

The Predictive Validity of the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices Test for the Academic Results of First Year Engineering Students.

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Declaration:

A research project submitted in partial fulfilment of the requirements for the degree of MA by coursework and Research Report in the field of Industrial Psychology in the Faculty of Humanities, University of Witwatersrand, Johannesburg, 14 February 2015.

I declare that this research report is my own, unaided work. It has not been submitted before for any other degree or examination at this or any other university.

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Abstract

This research project examined the predictive validity of the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices on the academic results of first year engineering students. Additionally, biographical variables were examined in order to assess their contribution to the student's scores on the psychometric tests. This research is important as the engineering department were looking to combat the high failure rate amongst first year engineering students. The department was looking to use the ART and the Raven's to foresee the subjects in which students would struggle, enabling them to prepare extra assistance in this regard. The sample was the 2013 and 2014 first year engineering students at the University of the Witwatersrand, Johannesburg (N=395). The analysis showed that the ART and Raven's do not predict the academic results of engineering students in their first year of study. The academic results refer to the marks obtained in the first year subjects of Chemical and Metallurgical Engineering, Physics, Chemistry, Economics and Mathematics. However, the biographical variables (especially those of home language and race) play an important role in contributing to the scores achieved on both psychometric tests.

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Chapter 2: Introduction

2. Introduction

In South Africa there is a critical skills shortage which means that the professional sector lacks individuals with certain skill sets – such as engineers (Daniels, 2007). The skills shortage can be linked directly to the fact that there are many Grade 12 pupils who qualify for university acceptance who are products of a schooling system which does not place emphasis on skills such as mathematics, science and technology-based programmes (Zaaiman, van der Flier & Thijs, 2001, Christie, 1998). This inadequate schooling produces university candidates who struggle to achieve well in courses for which these skills are essential (such as engineering) (Zaaiman et al., 2001). These education problems are ones for which many universities are still struggling to find a solution (Zaaiman et al., 2001). The possibility of using psychometric and other tests which will highlight these inadequacies is an appealing one as it will allow lecturers to identify the weaknesses within the skill sets of the students, as well as pinpoint which students may require extra tutoring (Zaaiman et al., 2001, Schaap & Luwes, 2013). Most universities are finding that Grade 12 results are no longer a reliable predictor of what the students are capable and are searching for other measures which will add to and enhance the selection process (Schaap & Luwes, 2013).

The engineering department at the University of the Witwatersrand has archival data regarding first year engineering students from 2013 and 2014 on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices. The aim of this research report is to ascertain whether these tests have any predictive value with regard to mid-year and end of year academic results. If this occurs, the engineering department will be able to identify early in the year, which students may require extra tutorage, and possibly, which subjects are weak in terms of both individuals and the group as a whole. The variables in this study are the scores students achieved in both tests (the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices) as well as the mid-year and end of year results for their first year of tertiary education.

This research report contains a theoretical and conceptual background, a methodology, analysis and results, and discussion. The theoretical and conceptual background will give a more in-depth discussion regarding the education problem and skills shortage in South Africa, a brief overview of the tests to be used and the qualities they are designed to measure. The methodology will contain more information regarding the design and construct of the study, while the final two chapters will show and explain the results found.

Chapter 3: Theoretical and Conceptual Background

3. Theoretical and Conceptual Background

3.1 Education in South Africa

The problems within the schooling system can themselves be attributed to problems that arose during the Apartheid era and that have not yet been rectified (Christie, 1998). Most of the schools in which there are currently problems with education and learning are schools that were previously in black-sectioned areas where goals to excel in schooling were ignored by the Apartheid government (Christie, 1998). The academic results recorded for the National Senior Certificate (NSC) exams showed that in South Africa, 29.8% of Grade 12 pupils failed to pass their exams, while only 24.3% of learners qualified to attend university (Department of Basic Education, 2013). While the education programme has been gradually addressed from the 1980's, the lack of education that preceded this period is generally blamed for the 'skills shortage' we have in South Africa (Chisholm, 1983). Chisholm believes that the inequality in South Africa with the high unemployment and lack of education within the population will continue to work towards a lack of skills within our country (Chisholm, 1983). Although Chisholm's article is several years old, it can be seen that what the author feared is indeed still a problem in our society with many of our population remaining uneducated and the schooling system much in need of help (Christie, 1998, Department of Basic Education, 2013). One's level of education directly influences one's ability to find employment (<http://beta2.statssa.gov.za/>). 97.3% of graduates are employed in the formal sector, whereas only 52.9% of

candidates who have less than a Grade 12 education level are thusly employed (<http://beta2.statssa.gov.za/>)

There have been many attempts to reform the education system – most of which have failed. One such attempt, put into place to help the post-Apartheid education system was outcome-based education (OBE) (Jansen, 1998). The fundamental principles of this intervention were to furnish schools/teachers/principals with the outcomes that the students are expected to achieve (Jansen, 1998). However, there were a number of drawbacks to this system (Jansen, 1998). Firstly, it proved too difficult for educators to manage and apply to their pre-set curriculums (Jansen, 1998). Secondly, there was no evidence that changing a schooling process or outcome will have any impact on South Africa's failing economy and skills shortage (Jansen, 1998). Thirdly, the outcomes that have been decided on, do not address values and the teaching of values to students which is so important in a society that is trying to shake off the monstrosities of Apartheid (Jansen, 1998).

Some of the problems stemming from this absence of value-teaching include lack of authority being held by both principals and teachers, poor attendance on behalf of both students and teachers alike, demotivation and a low willingness to teach and be taught and poor school results (Christie, 1998). Often the issues from the surrounding community will spill over into the school environment with the children displaying problems with alcohol and drugs, affiliation with gangs, violent tendencies and criminal activities (Christie, 1998). All of these problems result in the emphasis not being placed on education which will have an impact on poor understanding, learning and final marks (Christie, 1998).

3.2 Economics and the skills shortage in South Africa

One's success in academics is intrinsically linked to one's success in future life in terms of career choice and future opportunities (Laidra, Pullmann & Allik, 2006). It can be argued that a test used prior to acceptance into a university course, which would enable the department to separate those who should excel in the course, from those who might fail (and thus require extra help during their time at university), would be an important tool to ensure that universities are able to produce as many qualified people as possible for the working world. The need for qualified engineers in the South African context, particularly in terms of government projects such as

road infrastructure, is steadily increasing (Schaap & Luwes, 2013). There is also a growing world-wide need in the international infrastructure for engineers (Schaap & Luwes, 2013). As many qualified graduates (in various sectors) leave South Africa to work abroad, it is important to have as large a pool of engineers as possible in order to ensure that the need for engineers in the South African context is satisfied (Schaap & Luwes, 2013).

It has been said that the most important economic question is how to increase growth of output for each individual (Romer, 2001). The output of an individual is what he/she is able to accomplish and provide for his/her organisation and country's economy (Romer, 2001). A small increase of the growth rate will lead to a cumulative effect on the standard of living within the country (Romer, 2001). The twentieth century in the United States was a stage characterised by rapid technological growth which led to a high standard of living and, additionally, an education system which provided the fast-paced output of technology that was needed in this innovative period (Romer, 2001). It is believed that sustaining and improving this trend of growth in the United States revolves around the improvement and focus on the tertiary education of scientists and engineers (Romer, 2001). Romer's article focuses on the importance of this growing trend and predicts that faster growth would be able to monetarily resolve any budget difficulties as well as provide resources for the many social problems we face (Romer, 2001). As such, it shows the economic benefits that one can expect from the training of a large base of engineers (Romer, 2001).

South Africa is not as fortunate as the United States in terms of skilled professionals as SA suffers from a skills shortage (Daniels, 2007). The skills shortage can be understood through the premise that the demand for skills far exceeds the supply (Daniels, 2007). Labour supply is defined as the human capital who participate in the labour market, while labour demand refers to the organisations that employ the human capital (Daniels, 2007). Between these two are the arrangements that help form the demand and supply relationship including the universities that train the human capital/labour force (Daniels, 2007). When Daniels' paper was researched, South Africa's economy was in an upswing after Apartheid in which increasing skills amongst the labour force played an important part (Daniels, 2007). Currently, only 25% of the South African population are employed in skilled positions, with 46% in

semi-skilled positions and 29% in low-skilled occupations (<http://beta2.statssa.gov.za/>). In terms of the Government's definition, skills are comprised both of qualifications and experience in the field (Daniels, 2007). A *scarce skill* is defined as "a scarcity of qualified and experienced people, currently or anticipated in the future, either (a) because such skilled people are not available, or (b) because they are available but do not meet employment criteria" (as cited in Daniels, 2007). Absolute scarcity of these skills is defined in (a) above, where people do not hold the skills that are required, whereas relative scarcity refers to (b) above (Daniels, 2007).

