1.1.1 Statistical literacy

It is important for future researchers to possess statistical literacy. This is defined by Schield (2004) in Koh and Zawi (2014) as the mathematical approach to identifying patterns and significance, combined with the statistical approach of seeing the importance of context, conditional reasoning and variation within information. It requires one to use quantitative methodology on data and then go further and read, interpret, and communicate the findings thereof (Koh & Zawi, 2014). Ramirez, Schau and Emmioğlu (2012) describe the goal of statistics education as being to teach students to critically apply statistical thinking. Statistics education is unique though, because this can be achieved through engagement with introductory courses (Ramirez *et al.*, 2012), where the fundamental concepts of statistics are taught. This is not the only intended outcome of introductory statistics courses, however, as students also need to believe in their own ability to understand and use statistics, identify its application in their personal and professional lives, find the subject matter interesting, as well as be willing to invest time and effort into learning statistical concepts whilst recognizing that the difficulty of statistics can be overcome (Ramirez et al., 2012). These outcomes all pertain to the attitude that students have towards statistics, and literature suggests that a relationship exists between the attitude of students and their subsequent performance and achievement in statistics courses.

1.1.2 Statement of the Problem: Statistics Education in South African schools and universities

The Department of Basic Education designed the National Curriculum Statement (NCS) for Grades R-12, which prescribes the knowledge areas that South African children will explore in their years at formal schooling. The Further Education and Training Phase (FET: Grades 10-12) refers to the final schooling years of a learner that will also determine entry into tertiary education. Hence, it would be of interest to investigate the Mathematics and Mathematical Literacy curriculum for this phase and investigate the knowledge of statistical concepts that incoming university students are likely to possess. In the Curriculum Assessment Policy Statements (CAPS), the only topic that resembles Statistics for Mathematical Literacy is “Data Handling”, and a median of 5 weeks per year is spent on this topic (Department of Basic Education, 2011a). The learning outcomes specified for Data Handling stipulate that students can develop questions, collect, classify and organise data, summarise and represent data, and conduct some data analysis and interpretation (Department of Basic Education, 2011a); however, it should be noted that this data only pertains to data deemed relevant to the pupil’s personal life and social context, and no formal statistical operations are taught during data analysis and interpretation. Mathematical Literacy is offered as a subject option for those learners in the FET phase who do not have a passion or aptitude for Mathematics per se. 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.

For those learners choosing Mathematics as a subject, a mere two to three weeks are dedicated to Statistics in Grades 10-12 (Department of Basic Education, 2011b), and the curriculum focuses on descriptive statistics. In Grade 10, pupils focus on data collection, organization and basic statistical interpretation using measures of central tendency and dispersion, as well as visual representations of data such as box-and-whisker diagrams (Department of Basic Education, 2011b). The Grade 11 syllabus introduces graphical representations of central tendency and dispersion and the manual calculation of these values, as well as the representation of skewed and outlying data (Department of Basic Education, 2011b). In Grade 12, bivariate data is explored for the first time and pupils are expected to determine the goodness-of-fit of data to linear, quadratic or exponential models; regression and correlation models are also calculated (Department of Basic Education, 2011b). According to an Introductory Statistics curriculum designed by Illowsky and Dean (2018) in *Collaborative Statistics*, the syllabi for statistics in the FET phase only encompasses three topics in basic statistics education – Sampling and Data, Descriptive Statistics, and rudimentary levels of Regression and Correlation. This is not an adequate foundation, as other fundamental statistical concepts such as Probability, Distributions, Confidence Intervals, Hypothesis Testing and Analysis of Variance, are not even introduced.

Rhodes University's Department of Statistics offers three introductory courses in Statistics: Statistics for Science (1S1), Statistics for Pharmacy (1P1) and Statistics for Commerce (1C2) (Radloff & Baxter, 2020). Statistics 1C2 teaches fundamental concepts and techniques of statistics that one would expect to use in business; the topics in the course include Numerical and Graphical Descriptive Statistics, Probability, Sampling, Estimation and Hypothesis Testing, Correlation and Regression, and Time Series Analysis (Radloff & Baxter, 2020) – a comprehensive introductory course according to Illowsky & Dean (2018). Statistics 1P1 is a prerequisite for third-year Bachelor of Pharmacy students, and Statistics 1S1 is described as the introductory course for all students who would make use of data analysis and interpretation in their studies, namely, biological sciences students (Radloff & Baxter, 2020). These course curriculums include all the components of the Statistics 1C2 course including Time Series Analysis, and with the addition of Probability Distribution, analysis of categorical data and questionnaires, and instruction in non-parametric procedures, factorial design ANOVA, and survival curves, estimators and models (Radloff & Baxter, 2020).

1.2 Statistics in Social Science

1.2.1 The usefulness of Statistics in the Social Sciences

The application of statistics is not limited to Biological Sciences, Mathematics and Commerce fields; Coetzee and van der Merwe (2010) note how Statistics forms an important part of most tertiary level studies, specifically in the Social Sciences. The Social Sciences refers to subjects such as Psychology, Anthropology and Sociology – all of which are offered as major subjects at Rhodes University. Here, as with other sciences, statistical concepts are used in research for quantitative data collection, analysis and interpretation. However, Bose (2017) notes that many tertiary-level students neglect to realise that the scope of their fields of study may include auxiliary subjects that focus on building and refining research skills, such as Statistics. Ncube and Moroke (2015) and Onwuegbuzie and Wilson (2003) further emphasise the teaching of quantitative methodology as an integral part of undergraduate Psychology and Social Sciences courses, and this is extended in postgraduate studies where the evaluation and interpretation of empirical research findings is a core aspect of professional training in fields such as Psychology (Coetzee & van der Merwe, 2010). The perpetuating problem is that Statistics continues to be treated as merely a topic taught to enhance research in the Social Sciences field, when there should be more emphasis on integrating statistical concepts and practical applications throughout the coursework of the field. The use of Statistics in these fields is immense but it is still treated as an afterthought in coursework design.

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. 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. It is important to reiterate an observation made by Ncube and Moroke (2015) above, where many students 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 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.

1.2.2 Attitudes in Social Sciences towards Statistics

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. Zimprich (2012) reported a certain aversion that Psychology students at the University of Zurich had towards their compulsory statistics course. Liau, Kiat and Nie (2015) quoted a study by Griffith *et al.* (2012) where 39% of Psychology majors were shown to have negative attitudes towards statistics as a result of their experiences. Reasons given for this included the subject being described by the students as too difficult as well as irrelevant for their future career paths, and also because of a predeveloped dislike for Mathematics (Liau *et al*., 2015). Ncube and Moroke (2015) noted that within the South African context, Behavioural Sciences and Social Sciences students enrolled at the University of South Africa, had a perfunctory disposition towards statistics. Similarly, amongst 235 Industrial Psychology students at another South African university, Coetzee and van der Merwe, (2010) found that while students were interested in statistics and had mostly positive attitudes towards it, the students also reported feelings of insecurity, stress and frustration. These feelings can culminate into a defined phenomenon experienced by students, namely, Statistics Anxiety.

1.3 Statistics Anxiety as a result of a negative attitude towards statistics

Statistics Anxiety is defined by Zeidner (1991) as an individual experiencing extensive worry, intrusive thoughts, mental disorganization, tension, and even physiological arousal as a result of stress when they are confronted with statistical concepts or problems, in such a manner that it impairs the performance of the individual in statistics tasks. Statistics Anxiety is a markedly unique and discrete concept to that of Mathematics Anxiety. The skills required of the individual to engage in statistical work, including interpretation and analysis, are different to the thinking processes involved in mathematics (Ruggeri, Dempster, Hanna & Cleary, 2008). Onwuegbuzie (2004), quoting Cruise *et al*. (1985), created a similar multidimensional construct of the experience of Statistics Anxiety which includes the *worth* of statistics, anxiety of *interpretation* of results, anxiety regarding *assessments* including tests and classes, computational *self-concept*, not wanting to ask for help, and *fear* of those teaching statistics. 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. Hence, attitudes of students towards statistics, and the consequent feelings of anxiety as a result of negative attitudes, may be a predictor of academic achievement in Statistics courses. There is thus a need to quantify these particular attitudes of Social Sciences and Psychology students in order to attempt to decrease statistics anxiety when undertaking Research Methodology courses.

1.4 Achievement in Statistics

A key aspect of assessing attitudes towards statistics is relating this to the student's performance in the subject – namely, their achievement. 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. In terms of statistics achievement, Coetzee and van der Merwe (2010) and Zimprich (2012) opted to use high school mathematics results of undergraduate students taking statistics courses as a measure of statistics achievement. The authors reported statistically significant correlation results between achievement and most aspects of attitudes toward statistics. Emmioğlu and Capa-Aydin (2012) measured success by reporting students' current statistics grades and exam grades as a measure of statistics achievement that was of statistical significance. The authors additionally reported studies using standardised instruments to assess achievement, namely the Statistical Reasoning Assessment (SRA) and Statistics Concept Inventory (SCI), that assess students' reasoning with, and understanding of, statistical concepts (Emmioğlu & Capa-Aydin, 2012).