Critical skills refer to specific skills within an occupation (Daniels, 2007). This can be divided into two groups: generic skills and particular occupational skills (Daniels, 2007). The former skills include double-loop learning, language, literacy and team-player skills whereas the latter are skills specific to the occupation in which the individual is working (Daniels, 2007). It is important to keep all of the above definitions in mind when contemplating the skills shortage (Daniels, 2007). Various changes between sectors in our economy can also contribute to skills shortages and structural unemployment (Daniels, 2007). An example of this between-sector change could be a decrease in employment in the primary sector and an increase in available jobs in the tertiary sector (Daniels, 2007). The primary sector comprises the agriculture, mining and petroleum industries, while the tertiary sector includes real estate, transport and finance (Coughlin & Segev, 1999). This will result in the problem of people in the primary sector being left without jobs while positions in the tertiary sector are waiting for people who are able to fill them (Daniels, 2007). Unfortunately, the people from the primary sector are not able to fill these open positions due to their lack of the required skills (Daniels, 2007). A within-sector change would mean changes within organisations that require employees to be re-trained or taught new skills. At an economy-wide level, this could result in a critical skills shortage (Daniels, 2007). This shows that South Africa is not only having to deal with the skills shortage as a result of Apartheid education, but also skills based changes due to reintegration with the international market (Daniels, 2007, Kingdon & Knight, 2005). The result of this is that the labour demand was not great enough to support the labour supply and as a result we have a mismatch between demand and supply (Daniels, 2007, Kingdon & Knight, 2005).

In an attempt to curb this mismatch and to produce more skilled workers (as there is greater opportunity and demand for them than unskilled labour) the Skills Development Act was passed (Daniels, 2007, Kingdon & Knight, 2005). This Act outlines what needs to happen for skills development to be changed and how organisations are expected to train workers (Daniels, 2007, Kingdon & Knight, 2005). This led to the Human Resources Development Strategy which tried to target three levels of skills development by focusing on the linking of schooling (and adult) education, human resource development (including tertiary education), demand-side dimensions (skills that are to be given by the employers) and finally, national systems of innovation, research and development (Daniels, 2007). However, the impact of this has not yet been seen in the engineering sector.

In 2011, 9 287 students graduated as engineers in South Africa (Esterhuizen, 2013). This number fell short of the goal set by the Higher Education and Training Minister, Dr Blade Nzimande who was hoping to see 10 093 engineering science graduates (Esterhuizen, 2013). Dr Nzimande reported that interventions were being put into place in order to increase this number, but that changes would only be evident in 2015/2016 (Esterhuizen, 2013). In the mean time, only 16% of enrolled students have graduated, below that of the international calculation of 24% (Seggie, 2012). The graph below displays the difference for the past number of years between the number of students enrolled in engineering courses, compared to the percentage that graduate as qualified engineers (Seggie, 2012). The graph shows the number of students who registered in a given year, as well as the number of students who graduated in that year (Seggie, 2012). So while it is not a direct comparison between the same students, it does still serve to illustrate the gap between the number of students a university will accept every year, compared to the number of engineers they are able to produce into the working world (Seggie, 2012). As discussed above, these figures should steadily increase throughout the upcoming years.

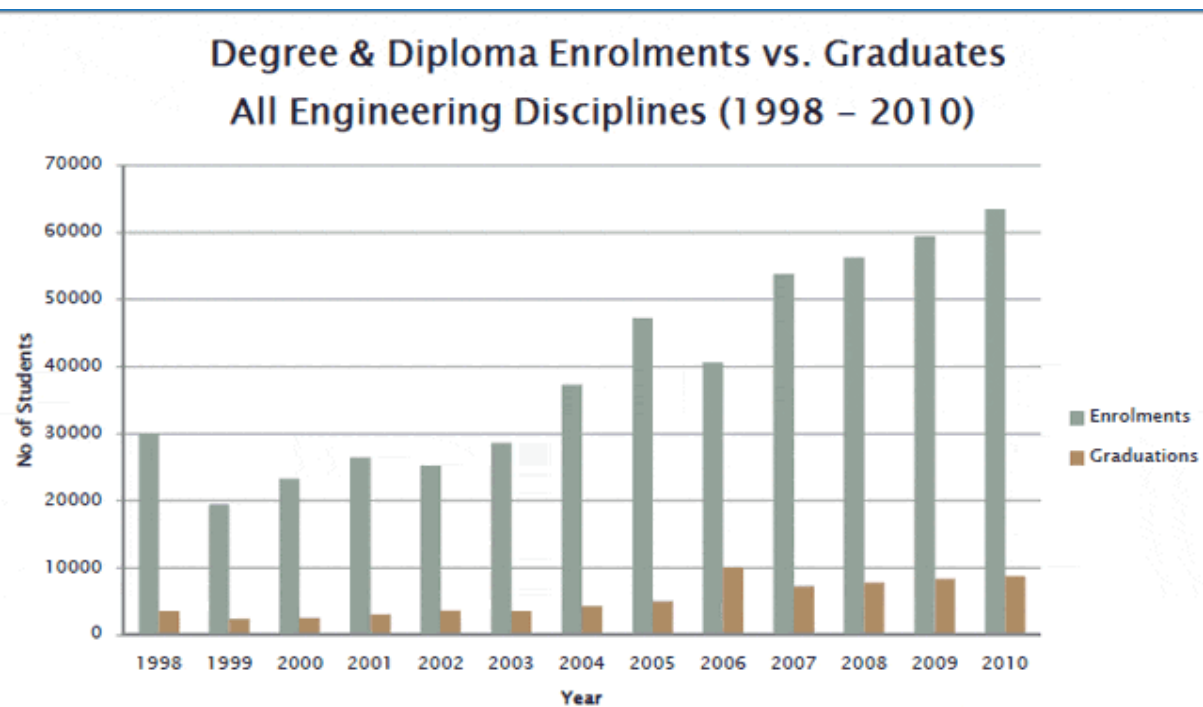


Figure 1: Degree & Diploma Enrolments vs. Graduates

South Africa is not the only country that is experiencing problems with identifying suitable candidates and ensuring that these students complete the engineering course to qualify. In an Australian study from 2002 to 2006, it was discovered that only around 20% of the students who started the four-year engineering course were able to graduate during those four years with 60% of their peers dropping out of the course completely (Cuthbert & MacGillivray, 2007). It was also discovered that if an extra support programme in mathematics was attended, then the student was twice as likely to complete the course as one who did not (Cuthbert & MacGillivray, 2007). This paper goes farther afield than Australia by additionally quoting a source from the UK which states that there are drop-out rates of more than 20% and the main concern is that students will be missing out on an invaluable education opportunity by leaving the course (Cuthbert & MacGillivray, 2007). The United States is also familiar with this problem with reportedly 50% of their engineering students dropping out within the first two years of the course (Cuthbert & MacGillivray, 2007). In most countries, this results in a constant struggle between the government (who want the universities to produce as many graduates as possible) and the forever dwindling pool of students who are able to complete these courses (Cuthbert & MacGillivray, 2007). In an attempt to try and keep as many students in the programme as

possible, many universities have developed courses that will run alongside the tertiary syllabus and give the students the extra help and guidance they need (Cuthbert & MacGillivray, 2007).

The greatest challenge within engineering courses appears to be the mathematical content (Rylands & Coady, 2009). This is not purely a South African problem but is seen in countries such as Australia, the UK, Ireland and the United States (Rylands & Coady, 2009). This inability to cope with the mathematics component seems to cause a high failure and drop-out rate, not only in engineering, but in other mathematically based courses such as science and health subjects (Rylands & Coady, 2009). Possibly one of the reasons for large failure rates is that students are selected generally based on one number (which in South Africa would be their matric average or their mathematics results) and they are then put into a class where mathematics is taught to a broad range of students with various backgrounds and various course choices (Rylands & Coady, 2009). In some instances, the solution was to lower the level of mathematics that is taught (as we can see in our South African schooling system) which resulted in students not gaining the skills they required for future learning in other related courses (Rylands & Coady, 2009). The study done by Rylands and Coady (2009) aimed to find a relationship between secondary school mathematics results and first-year tertiary education mathematics results. It was found that there was indeed a relationship between the secondary school marks and the first-year university marks (Rylands & Coady, 2009). This bodes badly for South Africa where basic education is a problem (Christie, 1998). There are very few options available to those students who are studying engineering but are unable to grasp the mathematics component (Rylands & Coady, 2009). Their three options are to either repeat the year (which they can only do once), change to a course that is not so mathematically based or to leave the university altogether (Rylands & Coady, 2009). These solutions which are available to failing students can only lead to adding to our skills shortage and specifically, the shortage of qualified engineers. The authors of this study did not feel that it was plausible to include a course alongside the current syllabus due to time constraints, but they came up with the solution of a bridging course (Rylands & Coady, 2009). Students whose mathematics results (before their tertiary education) are poor should be asked to attend a preparatory mathematics course prior to commencing their engineering

degree (Rylands & Coady, 2009). They recommended that only those who are able to pass this course should be entered into the engineering programme (Rylands & Coady, 2009).