1.5 Application of Theoretical framework to Survey Analysis: The SATS

1.5.1 The Survey of Attitude Towards Statistics ©

A popular method of quantifying attitudes and dispositions towards statistics is using scales that measure students' attitudes towards statistics, such as the Survey of Attitudes Towards Statistics (SATS), created by Candace Schau (2000). There are two copyrighted version of the SATS, namely the SATS-28 and SATS-36, comprising of 28 and 36 items respectively. There are six attitude components in the SATS-36 that are designed to assess participants' feelings regarding learning and practicing statistics. *Affect* is the measure of how students feel about Statistics as a subject (Coetzee & van der Merwe, 2010). *Cognitive Competence* is concerned with how students rate their own understanding and skills in Statistics. According to Schau (1995), as quoted by Onwuegbuzie (2004), *Value* is the measure of the usefulness of Statistics as seen by students in their everyday and professional lives. *Difficulty* is simply how difficult the coursework and activities are for the students, whilst *Interest* and *Effort e*merge from this as being identified as the students' interest in Statistics as a subject, and the amount of work they are willing to devote to learning the subject (Vanhoof *et al*., 2011).

In research utilizing surveys that measure students' attitudes towards statistics, such as those of Gal *et al.* (1997), Nolan, Beran and Hecker (2012), and Ramirez, Schau and Emmioglu (2012), the SATS is favoured for being comprehensive, thorough, and non-threatening in nature. These enquiries are quoted by the aforementioned researchers in above sections, and additionally by Ashaari *et al.* (2011), Chowdhury *et al.* (2018) and Emmioğlu and Capa-Aydin (2012), as reasons for the specific use of SATS in their research. Emmioğlu and Capa-Aydin (2012) found "adequate to high internal consistency values for all components" (pp. 96) using Cronbach's alpha values. Coetzee and van der Merwe (2010) recorded acceptable levels of internal consistency among the components and also concluded that the SATS-36 could be used to assess South African students’ attitudes.

1.5.2 Examples of Studies using SATS

Ncube and Moroke (2015) conducted a survey with 913 students taking introductory statistics courses at a South African university, and 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. The German version of the SATS-36 was used to conduct research on 346 Psychology students at the University of Zurich who were enrolled in a Statistics course that was made compulsory for graduation with a Psychology degree (Zimprich, 2012). To measure achievement in Statistics, the students were asked to rate the last high school Mathematics grade they had achieved on a scale, and 301 of the students also took a written Statistics test (Zimprich, 2012). The research found a strong correlation between achievement and *Affect* and *Cognitive Competence* (Zimprich, 2012) which aligns with the results reported by Ncube and Moroke (2015).

Another South African example is that of the cross-sectional survey design of Coetzee and van der Merwe (2010). 235 Organisational Psychology students at a South African university participated in a SATS-36 survey, and results showed that while *Interest* and *Effort* were markedly high for the sample, their overall feelings towards statistics and its usefulness were neutral, and they negatively rated its difficulty level (Coetzee & van der Merwe, 2010). The high school mathematics results of students were used as a measures of achievement (Coetzee & van der Merwe, 2010). This indicates that, overall, the subject does seem to be daunting for Social Sciences students, despite them being enthusiastic for the subject itself – but also that its worth is still underestimated. Dempster and McCorry (2009) also made use of high school mathematics results as a measure of achievement in their study with 82 Psychology students who participated in a SATS-28 survey, and noted that the competency that students feel towards statistics is influenced by prior achievement, and can be a predictor for later attitudes.

Final results in a Statistics course are also found to relate to attitudes towards statistics. Finney and Schraw (2003) investigated the relationship between Statistics course percentages of 103 Educational Psychology students, their attitudes towards statistics, and their own reported self-efficacy in the subject. It was found that there was a moderate relationship between statistics self-efficacy and statistics anxiety (r = -0.57). Hood, Creed and Neumann (2012) also used the final Statistics course results for 149 Psychology students as an outcome variable to relate to attitudes towards statistics. *Cognitive Competence* and *Value* were found to be significantly correlated to achievement (Hood *et al.*, 2012).

Liau, Kiat and Nie (2015) made use of a pre-test, post-test design to assess interventions put in place to improve attitudes towards statistics by utilising more tutors, hands-on activities, collaborative learning and scaffolding activities designed to address attitude. 103 Psychology students at a Malaysian university were enrolled in this programme, with 66 completing the SATS-36 and EPAS as the measurements for attitudes towards statistics (Liau *et al.*, 2015). The pre-test post-test analysis for the SATS showed significant positive changes in *Affect* and *Cognitive Competence*, a negative change in *Effort* and no other reported significant changes (Liau *et al.*, 2015). This highlights the power of intervention strategies aimed at supplementary support for Social Sciences students on their attitude towards statistics and reduced statistics anxiety, which can lead to improved achievement and performance in the subject.

1.6 Aims of the study

The meta-analysis study conducted by Emmioğlu and Capa-Aydin (2012) is of interest to this research, as it relates to the above cited literature in investigating the relationship between attitudes towards statistics as measured by SATS, and achievement in statistics in student populations. Emmioğlu and Capa-Aydın (2012) capitalize on the absence of literature on the relationship between statistics attitudes and statistics achievement, by performing a meta-analytical study in order to consolidate the findings of existing studies. Findings from the study are that *Cognitive Competence* and *Affect* generally had higher correlations to achievement than *Value* and *Difficulty* (Emmioğlu & Capa-Aydin, 2012). Global correlation coefficients for the components were 0.30 for *Affect,* 0.30 for *Cognitive Competence,* 0.21 for *Value* and 0.20 for *Difficulty*. This inquiry aimed to revisit the meta-analysis of Emmioğlu and Capa-Aydın (2012), but with a narrowed scope of investigating the relationship between attitudes of Psychology students towards statistics, as measured by SATS, and the achievement of these students in statistics. This will hopefully form the basis of designing a Statistics courses for Psychology students at Rhodes University that caters to reducing statistics anxiety amongst Psychology students as a result of negative attitudes.

2. AIMS AND METHODOLOGY

2.1 Aims and Objectives

2.1.1 Research Objectives

My study seeks to expand on the four research questions in the meta-analysis performed by Emmioğlu and Capa-Aydin (2012), entitled "*Attitudes and achievement in statistics: A meta-analysis study*". The findings of Emmioğlu and Capa-Aydin (2012) suggested that there is a medium statistically significant relationship between statistics achievement and components of the SATS (i.e., *Value*, *Cognitive Competence, Effort/Difficulty, Affect, Cognitive Competence, and Interest*). My study seeks 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. No additional meta-analyses have been published in the 8 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, and achievements in, statistics.

2.1.2 Research Questions and Hypothesis

The main research question thus investigates the relationship between statistics anxiety and achievement in the subject. My proposed research questions derive from those asked by Emmioğlu and Capa-Aydin (2012) with the addition of sources from other studies. The key questions I will seek to answer are:

1. What is the relationship between Psychology students' *Affect* toward statistics as a subject and subsequent statistics achievement?

2. What is the relationship between Psychology students' self-defined *Cognitive Competence* and skills concerning statistics and statistics achievement?

3. What is the relationship between Psychology students' measure of the *Value* of statistics in their own lives and professional identities and statistics achievement?

4. What is the relationship between Psychology students' perceived *Difficulty* of statistics and statistics achievement?

My hypothesis remains the same as that postulated by Emmioğlu and Capa-Aydin (2012), and this is not expected to have changed in the 8 years since the study. It is hypothesized that there is a statistically significant relationship between the attitudes of students towards statistics and their subsequent performance and achievement in the subject.

2.2 Instruments

2.2.1 Structure of SATS-28 and SATS 36

There are 4 components of the SATS-28 and 6 components of the SATS-36. There are multiple items and variables within these components that further describe the measures, which add up to 28 items in the SATS-28 and 36 in the SATS-36. The items are worded as statements with which one can either agree or disagree to varying degrees. A 7-point Likert response scale is provided for each item, where 1 = "Strongly Disagree", 4 = neutral response, i.e. "Neither Agree Nor Disagree", and 7 = "Strongly Agree" (Ramirez *et al.*, 2012). This response style is purposeful as it means that higher scores correspond to more positive attitudes (Schau, 2000). However, in negatively worded items that are indicated with an asterisk, a lower score would indicate a positive attitude, so the scoring is reversed (Schau, 2000). This means that if a score of "7" is selected for a negatively-phrased item, then the score for the item is tallied as 1.

2.2.2 SATS Components and Items

Affect has six items that include statements such as "I will like statistics" and "I am scared by statistics" (Gal, Ginsburg & Schau, 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). Cronbach's alpha values were reported by Schau (2019) for each component based on studies that utilized SATS-28 or SATS-36 in research. 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.

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. This component has the lowest range, and the minimum value is below the recommended range of acceptable Cronbach's alpha values, at 0.70 (Tavakol & Dennick, 2011).

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.

2.3 Methodology

2.3.1 Research Design for Meta-Analysis

The nature of the research questions lends itself to quantitative research – more specifically, the research design of a meta-analysis was used for analysis. Emmioğlu 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 that could result in supposed conflicting results in research. This proves useful when noting that the answers for the components in SATS will differ amongst the studies used in a meta-analysis, since all use student samples that are independent to other reported studies. This 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 the nature of this study which seeks to investigate a relationship between SATS results of students and their achievement in statistics courses, Pearson's correlation coefficient was selected as the most appropriate effect size. This is also the effect size used in the study by Emmioğlu and Capa-Aydin (2012), and it is the most common effect size utilized in social science research (Field & Gillett, 2010).

Meta-analysis also addresses a challenge that Rosenthal and DiMatteo (2001) identify for quantitative research with numerical results – the responses to SATS are nominal, and hence it seems there is no meaningful way to represent these results that would allow for interpretation. By employing a meta-analytic approach, key correlations can be discovered and used to verify the overall findings of the studies, making the conclusions drawn more credible than if one confirmed the hypothesis with a single data set. The framework that informed my meta-analysis inquiry was derived from Schau's (2000) conception of ‘statistics anxiety’ as summarised in the SATS-36. Four components of the SATS are considered as per the research questions, namely *Affect*, *Cognitive Competence*, *Value* and *Difficulty*, and each component is then correlated against statistics achievement.

2.3.2 Inclusion and exclusion criteria for selected studies

In aligning with the nature of a meta-analysis, the sampling procedure takes on a different scope than when identifying a sample group on which to apply the units of analysis, where samples are found amongst existing published research. Studies using other surveys, other than the SATS-28 and SATS-36 to measure attitudes towards statistics anxiety were excluded. The difference between SATS-28 and SATS-36 lies in the components *Interest* and *Effort* appearing in the SATS-36. Since only *Affect*, *Cognitive Competence*, *Value* and *Difficulty* were of interest, studies included in this inquiry could make use of the SATS-28 or SATS-36 interchangeably. Emmioğlu and Capa-Aydin (2012) reported that both structures of the SATS have been validated using confirmatory factor analysis, and their meta-analysis studies reported adequate to high internal consistency values within all components.

Only studies reporting on the relationship between the SATS and achievement, with regard to Psychology students, were included in the meta-analysis. The meta-analysis included data from undergraduate and postgraduate Psychology students. Studies also had to include a measure of achievement as the outcome variable. Outcome variables denoting achievement included studies reporting both mathematics results and/or statistics tests marks and grades. Similar to Emmioğlu and Capa-Aydin (2012) my meta-analysis included studies that report Pearson's correlation coefficient (*r*) as the measure of the relationship between the attitude component of the SATS and achievement.

2.3.3 Search strategies

The unit of analysis in this meta-analysis was literature in the form of journal articles pertaining to statistics anxiety, the SATS and achievement. Relevant studies were obtained through a search of the phrases including the name of the available SATS versions, namely "SATS-36" and "SATS-28". This was paired with "Social Sciences" and "Psychology" filters in order to specify the type of students included. The scope of this study was delimited exclusively to a sample of psychology students whose attitudes towards Statistics would then be included in the literature search and subsequent meta-analysis.

Data collection for this research project would require the use of online databases. A heavily utilised database in this study was ResearchGate, wherein some authors make their articles directly available – this proved useful. The original meta-analysis by Emmioğlu and Capa-Aydin (2012) also provided usable studies for inclusion in this meta-analysis. The author of the SATS keeps record of publications that use the survey in research, so this database was also accessed (Schau, 2019)

2.4 Statistical methods

Effect sizes for the studies were calculated as being the correlation coefficients between students' attitudes and achievement. The initial meta-analysis of Emmioğlu and Capa-Aydin (2012) and descriptive statistics used in the study were utilised to inform the initial procedures of statistical analysis. A random-effects model was used for the study in accordance with suggestions made for social science research (Field & Gillett, 2010). A random-effects model, as opposed to a fixed-effects model, allows for inferences that generalize beyond the studies being used in the meta-analysis (Field & Gillett, 2010). The advantage of using this model is that the assumption is then that of one true effect size, with differences being explained as sampling error (Borenstein *et al.*, 2009).

Furthermore, the method of meta-analysis used in my study was the Hunter-Schmidt method which focuses on isolating and correcting sampling errors, and ensuring reliability of measurement variables (Field & Gillett, 2010). In this method, the population effect is estimated by weighting each study effect size r with its sample size N; then the sum of these weighted effect sizes is divided by a sum of the sample sizes (Field & Gillett, 2010). Hence, in aligning with the nature of the meta-analysis of Emmioğlu and Capa-Aydin (2012), analysis was performed on the statistical significance of estimated effect sizes, as well as the magnitude and homogeneity of these. This was done for each of the attitude components separately (*Affect*, *Cognitive Competence*, *Value*, *Difficulty*). Jamovi software was utilised to assess heterogeneity measures, including the Q-statistic and derived values H^2 and I^2 (Higgins & Thompson, 2002). Cohen's criteria was applied when assessing magnitudes of effect sizes, namely large ($r \geq 0.50$, $r^2 \geq 0.25$), or moderate ($0.30 \leq r < 0.50$, $0.09 \leq r^2 < 0.25$), or small ($r < 0.30$, $r^2 < 0.09$) (Emmioğlu & Capa-Aydin, 2012). The p-value used was 0.01 at a 99% level of confidence (Emmioğlu & Capa-Aydin, 2012). The meta-analysis was performed on the *Comprehensive Meta-Analysis* software.

2.5 Ethical Considerations

The ethical considerations that accompanied the research project were minimal, as the meta-analytic study did not include human participants (Cooper & Dent, 2011). Meta-analysis relies on studies gathered from research databases, and similar to Cooper and Dent (2011), Rosenthal and DiMatteo (2001) express the concern that meta-analysis studies may lead to sampling bias, where relevant research is not included in a study due to inaccessibility, or by setting exclusion criteria which may lead to key findings being omitted. To correct for this, as many possible studies as were available and accessible, were sourced from multiple databases. Since ethical enquiries were made by the researchers of the studies being used when they were conducted, there was no need to apply for additional ethical approval. Nonetheless, ethical approval for my study was granted by the Rhodes University Ethics Standards Committee through the supervisor of the aforementioned project.

3. RESULTS

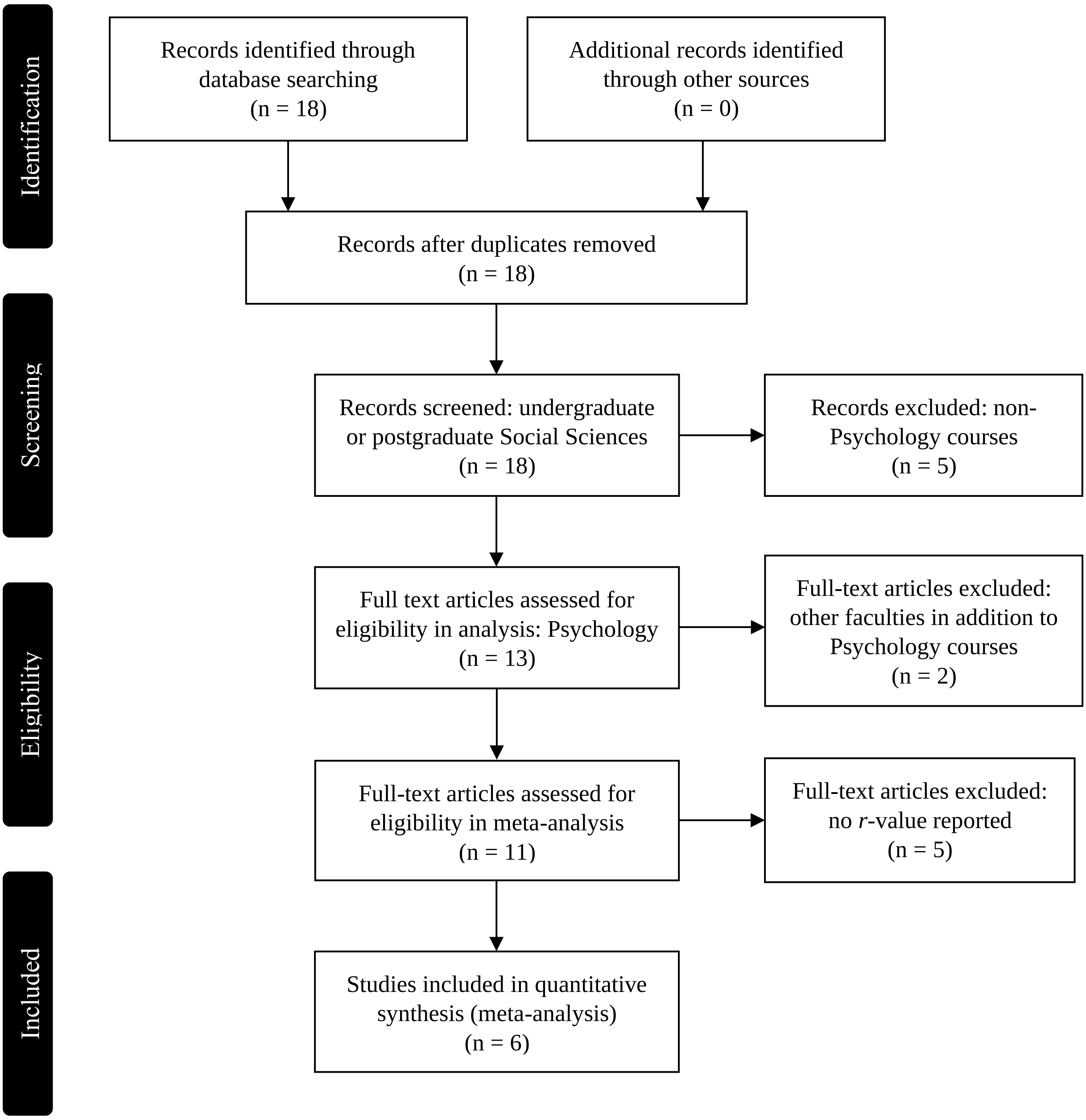
3.1 Study Selection

3.1.1 Retained studies

Based on the exclusion criteria set for the meta-analysis, PRISMA guidelines were followed in order to identify and screen studies for eligibility and inclusion in the meta-analysis (Moher *et al.*, 2009). This was compiled as a flow diagram in Figure 1.

Figure 1.