3.3 Understanding the concept of Validity

Before examining the tests to be studied as well as studies of a similar nature, it is important to understand the concepts of validity and predictive validity. Validity can be defined as the examination of what the test measures and how well it does so (Anastasi, 1990). It aids in understanding what can be inferred from the test scores (Anastasi, 1990). There are many types of validity which will be discussed below, concluding with a definition of predictive validity which is crucial to this study.

Descriptive validity is the initial type of validity one would encounter in a study as it involves the processes used when data gathering (Winter, 2000). Descriptive validity would examine whether the processes of gathering the data were the same throughout data collection and that the processes of coding the data were kept consistent (Winter, 2000). Interpretative validity is how the researcher interprets the data (generally based on how he has worded it and captured it initially) (Winter, 2000). The interpretation of the data needs to be kept consistent throughout the analyses (Winter, 2000). Evaluative validity refers to an application of an 'evaluative framework' when interpreting the data (Winter, 2000). The 'evaluative framework' will aid the researcher in keeping the interpretation consistent and without error (Winter, 2000).

Content validity refers to how well the test measures the subject matter that is being examined (Messick, 1987). Criterion-related validity compares external criteria to the test matter in order to ensure that the subject matter which it claims to test, is actually being tested (Messick, 1987). Construct validity looks at the degree to which explanatory concepts account for one's performance on the assessment (Messick, 1987).

Predictive validity refers to the ability to use the test (or any other variable) to predict/foresee other (possibly unrelated) factors (Anastasi, 1990). In this instance, the predictive validity is using the test scores in an attempt to predict what the student will be achieving in terms of academic results.

3.4 Intelligence Testing and Engineering

Both of the tests used in the current study are broadly referred to as measures of intelligence (Babcock, 1994). Over the years intelligence has been a concept of interest and has sparked debate which has led to several definitions; some of which will be outlined here. Firstly, Intelligence can be defined as how well a person will perform in various environments (Hernandez-Orallo & Dowe, 2010). An alternative way of defining intelligence is that intelligence itself involves information processing and that the action of processing can be measured through certain cognitive tasks (Fagan, 2000). Yet another view of general intelligence is that it is the ability to gain knowledge from one's external environment and then apply it in an attempt to understand and navigate new situations (Lam & Kirby, 2002). This definition speaks most to the engineering subject of mathematical ability. The students will be taught underlying theory and problem-solving reasoning, after which they will be expected to apply it to new and abstract mathematical problems. This definition comes with some basic underlying assumptions. Firstly, it assumes that people are born with their potential intelligence and that it is a fixed asset. This base intelligence will then be worked on to gain the newer knowledge and understanding, but this will only build up to a certain level. Once the student has reached the peak of his/her potential intelligence, s/he will not be able to build on that further. Secondly, it assumes that general intelligence is measurable through tests that pose problems such as completing number series, recognising patterns and analogies which will make use of mathematical reasoning, verbal abilities and spatial-visualisation (Lam & Kirby, 2002). As the Raven's Advanced Progressive Matrices and the Abstract Reasoning Test are both tests of pattern recognition and abstract thinking, by the above definition, they are able to measure general intelligence (Lam & Kirby, 2002). The definition of intelligence came to spark such debate that 52 experts colluded to give the following all-encompassing definition: "A very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book-learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings – 'catching on', 'making sense' of things or 'figuring out' what to do" (Gottfredson, 1997)

as cited in Lubinski, 2004). Engineering subjects such as mathematics, that may be based more on one's reasoning and abstract thinking ability would relate back to Gottfredson's thinking rather than subjects such as Economics which would require 'book-learning'.

There is a variety of intelligence tests, but there are three criteria which are common to all the tests and which have to be examined when deciding on which test to use (Hernandez-Orallo & Dowe, 2010). These three specifications are that there is a subject to be tested, that a set of questions is posed to this subject and the scoring of these questions correlate to a specific meaning (Hernandez-Orallo & Dowe, 2010). Both tests used in this study measure a participant's general intelligence, which is a concept coined by Spearman and thus referred to as 'Spearman's g' (Duncan, Seitz, Kolodny, Bor, Herzog, Ahmed, Newell & Emslie, 2000, Embretson & McCollam, 2000). Spearman noticed that participants who performed well in cognitive tasks almost universally performed well in other, very different tasks (Duncan et al., 2000). In order to understand this phenomenon, Spearman reasoned that those participants must have a high g factor (general intelligence) which enables them to perform well in various tasks (Duncan et al., 2000). Spearman also acknowledged that a participant might only perform well in a specific task, which has become to be known as Spearman's 's' – specific factor intelligence (Embretson & McCollam, 2000). One of the tests in which high scores will correlate with a high g factor is the Raven's Progressive Matrices (Duncan et al., 2000). Thomson added to this argument by stating that high g factor levels show the overall efficiency of the participants' cognitive functions (Duncan et al., 2000). A student of Spearman, John Raven, developed a test which he felt would aid in measuring general reasoning (Embretson & McCollam, 2000). This test was one of the predecessors to the Advanced Raven's Progressive Matrices as it contained the same three-by-three array of patterns in which the ninth one had to be selected from a variety of choices (Embretson & McCollam, 2000). As such, it can be argued that high scores on general intelligence measures such as the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices will show high cognitive abilities such as pattern recognition and general intelligence in the participants, and an ability to perform well academically.

Analytical reasoning is also an important concept when understanding these tests and what they measure. Analytical reasoning is generally examined in relation to complex problem solving such as may be found in a Mathematics engineering course (Prietula & Simon, 1989). Analytical reasoning happens when the participant gathers information, uses the knowledge that he or she already possesses and then proposes a solution once they have fully understood (through observation) the situation at hand (Prietula & Simon, 1989). This is based upon the idea that a person will consider the different options available to them before choosing the one they feel will work best (Prietula & Simon, 1989). This theory can be used to understand the process the participants must go through in terms of the psychometric tests in this study. They will need to use their knowledge and reasoning power to analyse the pattern and the different options available to finish the pattern before choosing the one they feel is the most correct.

Biographical variables will play an important part in the understanding a student has in terms of psychometric tests and university learning. The language in which a student is taught (and how that might differ from his/her home language) is such a biographical variable (Schaap & Luwes, 2013). The proficiency with which a student is able to understand and interpret the language that is used when teaching subjects, such as mathematics, which require strong reasoning and strategic skills, is important (Schaap & Luwes). As such, if the participant's home language is not English, it is important to investigate this variable and whether or not it has an impact on the psychometric test scores and/or the academic results achieved by that student (Schaap & Luwes, 2013).

Finally, gender has also been examined in the context of subjects that are strong in mathematical and scientific content (van Langen & Dekkers, 2005). From secondary school upwards, females are half as likely as males to choose subjects that are based in science or mathematics (van Langen & Dekkers, 2005). This will inevitably lead to engineering continuing to be a male-dominated field (van Langen & Dekkers, 2005). Although in most Western countries the number of females in engineering is constantly rising to equal the number of men, this is not yet the case in all countries (van Langen & Dekkers, 2005). Interestingly, van Langen and Dekkers (2005) looked back over school subject choices and identified that there were many candidates who would be qualified to study engineering, if they had taken the required subjects,

which they did not, despite being academically qualified to do so. They described this loss of candidates as ‘spillage’ from the pipe that would service the need for engineers and attribute some of this to the reason there is a shortage of qualified people in this field (van Langen & Dekkers, 2005).