2009 *PRISMA Flow Diagram of Retained Studies for Meta-Analysis*



Eighteen studies involving SATS testing on Social Sciences students were discovered. When the scope of this meta-analysis was narrowed to SATS testing on Psychology students, five studies involving Educational Studies' students were excluded. Two studies conducted on Psychology student participants, but including students from additional faculties, were excluded. Many studies reported achievement measurements, but Pearson's correlation coefficients to the attitude scales were not always provided, and these studies were thus excluded in aligning with the exclusion criteria as set by Emmioğlu and Capa-Aydin (2012). Hence, five studies with Psychology students and SATS testing, but with no reported correlation coefficient to achievement or means to calculate *r* were excluded. Six studies were retained.

3.1.2 Study characteristics

Chiesi and Primi conducted correlational analyses on a pre- and post-course study comprising 232 Psychology students, and then later published an additional correlational analysis on their original sample of 487 Psychology students (Chiesi & Primi, 2009, 2010) – these were recorded as separate studies for analysis as it was done in Emmioğlu and Capa-Aydin (2012). Four of the studies appeared in the original meta-analysis completed by Emmioğlu and Capa-Aydin (2012). The six retained studies are summarised in Table 1. Information enclosed in Table 1 include demographics about where the study took place, the number of student participants (*n*) the students' major (Psychology or some variant), as well as the chosen measure of achievement used. Two studies made use of high school Mathematics final results as an indicator of statistics achievement (Coetzee & van der Merwe, 2010; Dempster & McCorry, 2009). Two studies opted to use the percentage obtained from the Statistics courses that Psychology students participated in to measure statistics achievement (Finney & Schraw, 2003; Hood *et al.*, 2012). Chiesi and Primi (2009, 2010) administered statistics assessments to Psychology students to measure statistics achievement in their research.

Table 1.

Study characteristics of retained studies for meta-analysis

Study	**Country**	**Student Major**	***n***	**Measure of statistics achievement**
Finney and Schraw (2003)	US	Educational Psychology	103	Statistics course percentage
Chiesi and Primi (2009)	Italy	Psychology	232	Statistics assessment
Dempster and McCorry (2009)	UK	Psychology	82	High school mathematics final result
Chiesi and Primi (2010)	Italy	Psychology	487	Statistics assessment
Coetzee and van der Merwe (2010)	South Africa	Organisational Psychology	235	High school mathematics final result
Hood *et al*. (2012)	Australia	Psychology	149	Statistics course percentage

3.2 Meta-Analysis Results

A meta-analysis was performed on the eight retained studies using Comprehensive Meta-Analysis (CMA) and Jamovi Statistics Software. The output data is found in the Appendix. In this meta-analysis, the effect sizes were calculated as the correlation between the SATS components, namely *Affect*, *Cognitive Competence*, *Difficulty* and *Value,* and the measure of achievement in Statistics. As previously noted, achievement was denoted by high school mathematics final results, statistics course percentages, or compiled statistics assessments. A fixed-effect model was used, which uses the assumptions that there is one true effect size, and that any differences in effect sizes are as a result of sampling error

(Borenstein *et al*., 2009). This was used over a random-effects model because no significant covariates impact the effect sizes in a way that would warrant a random-effects approach.

3.2.1 Heterogeneity measures

Heterogeneity is the means by which we can draw meaningful conclusions about results obtained in a meta-analysis by measuring between-studies variance (Higgins & Thompson, 2002). While variance between studies is inevitable due to methodological or clinical heterogeneity (differences in study conduct, outcomes measured, participants), it is useful to measure if the variation between the results of the studies is above this, i.e. there is statistical heterogeneity (Higgins & Thompson, 2002). It was necessary to assess heterogeneity for this meta-analysis, since studies differed in various ways, including the location of the studies and even the means by which achievement was measured. Comprehensive Meta-Analysis Software was utilised to assess heterogeneity within the studies for each component. Table 2 shows the output data for heterogeneity measures.

Table 2

Heterogeneity statistics for effect sizes

Heterogeneity Statistic	Affect	Cognitive Competence	Value	Difficulty
Q	7.246	1.953	1.067	10.929
$df\ (Q)$	5	5	5	5
p	0.203	0.856	0.957	0.053
H^2	1.449	0.391	0.213	2.186
I^2	30.998%	0.0%	0.0%	54.248%

Cochran's Q-statistic is the observed weighted sum of squares amongst studies in a meta-analysis (Borenstein *et al.*, 2009). The Q-test (or Q-statistic) and its p-values can be used as a test of significance (Borenstein *et al.*, 2009), but in meta-analyses with few studies, these values do not provide meaningful heterogeneity measures alone (Higgins & Thompson, 2002). However, when this standardized measure is compared as a ratio to the degrees of freedom in the meta-analysis, it can represent excess variation (Borenstein *et al.*, 2009). The degrees of freedom (df = k-1, where k = number of studies) are treated as the expected weighted sum of squares in the meta-analysis, with the assumption that studies in the meta-analysis share a common effect (Borenstein *et al.*, 2009). Comparing the observed weighted sum of squares to the expected sum of squares will hence reveal excess variation which is attributed to differences in the true effects of the studies. This indicates heterogeneity in results. Calculating $Q - df$ will reflect the excess dispersion.

For this meta-analysis, the degrees of freedom were calculated as 5. Hence, for *Affect*, excess dispersion was calculated as 7.246, indicating that the observed variation between studies is greater than what is expected for between-studies error. *Difficulty* also showed a significant amount of excess dispersion, 10.929. For *Cognitive Competence* and *Value*, Q was less than df, so observed variation between studies for these components is less than what is expected for between-studies error.

Quantifying of heterogeneity is possible through use of the H^2 and I^2 statistics. A ratio of relative excess in Q to degrees of freedom $k-1$ provides the statistic H^2 as a measure of heterogeneity. Homogeneity is observed when H = 1. This was not true for any component. The H^2 measure is usable on small meta-analyses and is robust for 8 studies. I^2 is related to H^2 in the relationship denoted by Higgins and Thompson (2002):

$$I^2 = \frac{H^2 - 1}{H^2}$$

The I^2 value is expressed as a percentage as a degree to which variability in effect sizes is due to heterogeneity in results. The obtained value of 0% for I^2 in *Cognitive Competence* and *Value* indicates that all variability in effect sizes is due to sampling error within trials, and not due to heterogeneity in results. The I^2 value for *Affect* indicates that 30.998% of result variability is attributable to between-study variation. According to guidelines produced by Higgins and Thompson (2002), this means there is mild heterogeneity in *Affect*. 54.248% of result variability in studies for *Difficulty* is due to between-study variation, which is verging on notable heterogeneity, according to Higgins and Thompson (2002).

3.2.2 Forest plots

It is necessary to make use of forest plots to illustrate and contextualise the results obtained from the meta-analysis. Forest plots depict each study and summary effects as point estimates with confidence intervals (Borenstein *et al.*, 2009). Forest plots were obtained using Jamovi statistical software. A fixed-effect model estimator was used with the raw correlation coefficients coded as the model measure. A 95% confidence interval was utilised, and no moderators were applied.

A large amount of information can be extrapolated from this: firstly, forest plots show the extent to which the overall effect is based on the studies used – i.e. the weight that the studies carry (Borenstein *et al.*, 2009). 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 how the correlations between the attitude components and achievement measures, and compare in terms of the correlation coefficients. Forest plots are also used to corroborate heterogeneity statistics. The individual forest plots for each component and its correlation to achievement measures are shown in Figure 1-4.

Figure 1.

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

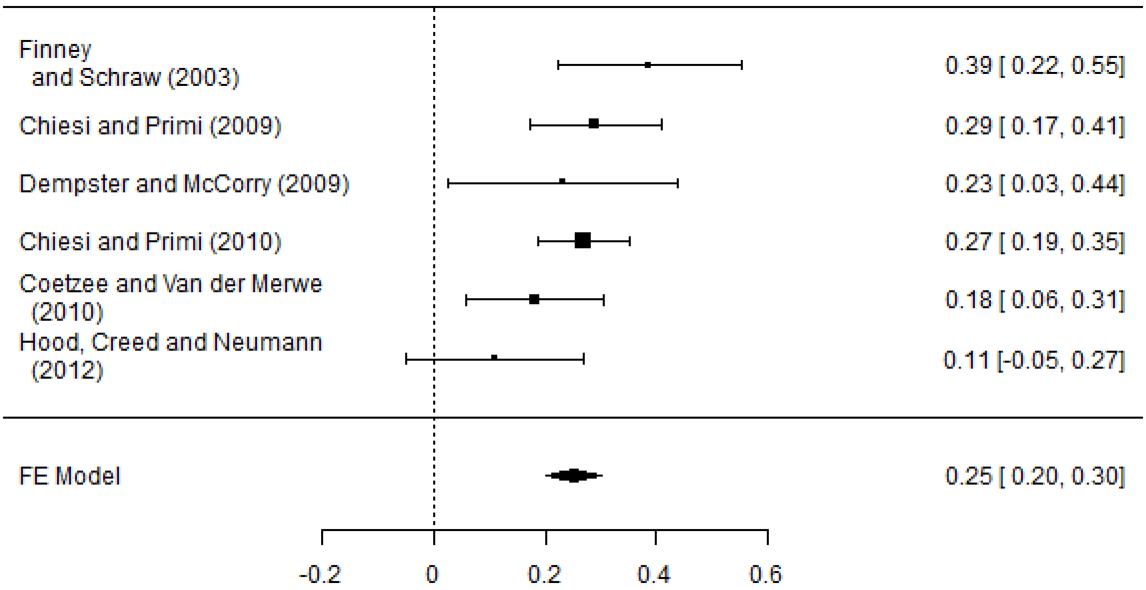


Figure 2.