3.5 The psychometric tests in this study

One way to tackle the skills shortage problem is through the use of psychometric testing when students are accepted into engineering courses. If these tests are able to predict the end of year academic results of the students, as well as show their weak points, the lecturers will be better equipped to dealing with these shortcomings, thus facilitating a high pass rate. Before examining the predictive value, one must first understand the tests themselves.

The Raven’s Advanced Progressive Matrices Test is a non-verbal psychometric test that is used primarily to measure analytical intelligence (Carpenter, Just & Shell, 1990, Hamel & Schmittmann, 2006). Analytical intelligence is a term that describes ones’ ability to solve problems using new information without having to rely on previous experience or knowledge, but rather one’s own reasoning power (Carpenter et al., 1990). In order to find an answer to a new cognitive problem, one will adapt one’s thinking (Carpenter et al., 1990).

The Raven’s Progressive Matrices Test examines two main constructs, namely ‘eductive’ ability and reproductive ability (Raven, 2000). Eductive ability is the ability to make sense of what appears to be confusing material (Raven, 2000). In order to do this, the participant will need the skill of being able to create high-level schemata which will enable the participant to understand what might initially be interpreted as chaotic or difficult data (Raven, 2000). Reproductive ability means that the participant is able to absorb data and recall it when needed (Raven, 2000).

The Raven’s Advanced Progressive Matrices Test is a non-verbal test which requires participants to complete a series of two-dimensional geometric shapes/patterns (Babcock, 1994, Raven, 2000, Laidra et al., 2006). The series of shapes are presented in a “three rows by three columns” format with the last (or ninth) shape missing (Babcock, 1994). The participant is then given eight alternative shapes and asked which one would best fit in the ninth place of the sequence (Babcock, 1994, Raven, 2000). The choice of this shape must ensure that the

pattern for both the row and column is continued (Babcock, 1994). An example of a test item is given in Figure 2. The test takes between thirty and forty minutes to complete, with 36 items in total (Babcock, 1994, Hamel & Schmittmann, 2006). The difficulty of the items will gradually increase as the test progresses (Hamel & Schmittmann, 2006). This test does not only test the thinking skills of the participant, but also their ability to think clearly (Babcock, 1994). It is important to note that there is a significant relationship between performance on the Raven's Advanced Progressive Matrices and other tests which are used to measure general intelligence (Babcock, 1994). However, there is no conclusive evidence as to whether or not one's performance on the Raven's Advanced Progressive Matrices is correlated to verbal or non-verbal abilities (Babcock, 1994). It is also important to note that there is additionally no conclusive evidence as to the relationship between the Raven's Advanced Progressive Matrices and memory tests (Babcock, 1994)

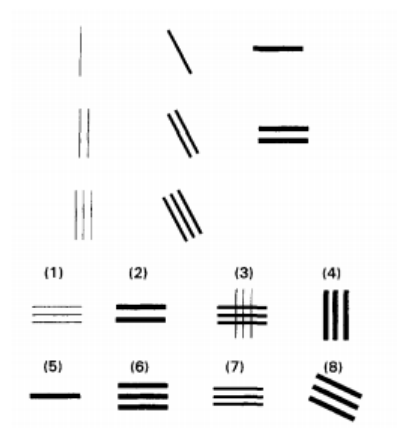


Figure 2: Example of an item in the Raven's Advanced Progressive Matrices test

The use of the Raven's Advanced Progressive Matrices Test to better understand the cognitive abilities of engineering students is not a new concept. A few studies in which the test was administered with a view to furthering various bases of knowledge regarding engineering students' cognitive abilities will now be discussed.

When using the Raven's Advanced Progressive Matrices Test in a South African university, it is important to consider the differences that might arise as a result of biographical variables such as socio-economic status and race (Rushton, Skuy &

Bons, 2004). A study which examines the construct validity of the Raven's Advanced Progressive Matrices Test in terms of African and non-African students was conducted at the University of the Witwatersrand in 2004 (Rushton et al., 2004). The sample comprised 177 African students, 57 Indian students and 72 White students. Out of the possible 36 problems in the Raven's Advanced Progressive Matrices, African students (on average) scored a 23 mean score, with the Indian students scoring 26, and finally, the White students scoring 29 (Rushton et al., 2004). Additionally, it was also found that the academic marks obtained by these student groups behaved in much the same pattern, with the White students obtaining the highest marks, followed by the Indian students and finally, the African students (Rushton et al., 2004).

The Spearman-Jensen hypothesis states that differences in race become more pronounced in tests that have a high general factor of intelligence (Rushton, Skuy & Fridjhon, 2002). As such, one must add a cautionary note about interpreting scores and linking them to the biographical variable of race (Schaap & Luwes, 2013). Although 10 years have passed since these findings (and therefore results may be different), one must keep these results in mind when interpreting the relationship between test scores and end of year marks as it has been acknowledged that Western tests may not properly reflect general and analytical intelligence in African students (Rushton et al., 2004). In terms of other biographical variables, it is found that race in South Africa links to socio-economic factors where previously disadvantaged African pupils are often victims of a schooling system that lacks the necessary infrastructure to give optimal learning opportunities (Schaap & Luwes, 2013). This will, in turn, lead to lower academic results at a tertiary education level (Schaap & Luwes, 2013).

The Abstract Reasoning Test (ART) is very similar to the Raven's Advanced Progressive Matrices test. It too comprises shapes/patterns in a 3x3 matrix for which the participant is required to choose the correct shape to complete the pattern in the 9th slot (Psytech, retrieved on 15/08/2014). This shape must complete the sequence both horizontally and vertically (Psytech, retrieved on 15/08/2014). Figure 3 gives an example of a test item. Participants are given 30 minutes to complete the 35 questions in the Abstract Reasoning Test, after which they are required to stop, regardless of whether or not they have completed the test (Psytech, retrieved on

15/08/2014). In the Abstract Reasoning Test, the participant is only given six possible choices from which to choose the shape that will complete the sequence (Psytech, retrieved on 15/08/2014). As the Abstract Reasoning Test is similar to the Raven's Advanced Progressive Matrices, it can be argued that the ART measures the same intellectual skills, cognitive skills and abilities as does the Raven's (Psytech, retrieved on 15/08/2014).

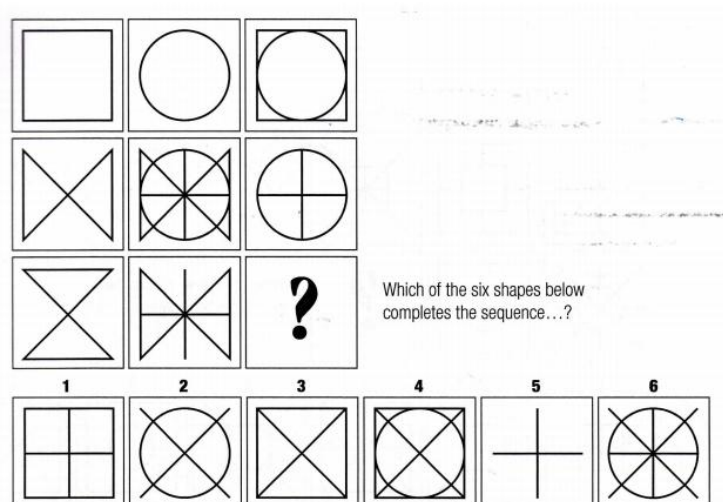


Figure 3: Example of a test item from the Abstract Reasoning Test

3.6 Background of similar studies

In essence, this study examines the relationship between the scores of students on analytical intelligence tests and their academic marks. In a study which examined school children between the level of Grade 2 to Grade 12, it was found that the Raven's Standard Progressive Matrices were the best predictor with regards to the overall year mark achieved by the students (Laidra et al., 2006). However, the authors warn that it appears that this correlation is stronger in younger children and declines with age steadily throughout their schooling and into their tertiary education (Laidra et al., 2006). However, they did acknowledge that this could possibly be due to smaller sample sizes relating to the lesser number of pupils to choose from as the population decreases as the education level increases (Laidra et al., 2006). The other possibility for this decline is that the standard of work does not stay the same in order to retain the same mark (Laidra et al., 2006). As one's level of education

increases, so does the standard of work one is expected to produce (Laidra et al., 2006).

Certain abilities of engineering students that can be tested and possibly improved have previously been studied. One of these studies examined spatial ability and visual imagery in relation to engineering students (Potter & van der Merwe, 2001). Before this study was conducted, the failure rate for the Engineering Graphics course at the University of the Witwatersrand was 36% (with an 80% failure rate being calculated for the African students) (Potter & van der Merwe, 2001). It must also be noted that on the whole, (although it was not statistically significant) female students struggled slightly more than their male counterparts with regard to these skills (Potter, van der Merwe, Kaufman & Delacour, 2006, Sorby, 2009). These authors have also mentioned that they felt the greatest contributor to this lack of skills could be traced back to the Apartheid era and the inferior education that some scholars are still receiving as a result (Potter et al., 2006). When tested, these students also showed low scores on various tests that measured spatial ability and general academic performance (Potter & van der Merwe, 2001, Sorby, 2009). However, it was found that students could be trained in perception and their ability to use mental imagery improved (Potter & van der Merwe, 2001, Sorby, 2009). Once the course was altered to improve the skills that were found to be weak, the pass rate went up to 88% which was considered to be a vast improvement (Potter & van der Merwe, 2001).

Table 1 shows the data gleaned from the Engineering Department regarding the pass rates from 1995 – 2001 (Potter et al., 2006). The overall success of these students was believed to be the result of changes to tuition and programmes that aided those students who were struggling in a particular field (Potter et al., 2006). The students were split into 2 groups, those who were seen to have weaknesses within this skill set and who attended a year long course (A) and those who were proficient in the skills and required a 6 month course only (B) (Potter et al., 2006).

Table 1: Academic Results in Wits Engineering students from 1995 to 2001

Year	Course	Pass Rate (%)
1995	A	84
	B	83
1996	A	89
	B	87
1997	A	94
	B	92
1998	A	87
	B	94
1999	A	95
	B	82
2000	A	94
	B	91
2001	A	93
	B	92

As the above information shows, the weaknesses of a particular group/class can be tested at the beginning of the year so as to alert the lecturers and class coordinators as to where they should focus in order to try and combat any weaknesses while improving the knowledge of the students. Using this knowledge, we can see that the differences between the group of students who may have failed and those who were likely to excel, was lessened, with all the students being given the opportunity to do well (Potter et al., 2006).

The great divide between students in terms of their education and skills prior to entering university and the skills they need to develop in the tertiary education forum is not only found in South Africa (Taylor & Morgan, 1999). In Australia, several challenges were found with regard to educating engineers in their first year of tertiary education (Taylor & Morgan, 1999). The main challenges were the spread of student abilities and the uneven preparedness within the class (Taylor & Morgan, 1999). This

meant that lecturers were at a loss as to where to start the curriculum and on which skills to focus (Taylor & Morgan, 1999).

This study aims to understand whether or not the Raven's Advanced Progressive Matrices and the Abstract Reasoning Test can be used to find weaknesses in the students at the beginning of the academic year. This information will give the lecturers a chance to develop a syllabus with an emphasis on improving these weaker areas, facilitating a higher pass rate which will benefit not only the students and the university, but the South African shortage of engineers too.

Using the information given above, there is a basis for the research in terms of finding a correlation between the Raven's Advanced Progressive Matrices test and the Abstract Reasoning Test and the academic marks engineering students will achieve in their first year. The predictive validity of the tests will be used to ascertain whether or not the psychometric assessments can be used as predictors of the academic results students will achieve in both their mid-year and end of year results. However, there is potential that biographical factors (for example, home language) may negatively influence the scores that participants will receive on the psychometric tests.

3.7 Research Hypotheses/Questions

1. The Abstract Reasoning Test scores predict first year engineering students' mid and end of year results.
2. The Raven's Advanced Progressive Matrices scores predict first year engineering students' mid and end of year results.
3. The Abstract Reasoning Test is a more powerful predictor of academic results than the Raven's Advanced Progressive Matrices.
4. Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices.

Chapter 4: Method

4. Method

4.1 Overall Research Design

This study was a non-experimental, cross-sectional, correlational design, using archival data.

4.1.1 Sample

The sample came from the Engineering Department at the University of the Witwatersrand. Specifically the archival data from the first year students from 2014 and 2013 was used. As such, this means that data was gathered through convenience sampling.

The potential maximum size of the sample is 410 students from 2013 and 305 students from 2014. As such, the total possible sample for this study is 715 participants. These figures are taken from the number of students in the archival data, however this number will be reduced as the students who did not participate in the psychometric testing or who did not give consent for their results to be used in the study are removed from the sample.

The archival data for 2013 recorded biographical variables such as education level, race, first language, whether or not the participant has a disability and whether or not their previous education was done primarily in English. The 2014 data has additionally recorded whether the participants attended a private or government school. It is also important to note that for both years, it was recorded whether or not the student was repeating first year.

Due to differences in the data between the years, this project has been split into two phases. These differences will be discussed in greater detail in the Results section of this report. In Phase One, the sample is analysed as a whole in order to gain information about the sample in completion, as well as overall trends. In Phase 2, the 2013 first year students and the 2014 first year students have been split and analysed separately.

The biographical variables were analysed for each phase and the following figures produced.

1.1.1 Phase 1: Biographical Information

Figure 4 displays the frequencies of sex within the total sample of students (both the 2013 and 2014 year)

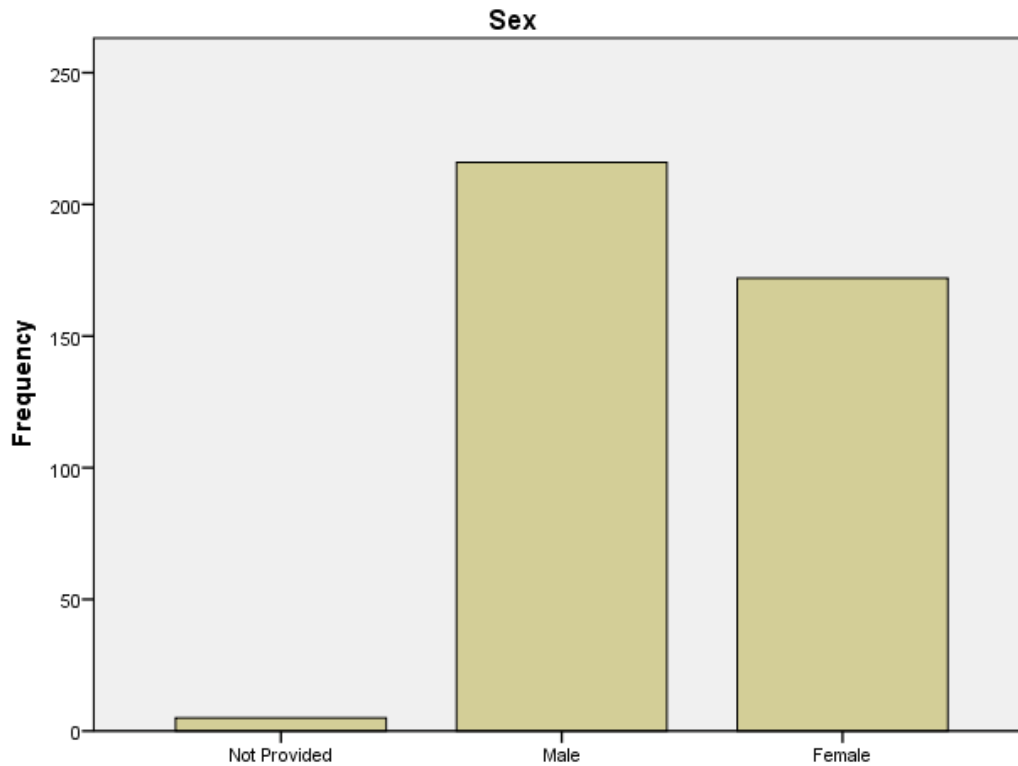


Figure 4: Frequency of gender distribution (N=393)

1.8% of the sample did not provide their gender, 216 participants are male and 172 are female. This results in a majority 54.7% of the sample as men.