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

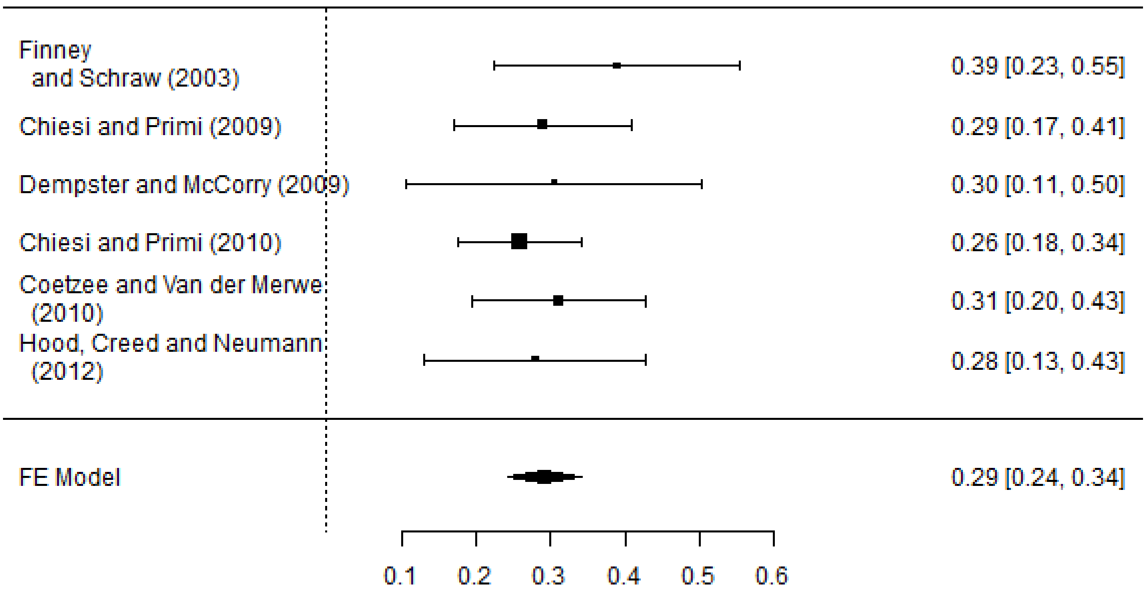


Figure 3.

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

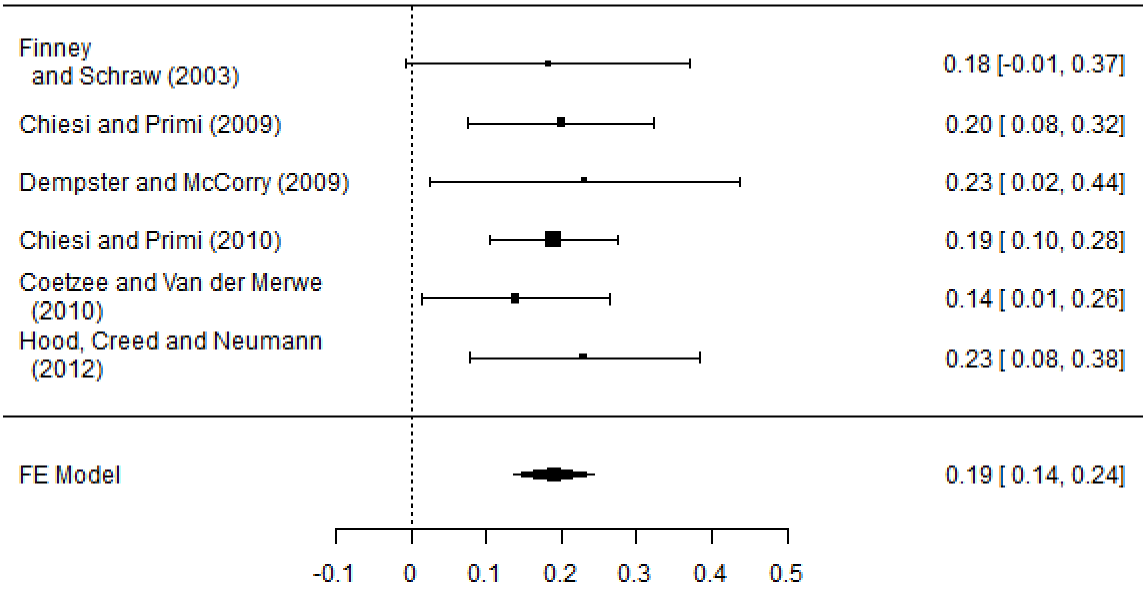
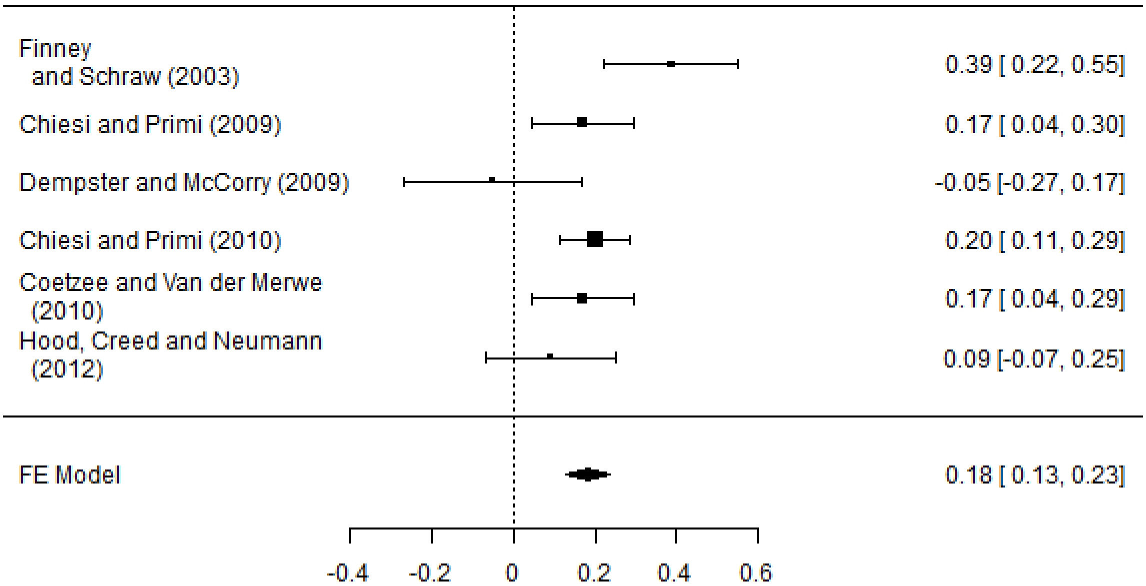


Figure 4.

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



The correlation coefficient (*r*) is represented by the middle point, and the weights of the studies are represented by the area of the square surrounding the *r* point. Highest weights were reported for studies with larger sample sizes, namely Chiesi and Primi (2010) (n = 487). The extending lines represent the 95% confidence interval. A longer line represents a wider confidence interval, which is directly related to study weight in fixed effects models (Borenstein *et al*., 2009). Ideally, confidence intervals are narrow, indicating a greater precision in studies (Borenstein *et al.*, 2009). Precision is an indication of variance, standard error and confidence intervals. Table 3 summarises the measurements of precision based on confidence intervals and interpretations of the forest plots. Table 4 contains the relative weights of each study for the four components.

Table 3.

Precision measurements from forest plots for SATS components

Measurement	**Affect**	**Cognitive Competence**	**Value**	**Difficulty**
95% C. I	0.20-0.30	0.24-0.34	0.14-0.24	0.13-0.23
Precision	Moderate	Low	Low	High
Heterogeneity (I^2)	30.998%	0.0%	0.0%	54.248%

Table 4.

Weights of studies in meta-analysis of SATS components

Study	**Affect**	**Cognitive Competence**	**Value**	**Difficulty**
Finney and Schraw (2003)	7.88%	7.89%	7.88%	7.89%
Chiesi and Primi (2009)	18.05%	18.07%	18.05%	18.06%
Dempster and McCorry (2009)	6.23%	6.24%	6.23%	6.23%
Chiesi and Primi (2010)	38.14%	38.20%	38.14%	38.17%
Coetzee and van der Merwe (2010)	18.20%	18.07%	18.20%	18.14%
Hood, Creed and Neumann (2012)	11.51%	11.52%	11.51%	11.51%

Within the studies, wide confidence intervals and lower weights were reported for Finney and Schraw (2003), Dempster and McCorry (2009) and Hood *et al*. (2012). Precision was the greatest in *Difficulty*, followed by *Affect*, and lowest for *Value* and *Cognitive Competence*. However, while small confidence intervals were noted for *Difficulty* and *Affect*, there was great variation in results, and significant heterogeneity was calculated. There was inconsistent overlap in confidence intervals for *Difficulty,* which indicates that while there is precision present, the results of the studies do not correspond. Hence, in the cases of *Difficulty* and *Affect*, a relationship is noted between the reported precision of the confidence intervals and heterogeneity, where greater precision noted means greater heterogeneity.

Whilst confidence intervals were wide for *Cognitive Competence* and *Value,* hence decreasing precision, all variation effect sizes for these components were accounted for as being sampling error and not due to heterogeneity. There was significant overlap in confidence intervals, indicating a significant amount of homogeneity of results. This will be important when ranges and significance of correlation coefficients are considered.

3.2.3 Correlation Coefficients

The correlation coefficients of the SATS components and achievement in statistics for each study used in the meta-analysis are shown in Table 5.

Table 5.