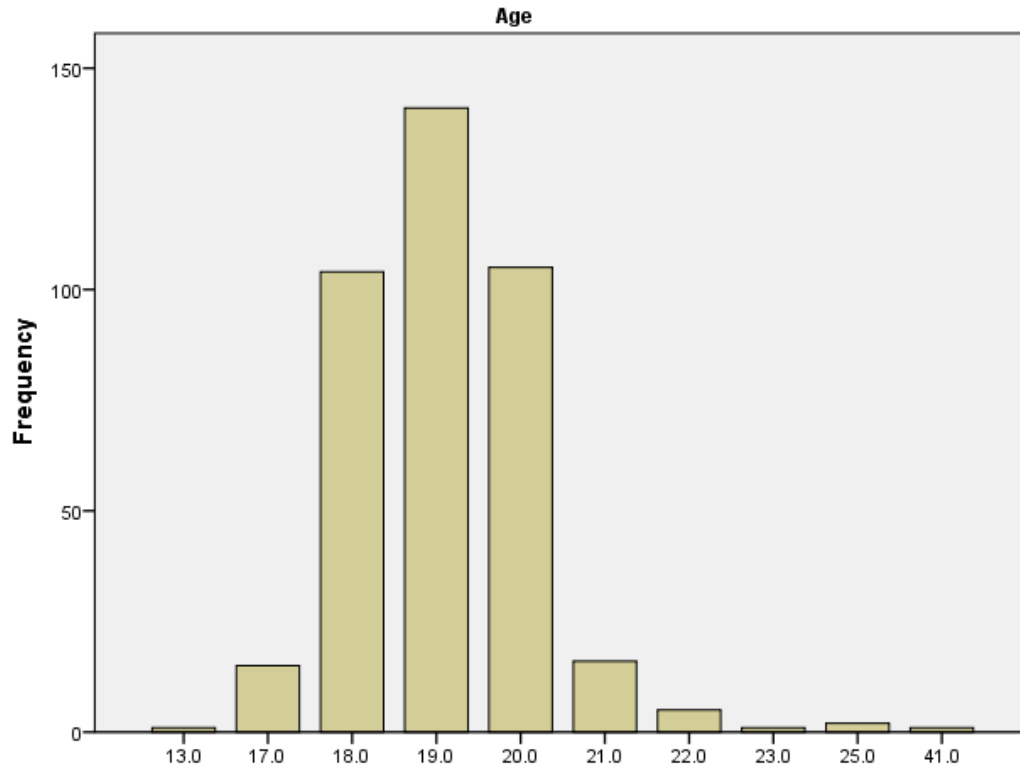


Figure 5: Frequency of age distribution among sample (N=395)

Figure 5 displays the frequencies for the different ages of students within the sample. 88.6% of the sample lay between the ages of 18 and 20 years old. The biggest age group is the 19 year old students with 141 participants, followed by the 20 year old and 18 year old students with 105 and 105 participants respectively.

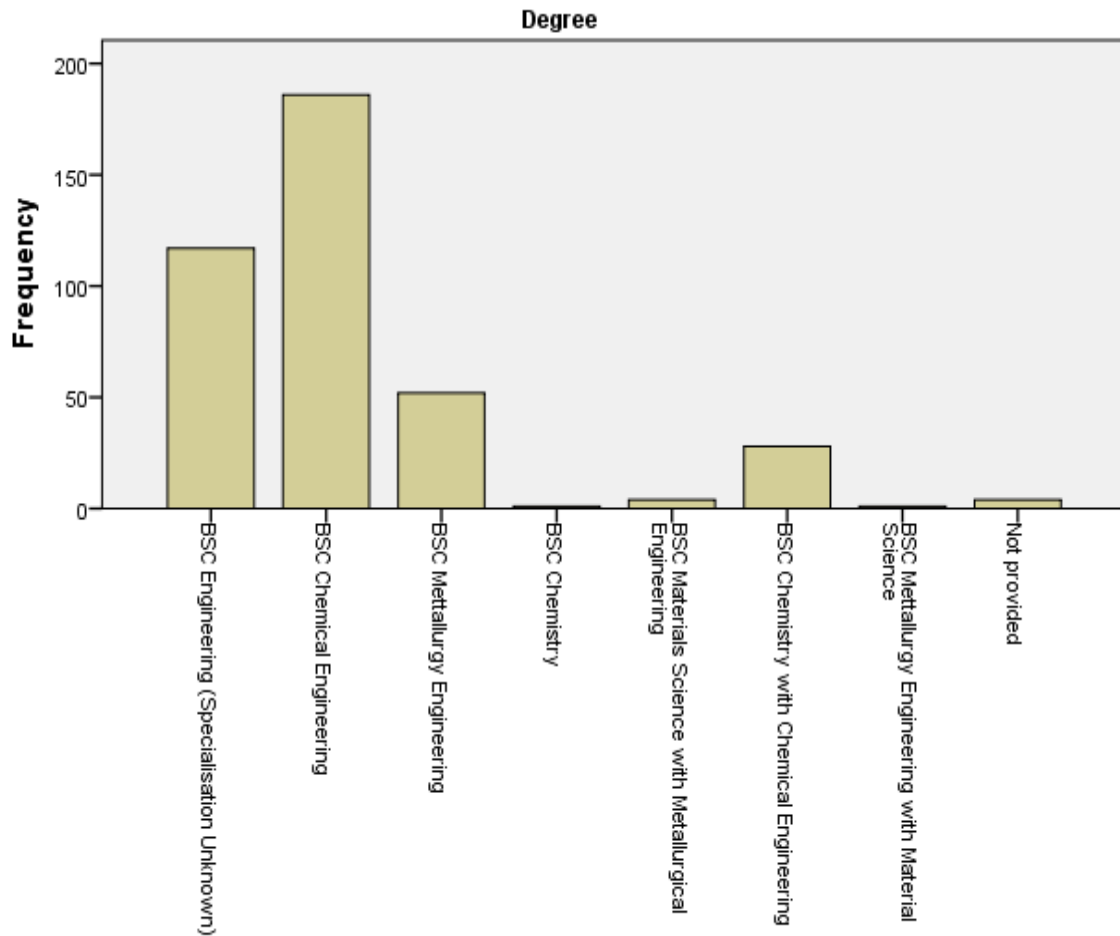


Figure 6: Frequency of degree distribution among sample (N=393).

Figure 6 displays the frequency of students studying towards each of the various degrees. The greatest grouping in the biographical variable of 'Degree' is the 186 students studying Chemical Engineering. The second highest group are the students studying Engineering but for whom no specialisation was given. The smallest groups according to Degree are the BSC Chemistry and the BSC Metallurgy Engineering with Material Science which comprise one student each in this sample.

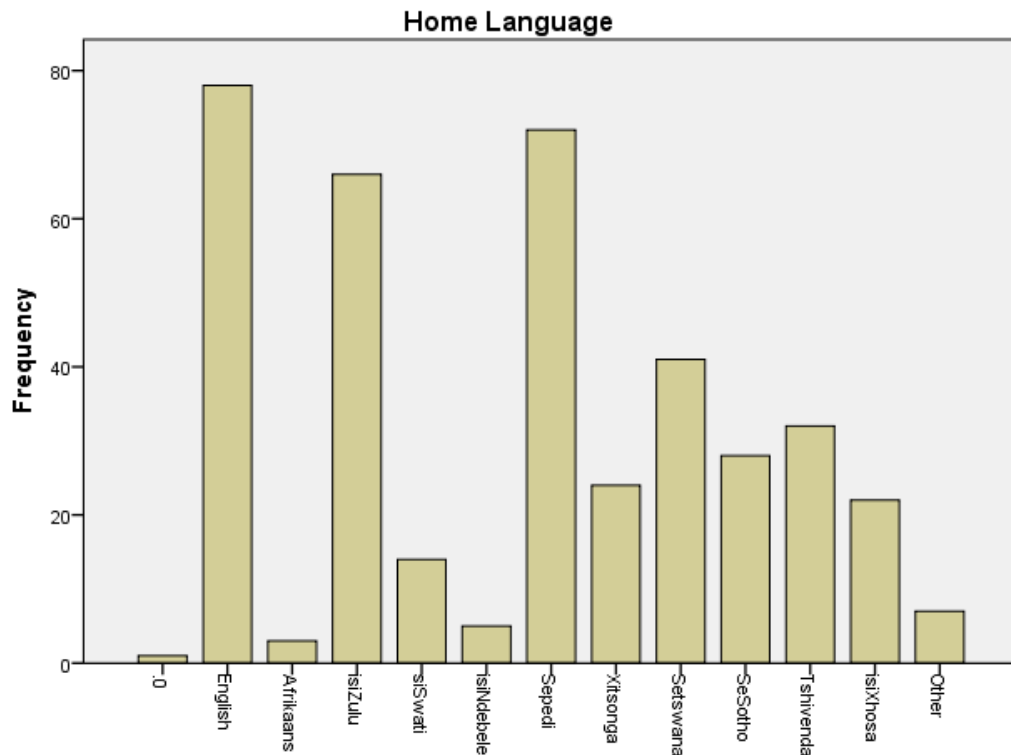


Figure 7: Frequency of home language distribution among sample (N=393)

Figure 7 gives an overview of the number of students who speak each language as their primary, home language. The largest group in terms of home language are the students who speak English as 19.7% (78 students) have English as their first language. This is closely followed by Sepedi (18.2%) and isiZulu (16.7%). In total, 77.4% of the sample were students whose home language was an African language. This is important to keep in mind in terms of the inherent, potential biases in psychometric tests such as the Raven's towards non-Western, non-English speaking participants (Rushton et al., 2004). This bias was discussed in the previous section and will be analysed with respect to the results in the Discussion section of this report. A test will show bias if members of a certain group achieve similar academic results as members of other groups, but lower scores on the test/assessment than those members (Rushton et al., 2004).

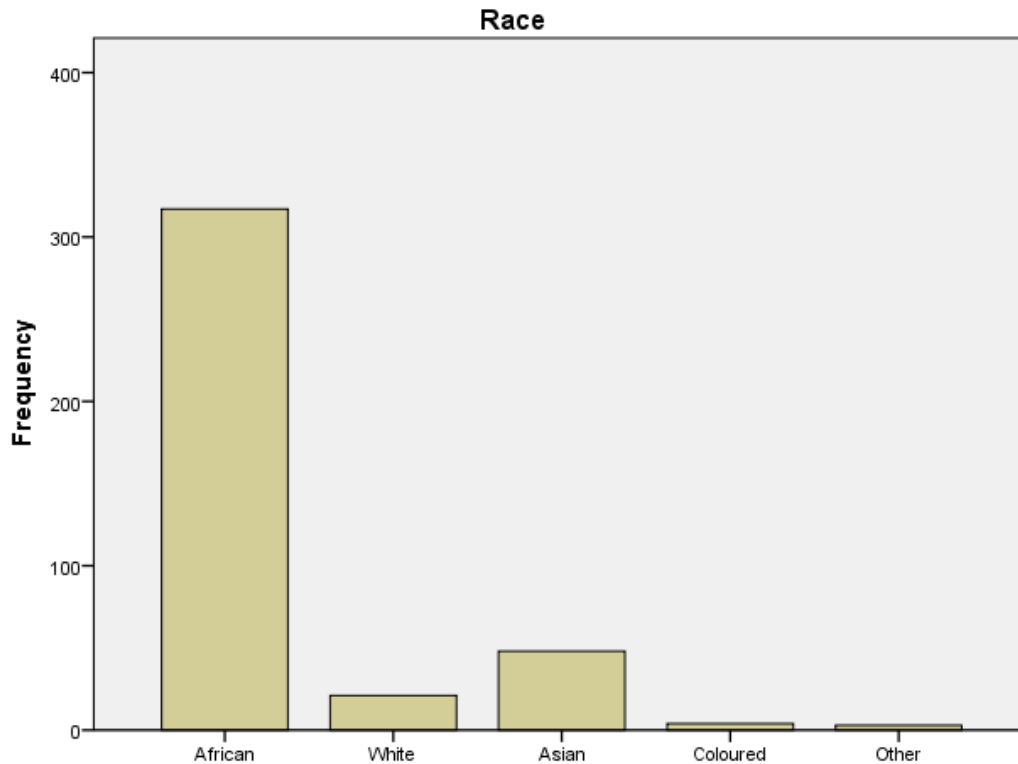


Figure 8: Frequency of race distribution among sample (N=393)

Figure 8 displays the distribution of race in this sample. 80.3% of the participants are African, 12.2% Asian, 5.3% White and 1% Coloured. As with the home language bias, the intricacies of Apartheid and the lack of education for African students (as discussed in the previous section) may also have an impact on this study and the bias that results from the use of psychometric tests on this sample.

1.1.2 Phase 2: Biographical Information

This section will outlay the biographical variables for the 2013 first year students and the 2014 first year students separately. This will allow for a comparison to be made between the two samples.

Table 2: Comparison of Gender Ratios between 2013 and 2014 first year students

Gender	2013 First Years	2014 First Years
Male	58	158
Female	54	118
N	115	278

Table 2 gives the sample sizes for each group in Phase Two of this report. In the 2013 group, males were a slightly bigger group with 50.4% of the sample comprising men. The 2014 group shows the same majority group (males) but with the slightly higher majority of 56.8% over the 42.4% of the female students. The difference in size between the two groups can be attributed to the difference between a first year class and a second year class. As permission was gained from the 2013 students only in 2014, a significant number of students had dropped out or failed.

Table 3: Frequency of students within each age grouping

Age	2013 First Year Students	2014 First Year Students
17 years old	1	14
18 years old	19	85
19 years old	50	91
20 years old	37	68
21 years old	8	10
22 years old	1	4
N	114	277

Table 3 shows that 19 year olds are the largest age group with 43.5%, with 20 year olds the second largest (32.2%) and 18 year olds the third largest (16.5%) in the 2013 first years' group. In the 2014 group, these results differed slightly with 19 year olds the largest (32.7%) followed by 18 year olds (30.6%) and finally 20 year olds (24.5%).

In terms of the degree that the student is studying towards, the 2014 group's archival data was more specific than the 2013 groups data. As such, the tables will be presented independently.

Table 4: 2013 students' degree specification (N=115).

Degree	Frequency within sample (%)
BSC Engineering (Specialisation Unknown)	28.7
BSC Chemical Engineering	54.8
BSC Metallurgy Engineering	16.5

Table 4 shows that in the 2013 first year students, the majority of the sample are studying towards a Chemical Engineering Degree. Table 5 shows the degrees to which the 2014 first year students are studying.

Table 5: 2014 students' degree specification (N=278)

Degree	Frequency within sample (%)
BSC Engineering (Specialisation Unknown)	30.2
BSC Chemical Engineering	44.2
BSC Metallurgy Engineering	11.9
BSC Chemistry	.4
BSC Materials Science with Metallurgical Engineering	10.5
Not Provided	1.4

In the 2014 sample, the largest group of students is also studying toward attaining a BSC Chemical Engineering degree. However, the specificity of the 2014 group makes it difficult to compare the two years.

The first language of the student's was analysed to produce the Table 6:

Table 6: Frequency of home language speakers for 2013 and 2014 students

First Language	2013 First Year Students	2014 First Year Students
-----------------------	---------------------------------	---------------------------------

English	14.8%	21.9%
Afrikaans	1.7%	.4%
isiZulu	16.5%	16.9%
siSwati	2.6%	4%
isiNdebele	0%	1.8%
Sepedi	23.5%	16.2%
Xitsonga	7%	5.8%
Setswana	9.6%	10.8%
SeSotho	8.7%	6.5%
Tshivenda	5.2%	9.4%
isiXhosa	7%	5%
Other	2.6%	1.4%
N	115	278

This table shows Sepedi first language speakers as the largest group followed by isiZulu and English first language speakers for the 2013 first year students. In the 2014 student group, English speakers were the largest group, after which isiZulu and Sepedi home language speakers were the next largest respectively.

Finally, race was examined in Table 7 in terms of the two years.

Table 7: Racial differentiation between 2013 and 2014 first year students

Race	2013 First Year Students	2014 First Year Students
African	98	219
White	7	14
Asian	7	41
Coloured	2	2
Other	1	2
N	115	278

As with Phase One, African students are in the vast majority for both groups, which again places emphasis on the cautionary point of interpreting and analysing the test results with caution.

4.1.2 Procedure

The following process was followed with regard to the data collection aspect of this research report:

1. The archival data was obtained from Lorenzo Woollacott in the Engineering Department
2. The students whose data was to be used in this research report were approached during lecture times and asked to sign the consent forms (Appendix A). Before signing the consent forms, the participants were given the participant information sheet to read through and keep should they have any further questions. There are two different participant information letters, one for students who were in second year at the time of data collection (Appendix B), and the other for students who were in first year at the time of data collection (Appendix C).
3. As the students who were completing their first year in 2014 had not completed the Abstract Reasoning Test, Psytech was contacted and asked to conduct the test during a lecture period where all the students were expected to be present.
4. The consent forms were cross checked with the data obtained from the Engineering Department and all students whose consent had not been given, were deleted from the database.
5. The analyses were then conducted.

4.1.3 Analysis

Cronbach's Alphas were used to calculate the reliability of the Abstract Reasoning Test. The overall score was .78 meaning that the scale can be credibly used in this research project. According to Gliem and Gliem, the following rules of thumb can be applied to Cronbach's Alpha: above .9 is excellent, above .8 is good, above .7 is acceptable, above .6 is questionable, above .5 is poor and anything below that score is not reliable (Gliem & Gliem, 2003). As such, this score reflects that the scale is reliable.