Pearson correlation coefficients (r) of SATS components and achievement

Study	***N***	Correlation coefficients (***r***)			
		Affect	**Cog. Comp.**	**Value**	**Difficulty**
Finney and Schraw (2003)	103	0.387*	0.39*	0.182	0.387*
Chiesi and Primi (2009)	232	0.29*	0.29*	0.2*	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*	0.2*
Coetzee and van der Merwe (2010)	235	0.182*	0.311*	0.139*	0.168*
Hood, Creed and Neumann (2012)	149	0.11	0.28*	0.23*	0.09
Overall	0.226*	0.247*	0.29*	0.189*	0.177*

*$p < 0.05$

All four attitude components in Chiesi and Primi (2009, 2010) and Coetzee and van der Merwe (2010) were found to have statistically significant relationships to achievement in Statistics ($p < 0.05$). All effect sizes for *Cognitive Competence* were found to be significant. Finney and Schraw (2003) reported the highest correlation between *Affect* and achievement of Psychology students in a statistics assessment, yielding a weakly moderate positive relationship ($r = 0.387$, $p < 0.005$). A weakly moderate positive relationship was reported by

Finney and Schraw (2003) between Psychology students' *Cognitive Competence* scores and final statistics course percentages (r = 0.39, p < 0.005).

Weaker correlations were reported for *Value* and *Difficulty* and Psychology students' Statistics achievements. A negative relationship was found between *Difficulty* and achievement by Dempster and McCorry (2009), but this was not found to be statistically significant (r = -0.052, p = 0.644). Finney and Schraw (2003) reported a weakly moderate positive relationship which was statistically significant (r = 0.387, p < 0.005). Dempster and McCorry (2009) found a weak positive relationship between *Value* and final high school Mathematics results in Psychology students as a measure of achievement (r = 0.231, p = 0.037). The minimum and maximum values and range are compiled in Table 6.

Table 6.

Minimum and maximum values and range of effect sizes

Descriptive Statistic	**Affect**	**Cog. Comp.**	**Value**	**Difficulty**
Minimum	0.11	0.26	0.182	-0.052
Maximum	0.387	0.39	0.231	0.387
Range	0.277	0.13	0.049	0.439

When comparing the range of effect sizes of the components to their heterogeneity measures, a relationship is clear. *Cognitive Competence* and *Value* have small ranges in effect sizes and no heterogeneity was reported between studies. A large range was noted in effect sizes for *Difficulty*, and significant heterogeneity values show inconsistency in effect size for this component. *Affect* had a larger range reported for effect size than *Cognitive Competence* and *Value*, but also had significant reported heterogeneity.

In overall attitude components, Pearson's correlation tests demonstrate a statistically significant relationship between the attitudes of Psychology students towards statistics and their achievement in Statistics as a subject. This relationship was noted in the individual components as well. *Cognitive Competence* had the highest correlation to performance (r = 0.29, $p < 0.005$), followed by *Affect* (r = 0.247, $p < 0.005$). *Difficulty* had the lowest correlation to achievement in students (r = 0.177, $p < 0.005$) but it was still found to be statistically significant. Students perceived *Value* of statistics had a low positive linear relationship to performance (r = 0.189, $p < 0.005$). Comprehensive Meta-Analysis software (See Appendix) Pearson's correlation tests show a statistically significant relationship between the students' overall attitudes and performance. This was a weak positive linear relationship (r = 0.226, C.I. 0.200-0.252, $p < 0.005$).

4. DISCUSSION

4.1 Context

The application of statistics is ubiquitous in tertiary level studies, both as a field of study, and for research purposes. Social Science research relies on descriptive and inferential statistics to inform and analyse important observations of human behaviour. In Psychology, this use of statistics often transfers into assessment and therapeutic practices as well. Despite the clear applications of statistics in Psychology, students studying Psychology at tertiary institutions often fail to understand its inclusion in their curriculum (Bose, 2017). Some Psychology students at a South African university even stated that Statistics is rather a professional tool that helps them to recognize when to outsource data to a Statistician, and not a central skill needed as a Psychologist (Coetzee & van der Merwe, 2010).

The misguided feelings or attitudes towards Statistics as a subject in Psychology students have often resulted in statistics anxiety. Even when Psychology students have been found to like Statistics, the overwhelming fear of failure, and feelings of frustration and stress clouded their immersion in the subject matter (Coetzee & van der Merwe, 2010). Extensive reviews of literature by Onwuegbuzie (2004) and Ruggeri *et al*. (2008) found many studies where statistics anxiety was shown to negatively affect the performance of Psychology students in Statistics and Research Methodology courses. Hence, there was an interest in collating research on these attitudes towards statistics and its relationship to achievement in the subject. This was done as a meta-analysis.

This meta-analysis was in response to a meta-analysis performed by Emmioğlu and Capa-Aydin (2012), entitled “*Attitudes and achievement in statistics: A meta-analysis study*”. This meta-analysis also investigated the relationship between students’ attitudes towards statistics using SATS and the students’ achievement in statistics. It was found that there is a medium statistically significant relationship between statistics achievement and components of the SATS. Studies included in the meta-analysis were for students from varying tertiary-level studies courses. No meta-analyses on this subject have been published since 2012, and there have been no related systematic reviews either. At the recommendation of Emmioğlu and Capa-Aydin (2012) to perform more research on attitudes towards and achievement in statistics, and with a specific scope into this relationship in Psychology students, this meta-analysis was formulated.

4.2 Reiteration of research questions and hypothesis

The research questions derive from those asked in the meta-analysis by Emmioğlu and Capa-Aydin (2012), which were based on the SATS attitude components.

1. What is the relationship between Psychology students' *affect* toward statistics as a subject and subsequent statistics achievement?

2. What is the relationship between Psychology students' self-defined *cognitive competence* and skills concerning statistics and statistics achievement?

3. What is the relationship between Psychology students' measure of the *value* of statistics in their own lives and professional identities and statistics achievement?

4. What is the relationship between Psychology students' perceived *difficulty* of statistics and statistics achievement?

The hypothesis is that there is a statistically significant relationship that exists between the attitudes of Psychology students towards statistics and their subsequent performance and achievement in the subject.

4.3 Summary of results

Results of the meta-analysis indicate that a statistically significant association was found between the SATS components and measures of achievement for Psychology students ($r = 0.226$, $p < 0.05$). This demonstrates that there is a weak relationship between the attitude of Psychology students towards statistics and their performance and achievement in statistics as a subject. Heterogeneity was noted between subjects for two components, *Affect* and *Difficulty*.

4.3.1 Affect and achievement

There was a statistically significant relationship between Psychology students' SATS scores for *Affect* and achievement in statistics ($r = 0.247$, $p < 0.005$). Mild heterogeneity was noted ($I^2 = 30.998\%$). However, as suggested by Deeks *et al.* (2020), in a fixed effect meta-analysis such as this, heterogeneity is often ignored, and for small sample sizes of studies, heterogeneity values are often questioned. For the scope and level of analysis performed for this inquiry, the mild heterogeneity and small confidence intervals for *Affect* are interpreted as having some relevance and effect on the overall effect size, which needs further analysis. This will be noted as a study limitation.

4.3.2 Cognitive Competence and achievement

The correlation between *Cognitive Competence* and achievement was statistically significant ($r = 0.29$, $p < 0.005$). The largest correlation for all components was noted for *Cognitive Competence*. There was no reported heterogeneity in the studies for *Cognitive Competence* effect sizes, and all variance was hypothesized to be due to sampling error. Forest plots illustrated a general agreeableness and cohesiveness between studies, where notable overlap between confidence intervals for all study effect sizes was visible. Thus, there is sufficient evidence that there is a statistically significant relationship between *Cognitive Competence* and achievement.

4.3.3 Value and achievement

A weak but statistically significant positive relationship was observed between *Value* and achievement ($r = 0.189$, $p < 0.005$). As seen in *Cognitive Competence*, no heterogeneity was reported, and variance between effect sizes of studies was hypothesized to be due to sampling error. Forest plots also illustrated that the effect sizes reported in studies did coincide with one another. Hence, there is sufficient evidence to suggest that there is a statistically significant relationship between *Value* and achievement.

4.3.4 Difficulty and achievement

There was a statistically significant but small correlation between *Difficulty* and achievement ($r = 0.177$, $p < 0.005$). Heterogeneity statistics revealed an I^2 value of 54.248%, indicating that considerable heterogeneity was seen in this statistic. A large range in effect sizes was also observed, with some moderate positive effect sizes being offset by a negative relationship in one study (Dempster & McCorry, 2009). In forest plots, high levels of dispersion were noted as there was not much overlap in confidence intervals of study effect sizes. Hence, as with *Affect*, further analysis and sophisticated interpretations will be needed, which will be highlighted as a limitation of this study.

4.4 Interpreting results

4.4.1 Answering research questions

The research questions will hence be answered as followed:

1. There is a weak but statistically significant positive relationship between the *Affect* of Psychology students towards statistics as a subject and their subsequent statistics achievement. Simply stated, this means that the feelings that Psychology students have towards statistics as a subject can affect their performance and achievement in the subject.

Particularly, negative feelings towards statistics could result in negative performance and lower achievement.

2. There is a weakly moderate positive relationship between Psychology students' self-defined *Cognitive Competence* and skills concerning statistics and statistics achievement. This means that Psychology students' perception of their possessed statistical knowledge and skills can affect their achievement in statistics as a subject. Resultantly, their own predicted ability to understand statistics concepts and equations and perform analyses could directly affect their ability to perform well in their statistics courses.

3. There is a weakly positive relationship of statistical significance between Psychology students' measure of the *Value* of statistics in their own lives and professional identities and statistics achievement. This suggests that the achievement of a Psychology student in statistics can be determined by the subject's deemed usefulness, relevance and worth to the student's own personal and professional life. A low value being placed on statistics could result in lower achievement.

4. There is a weakly positive relationship of statistical significance between Psychology students' perceived *Difficulty* of statistics and statistics achievement. This means that there is reason to believe that the perceived level of difficulty that a Psychology student has about statistics can then affect their achievement in the subject. Specifically, if students find aspects of the coursework academically challenging or overwhelming, they may also not achieve optimal results in their statistics courses.

The hypothesis that there is a statistically significant relationship that exists between the attitudes of Psychology students towards statistics and their subsequent performance and achievement in the subject is also accepted. The relationship is a weakly positive relationship of statistical significance.

4.4.2 Comparison to prior meta-analysis

Although Emmioğlu and Capa-Aydin (2012) make use of different studies comprised of results from students across faculties, it would be useful to compare results and discussion points with their study. Heterogeneity was noted across all components. When dividing studies into "U.S." (studies that were performed at universities in the United States) and "Non-U.S." region categories, heterogeneity was still noted in *Affect* and *Cognitive Competence*. In this meta-analysis, heterogeneity was noted in *Affect* and *Difficulty*.

Emmioğlu and Capa-Aydin (2012) offer some reasons for the heterogeneity. It was hypothesized to be due to sample differences, including differences across participants' gender, major, education level, and Statistics course structures (Emmioğlu & Capa-Aydin, 2012). Most importantly, the differences in measures that were used to assess achievement in statistics were different. In this meta-analysis, all participants had the same major – Psychology – but there were still gender differences, education level (postgraduate and undergraduate groups were included) variations as well as variances in statistics course structures. Analyses for these factors could be considered in future research once more familiarity with meta-analysis is established; this is highlighted in the study limitations.

Notably, there was a difference in measures used to assess achievement. Chiesi and Primi (2009, 2010) and Zimprich (2012) used results from a statistics assessment as a measure of achievement, while Finney and Schraw (2003) and Hood *et al.* (2012) used statistics course percentages. As noted by Emmioğlu and Capa-Aydin (2012), there is no way to ensure consistency with these measures and the structure of coursework and assessment. Most assessments were presumably created by course instructors, and these would not have been evaluated for psychometric properties – hence, there may be significant error. Furthermore, Dempster and McCorry (2009), Coetzee and van Der Merwe (2009) and

Zimprich (2012) used mathematics results as a measure of statistics achievement – this relies on predicted achievement in statistics, and there may be bias in this as a measure.

Emmioğlu and Capa-Aydin (2012) share views around the availability of studies that fit inclusion criteria and this too will be highlighted as a study limitation. The main problem faced in this inquiry and for Emmioğlu and Capa-Aydin (2012) was that many important study characteristics are omitted from studies. Hence the sample differences, as noted above, could not be included as factors. Emmioğlu and Capa-Aydin (2012) hypothesize that the true relationship between attitudes and achievement in statistics is likely stronger, as there are errors and bias in these construct measures that remain unknown. The same assumption should be applied to this meta-analysis.

4.5 Threats to internal validity

The first and fourth conclusions are met with some caution due to heterogeneity measures indicating large excess dispersion and between-studies variance for the components *Affect* and *Difficulty*. However, there are possible reasons for this. Using *Difficulty* as an illustrated example, there was a considerable range in effect sizes for *Difficulty* due to a negative relationship being reported between *Difficulty* and statistics achievement in the Dempster and McCorry (2009) study. It was hypothesized by another statistics researcher that the negative relationship could be due to suppression, and hence students who judged Statistics as being easy may have prepared less for the assessment and subsequently performed worse (Zimprich, 2012). In considering the implications for this research in statistics education for Psychology students, this phenomenon of suppression should be addressed.

Emmioğlu and Capa-Aydin (2012) 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 (Tavakol & Dennick, 2011). Adequate to high Cronbach's alpha value ranges were reported for *Affect* = 0.80-0.85, *Cognitive Competence* = 0.77-0.82, *Value* = 0.78-0.90, *Difficulty* = 0.64-0.75. The range for *Difficulty* straddles on what is deemed an acceptable level of Cronbach's alpha (Tavakol & Dennick, 2011). There is concern then, according to Tavakol and Dennick (2011), that there is poor interrelatedness and heterogeneity in *Difficulty*. This does coincide with the above concerns for the *Difficulty* measure, and this Cronbach's alpha value may be a possible explanation for the heterogeneity in results that were noted. This was not noted for *Affect*, which had high Cronbach's alpha values, so other causes for between-studies variance need to be considered.

4.6 Limitations of study

4.6.1 Availability of viable research

The study selection process of this meta-analysis revealed that the body of research available that meets inclusion criteria was quite small. Typically, when studies investigated statistics attitudes and achievement of Psychology students, the Statistical Anxiety Rating Scale (STARS) was the measurement used, as seen in McGrath *et al.* (2015), or a combination of SATS and STARS – the Composite Survey of Statistics Anxiety and Attitudes (COSSAA) – was used (Ruggeri *et al.*, 2008). While there were twelve studies identified as using SATS on Psychology students (Figure 1), there was no reported measure of achievement which could be correlated against SATS results. This omission prevailed despite the recommendation of the SATS author, Candace Schau, to include her additional items that ask about prior experience with mathematics and statistics, and a report of achievement in these subjects (Schau, 2000).

A SATS-36 survey was conducted with Rhodes University Psychology students which could have been included in the study (Ngantweni, 2019), but there was no investigation into a relationship between achievement in their statistics courses and their survey results. While a meta-analysis can theoretically be performed on as few as two studies, it is noted that some statistical measures, such as H^2, are not sufficiently robust for meta-analyses with less than 8 studies. This meta-analysis only found six viable studies. Even if it was possible to manually calculate effect sizes using provided data in the studies, achievement results were not reported in order for them to be correlated to SATS component responses. Additionally, it was noted that no SATS studies fitting the inclusion criteria were published since the meta-analysis by Emmioğlu and Capa-Aydin (2012), so most studies used were either already used in this meta-analysis, or were at least 8 years old.

The limited number of studies included in this meta-analysis also meant that meta-regression could not be performed. 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. Emmioğlu 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 could show insight into how Psychology student populations from different countries perceive statistics and could inform our educational practices in the subject. Further, two distinct achievement measures were noted: using high school mathematics results to predict statistics achievement, and using statistics assessments or statistics course results as a measure of statistics achievement. Regression analysis could reveal which of these measures is a more accurate representation of achievement.

4.6.2 Sample differences

As highlighted in the comparison to the meta-analysis performed by Emmioğlu and Capa-Aydin (2012), there are sample differences that exist between studies that were not reported in the studies. Hence these could not have been recorded as additional factors into the meta-analysis. Differences include gender, level of education, region, course structures, and achievement measures. There is interest in establishing gender differences in statistics attitudes (Chowdhury *et al.*, 2018) but most studies would not report on the correlation of the gender of participants to outcomes. Level of education was not an exclusion criterion, and studies using undergraduate or postgraduate Psychology 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. Course structure differences and discrepancies in achievement measures can also lead to bias.

4.6.3 A Posteriori Reflection and Future Research

The correlations reported by Zimprich (2012) were included in an earlier meta-analysis of these results. A moderate negative effect size was recorded for *Difficulty*, which differed significantly from most reported effect sizes. As a result, the I^2 value obtained for *Difficulty* was 95.24%, which is significantly higher than the results obtained in this meta-analysis. This was indicative of high heterogeneity and therefore raised concerns. Only after careful reconsideration of the inclusion of the Zimprich (2012) study, was it discovered that these correlations were in fact regression coefficients (β) and hence not the effect size measure used in this meta-analysis. Had significant time been afforded to understanding heterogeneity indicators, this study would have been subsequently removed. This is an example of how a better understanding of the nature of extrapolating effect sizes from research, and the process of a meta-analysis, could have lead to this study being excluded immediately with sufficient reasoning.

4.7 Implications of study

4.7.1 Future research

While the correlations found between the attitudes of Psychology students and their achievement in statistics were low, the relationships were still statistically significant. There is reason to believe the overall effect sizes would have been higher if sampling differences were available to be used as additional factors in the meta-analysis. It should be noted that future engagement with SATS measurements should include a measure of achievement, as recommended by Schau (2000); this could also lead to the carrying out of further meta-analyses in this area of research.

Additionally, future meta-analyses investigating relationships between students' attitudes towards statistics and achievement could make use of other measures. The STARS survey was previously mentioned, and although the SATS-28 and SATS-36 still rank better for having high validity and internal consistency (Nolan et al., 2012), the Statistics Attitude Scale (SAS) and Attitudes Towards Statistics Scale (ATS) also possesses high structural, content, substantive and external validity with internal consistency, but these scales are not as recent or in as much widespread use as the SATS-28 and SATS-36 (Nolan *et al.*, 2012).

However, this meta-analysis still contributes to the growing body of evidence that there is a relationship between how Psychology students perceive statistics, and their own capabilities in the subject, to how they will perform in the subject. Pre-test post-test analyses of SATS results by Psychology students showed a statistically significant improvement in attitudes and achievement after additional support interventions were implemented (Liau *et al*., 2015). Support for Psychology students must be implemented to improve quantitative research. At Rhodes University, this meta-analysis should stand as evidence that more support is needed for Psychology students in their quantitative research. My own lack of understanding in some areas of statistics is evident in this meta-analysis, although this process was a vital contributing factor to my increased interest in statistics education.

As discussed, there is no dedicated Statistics course for Social Science students at Rhodes University. This was originally what this meta-analysis aimed to highlight and challenge. However, a more emergent and immediate need has presented – which is the need for the implementation of a comprehensive Quantitative Research course for Psychology students. At a postgraduate level, this course should coincide with research projects such as this and thus serve as an important cross-reference tool while students undergo the research process. As outlined, there was no specific manual or set of instructions regarding the process of compiling a meta-analysis report and project for Psychology students, and I was fortunate to be afforded additional support and resources from my supervisor during this process. If this was structured as a course, along with the usual statistical methodology taught, there could be significant resultant implications in the calibre of quantitative research produced by the Rhodes University Department of Psychology.

Reflexive Response to the Research and Proposal for Future Research

4.7.2 Understandings of meta-analysis

A meta-analysis is a challenging and complex statistical procedure. During research project selection, what was discussed was the scope of a systematic view rather than the process of a meta-analysis, with the result that so much of the process of meta-analysis was therefore an unknown. The statistical methods involved in a meta-analysis are vast and require extensive engagement and practice. However, the process proved to be a valuable exercise in the understanding of what quantitative research means in Social Science research. Covid-19 and the National Lockdown made correspondence challenging, and this meta-analysis would have benefited from more engagement with the resources that were availed to me, including my supervisor.

4.7.3 Masters by Thesis Proposal

The apparent need for more instruction in compiling quantitative research in Psychology at Rhodes University lead me to my proposal for a Masters by Thesis with my supervisor. This would entail designing a comprehensive Quantitative Methodology & Research course for Psychology postgraduate students. An intervention strategy on the structure of the course will be investigated and designed which will make Statistics seem like a feasible subject and less stressful to students, whilst also emphasising its applicability and usefulness in research and professional identities. A possible solution which is already partially in the Psychology Honours Research Methodology curriculum is the instructional teaching of statistics software such as Jamovi.

It is hypothesized that including a strong emphasis on teaching statistics software will alleviate much of the stress around calculating statistics results, and make for more clear research interpretations (Canning, 2014). The curriculum will include practical sessions of engagement with the software, together with instructional seminars. Meta-analysis should form an integral aspect of the curriculum because of its usefulness in Social Science research. To ensure that students see the value of using statistics, specific strategies such as using South African examples to illustrate the work will be used. Andy Field (2009) is a famous research psychologist whose personal approach to teaching statistics includes the use of humour in guidebooks and examples, which has been enjoyed by his students.

Another aspect of the course will be the compiling of a manual or textbook to accompany students in their research with specific worked examples in Jamovi, since there are not extensive Jamovi tutorials or guidelines available online. Other options such as R, Strata, Python and other software are difficult to teach in limited teaching time, and particularly so to Social Science students with limited computer science experience when compared to students of other scientific fields; SPSS, while useful for Social Science statistics (Field, 2013), is not available for use at Rhodes University. Hence Jamovi remains the most viable option for teaching statistical analysis and interpretation at a postgraduate level when this is required, but more support should be availed for Psychology students as they partake in Jamovi.

Therefore, my future research following this meta-analysis, will seek to evaluate and design a course using Jamovi and R integration for postgraduate Psychology students in their Honours year of studies at Rhodes University, as part of their Research Methodology course. A model that will be used is that of the statistics textbook "*Discovering Statistics Using IBM SPSS Statistics*" (Field, 2013) which has been praised by students and educators for its user-friendly emphasis. The aim of this proposed course will be to improve the outcome of quantitative research for postgraduate Psychology students, through the creation of a comprehensive, structured course which will provide adequate support for students to succeed. This also aligns with the identified need for additional support in changing the attitudes of Psychology students towards statistics to improve achievement and performance in the subject.

4.8 Conclusion

This meta-analysis found a statistically significant relationship between the attitude that Psychology students possess towards Statistics and their achievement in the subject. *Cognitive Competence* and *Affect* had the strongest correlations to achievement. Heterogeneity was noted for *Affect* and *Difficulty*. Other differences in effect sizes were hypothesised to be due to factors that were not considered in the meta-analysis, namely sample differences, such as education level, gender and Statistics course structures, which may have caused wide confidence intervals. The findings of this meta-analysis aligned with those found in the meta-analysis by Emmioğlu and Capa-Aydin (2012). This meta-analysis process highlighted my own shortcomings as a researcher, but it also led me to conclude that a meta-analysis is an important research process that should be encouraged and taught at a postgraduate level.

If this meta-analysis were to be repeated, factors that lead to sample differences should be included in the meta-analysis. SATS research should also include recommended items by Schau (2000) that rate statistics achievement so that more correlational analyses on the relationship between attitude and achievement can be conducted. Meta-analyses using other measures such as ATS and SAS can also be performed. This research illustrated the need for more support for Psychology students in studying Statistics as a means of minimising negative attitudes towards Statistics as this can affect performance in the subject. My future research aims include designing an instructional course with practical elements in Statistical software, with a specific scope for facilitating quantitative research design. This proposed research possesses much latent value and should be afforded a greater emphasis at Rhodes University beyond theoretical courses. There is potentially a great opportunity for Psychology students to be able to engage in quantitative research and meta-analysis in a way that caters to their needs as both prospective psychologists and researchers.

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APPENDIX

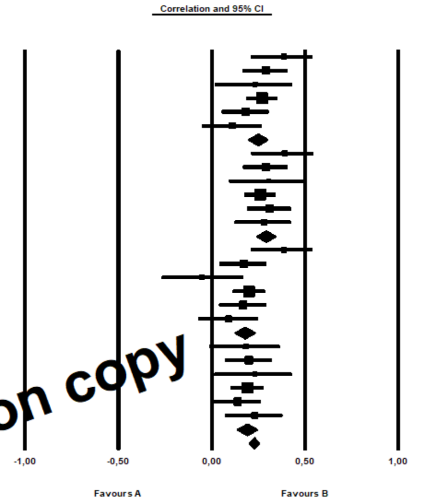
Table A

Output Data from Comprehensive Meta Analysis Results Showing Correlation at 95% Confidence Intervals for Studies Grouped by Component

Meta Analysis

Group by Outcome	Study name	Outcome	Statistics for each study					Relative weight	Relative weight
			Correlation	Lower limit	Upper limit	Z-Value	p-Value		
Affect	Finney and Schraw (2003)	Affect	0,387	0,209	0,540	4,083	0,000	7,88	
Affect	Chiesi and Primi (2009)	Affect	0,290	0,167	0,404	4,518	0,000	18,05	
Affect	Dempster and McCorry (2009)	Affect	0,233	0,017	0,428	2,110	0,035	6,23	
Affect	Chiesi and Primi (2010)	Affect	0,270	0,186	0,350	6,091	0,000	38,14	
Affect	Coetzee and Van der Merwe (2010)	Affect	0,182	0,055	0,303	2,797	0,005	18,20	
Affect	Hood, Creed and Neumann (2012)	Affect	0,110	-0,052	0,266	1,335	0,182	11,51	
Affect			0,247	0,195	0,298	9,000	0,000		
Cog. Comp.	Finney and Schraw (2003)	Cog. Comp.	0,390	0,213	0,543	4,118	0,000	7,89	
Cog. Comp.	Chiesi and Primi (2009)	Cog. Comp.	0,290	0,167	0,404	4,518	0,000	18,07	
Cog. Comp.	Dempster and McCorry (2009)	Cog. Comp.	0,305	0,094	0,490	2,800	0,005	6,24	
Cog. Comp.	Chiesi and Primi (2010)	Cog. Comp.	0,260	0,175	0,341	5,854	0,000	38,20	
Cog. Comp.	Coetzee and Van der Merwe (2010)	Cog. Comp.	0,311	0,190	0,423	4,867	0,000	18,07	
Cog. Comp.	Hood, Creed and Neumann (2012)	Cog. Comp.	0,280	0,125	0,422	3,476	0,001	11,52	
Cog. Comp.			0,290	0,239	0,340	10,645	0,000		
Difficulty	Finney and Schraw (2003)	Difficulty	0,387	0,209	0,540	4,083	0,000	7,89	
Difficulty	Chiesi and Primi (2009)	Difficulty	0,170	0,042	0,292	2,598	0,009	18,06	
Difficulty	Dempster and McCorry (2009)	Difficulty	-0,052	-0,266	0,167	-0,463	0,644	6,23	
Difficulty	Chiesi and Primi (2010)	Difficulty	0,200	0,113	0,284	4,460	0,000	38,17	
Difficulty	Coetzee and Van der Merwe (2010)	Difficulty	0,168	0,040	0,290	2,572	0,010	18,14	
Difficulty	Hood, Creed and Neumann (2012)	Difficulty	0,090	-0,072	0,247	1,090	0,276	11,51	
Difficulty			0,177	0,123	0,229	6,356	0,000		
Value	Finney and Schraw (2003)	Value	0,182	-0,012	0,363	1,841	0,066	7,88	
Value	Chiesi and Primi (2009)	Value	0,200	0,073	0,321	3,068	0,002	18,05	
Value	Dempster and McCorry (2009)	Value	0,231	0,015	0,427	2,091	0,037	6,23	
Value	Chiesi and Primi (2010)	Value	0,190	0,103	0,274	4,231	0,000	38,14	
Value	Coetzee and Van der Merwe (2010)	Value	0,139	0,011	0,263	2,126	0,033	18,20	
Value	Hood, Creed and Neumann (2012)	Value	0,230	0,072	0,377	2,830	[illegible]	11,51	
Value			0,189	0,136	0,242	6,822	[illegible]		
Overall			0,226	0,200	0,252	[illegible]	[illegible]		

Correlation and 95% CI



Meta Analysis