Unfortunately, the archival data did not contain the item scores for the Raven's Advanced Progressive Matrices and the reliabilities could therefore not be conducted.

To determine any differences in the data, skewness coefficients, T-Tests and Mann-Whitney U tests were run.

In order to calculate the predictive value of the test, correlations and regressions were used. A correlation was used to understand the strength and direction of the association between the psychometric test scores and the academic results of the students (Stangor, 2011). Regression was used to explore whether or not the test scores can be used independently to predict what the participants might receive as academic marks during their first year of study (Stangor, 2011).

Averages were calculated to compare the key variables (namely the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices) on the basis of certain demographics with ANOVAS and post-hoc tests used to ascertain where the significant differences were.

Finally, ANCOVAs were used to ascertain whether there were any significant differences on the high, medium and low scores on the ART and Raven's taking the different student years (2013 or 2014 first years) into consideration. How these three groups were formed is discussed in more detail in the results section of this report.

4.1.4 Measures/Instruments

The first measure that was used is the Abstract Reasoning Test. The second measure is the Raven's Advanced Progressive Matrices Test. Both of these tests have been discussed in detail in the literature review with an example question given for each.

Please note that due to copyright issues, these tests have not been placed in the appendices of this proposal. Should you require them, the Abstract Reasoning Test is available from Psytech and the Raven's Advanced Progressive Matrices from JvR.

4.1.5 Ethics

An application was made to the University of the Witwatersrand's Human Research Ethics Committee (non-medical) for approval before accessing or analysing any of the data from the Engineering Department. The ethical clearance certificate can be found in Appendix D of this report. However, this project falls under ethical approval which has already been obtained for research in the Engineering faculty (Appendix E).

3.1.5.1 Informed Consent

Participants were all asked to complete a consent form which gives me access to their test scores on the Raven's Advanced Progressive Matrices Test and the Abstract Reasoning Test as well as their mid- and end of year academic marks (See Appendix A). Participants who did not complete and return the consent form, have had their marks deleted from the database before any analyses were done.

Participation in the study was entirely voluntary and no negative or positive consequences will result from participation. It is also important to note that the participants of the study will receive no benefit from participating.

3.1.5.2 Anonymity

Participants were asked for their student numbers in order to match their consent forms to their test scores and academic marks. Once the database was cleaned of any students who were not willing to participate, the student numbers of the participants were deleted and the researcher had no further knowledge of which marks belonged to which students for the analyses.

Anonymity could not be guaranteed to the participants in terms of the matching of consent forms to test scores and academic marks, however, identities were kept strictly confidential and anonymity could be guaranteed in terms of analytic and final write-up purposes.

3.1.5.2 Confidentiality

Only the researcher and her supervisor (outside of the Engineering Department and Psytech) had access to the scores and marks with the student names/numbers. No individual results were reported. This ensured confidentiality of individual results and anonymity of individual results in the final report.

3.1.5.3 Potential harmful outcomes for subjects and procedures to deal with these

No potentially harmful outcomes were identified in this study. However, it must be added that there were no benefits to participants for participating in the study.

3.1.5.4 Debriefing

A summary of the results obtained will be made available to the Engineering Department at the University of the Witwatersrand. This summary will be emailed to the lecturers within the department who assisted with the data collection and the signing of consent forms.

This summary will be made available to students on public notice boards within their department where they are easily able to access that information. No individual scores will be given, just the overall trends that were found.

The results from the analyses will be reported in the research essay and possibly in journal articles and at conferences. The scores and academic marks will be kept for as much time as necessary and will be stored securely by the researcher's supervisor until all potential publications have been completed.

Chapter 5: Results

5. Results

This section is split into three phases. Phase one will analyse the sample as a whole, encompassing both the first year students from 2013 and 2014. Phase two will then be a division of the two groups, examining each year separately to analyse whether any changes are found. Finally, Phase three will examine the relationship between the scores achieved on the psychometric tests and the academic results achieved by the students, using the year as a covariate.

5.1 Phase 1: Combined sample

The initial step in the analysis was to describe the data and examine its normality (Table 8). The number of students who participated in each subject ranged from 212 (ECON1007 and CHEM1031 – both end of year results) to 391 (CHMT1000 – mid-year). There was a decrease in student numbers between the mid-year and final year results for each subject. This could be due to students failing or leaving the university or course.

The minimum and maximum marks obtained by the students are provided. The minimum mark¹ was 12% in CHMT1000 (End of Year results), and the maximum mark 98% for MATH1014 (End of Year Results). The means were fairly similar, with the lowest mean score obtained in CHMT1000 (mid-year) (46.9%) and the highest in MATH1014 (end of year) (64.85%). Finally, the standard deviations range from 10.27 to 15.39, with the largest standard deviation for MATH1014 (both mid- and end of year results).

¹ The score of 0 for CHMT1001 (End of Year) was discounted as it indicates non-participation in the subject.

Table 8: Descriptive Statistics for Academic Results

Subject	N	Min	Max	Mean	Std Dev.
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	391	17.76	79.68	46.9	11.38
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	293	12.00	90.00	51.59	11.22
CHMT1001 Mid-Year Marks (Physics)	291	23.71	92.13	61.18	11.86
CHMT1001 End of Year Marks (Physics)	213	.00	91.00	63.80	13.54
CHEM1031 Mid-Year Marks (Chemistry)	233	30.66	95.65	59.25	11.61
CHEM1031 End of Year Marks (Chemistry)	212	38.00	93.00	61.22	10.27
ECON1007 Mid-Year Marks (Economics)	236	35.00	96.00	64.41	10.76
ECON1007 End of Year Marks (Economics)	212	35.00	96.00	64.81	10.69
MATH1014 Mid-Year Marks (Mathematics)	246	13.80	95.33	62.97	15.39
MATH1014 End of Year Marks (Mathematics)	218	20.00	98.00	64.85	15.10

Table 9: Skewness of Academic Results

Subject	N	Skewness		Kurtosis	
		Statistic	Std. Error	Statistic	Std. Error
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	391	.14	.12	-.23	.24
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	293	-.13	.14	.51	.28
CHMT1001 Mid-Year Marks (Physics)	291	.13	.14	.21	.28
CHMT1001 End of Year Marks (Physics)	213	-.95	.16	3.47	.33
CHEM1031 Mid-Year Marks (Chemistry)	233	.24	.15	-.02	.31
CHEM1031 End of Year Marks (Chemistry)	212	.37	.16	-.08	.33
ECON1007 Mid-Year Marks (Economics)	236	-.09	.15	-.03	.31
ECON1007 End of Year Marks (Economics)	212	-.08	.16	-.08	.33
MATH1014 Mid Year Marks (Mathematics)	246	-.15	.15	-.36	.30
MATH1014 End of Year Marks (Mathematics)	218	-.14	.16	-.37	.32

Table 9 displays the skewness statistics as between -1 and 1, which means the data is normally distributed which will result in parametric tests being used in answering the research questions.

The remainder of this section is structured according to the research hypotheses.

5.1.1 H1: The Abstract Reasoning Test predicts first year engineering students' mid and end of year university results.

Pearson's correlations were conducted between the students' academic results in each subject and the Abstract Reasoning Test (Table 10). Throughout this section, the sample size differs according to the varying sizes of the class.

Table 10: Results of a Pearson Correlation between ART and academic results

Subject	N	r	p
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	390	.12*	.01
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	292	.11*	.04
CHMT1001 Mid-Year Marks (Physics)	291	.09	.10
CHMT1001 End of Year Marks (Physics)	213	.09	.17
CHEM1031 Mid-Year Marks (Chemistry)	233	.15*	.02
CHEM1031 End of Year Marks (Chemistry)	212	.15*	.02
ECON1007 Mid-Year Marks (Economics)	236	.14*	.02
ECON1007 End of Year Marks (Economics)	212	.12	.07
MATH1014 Mid-Year Marks (Mathematics)	246	.05	.36
MATH1014 End of Year Marks (Mathematics)	218	.02	.66

*p<.05

The significant correlations were found between the ART and CHMT1000 (both the mid-year results and the end of year results), CHEM1031 (both the mid-year results and the end of year results) and ECON1007 for the mid-year results. These significant correlations show a relationship between the Abstract Reasoning Test and these specific subjects. All of the relationships are positive, which indicate that as the ART score increases in value, so does the students' result in those subjects. However, all of these correlation scores are close to 0 and show a weak relationship between the psychometric test and the academic result.

In order to test the predictive value of the Abstract Reasoning Test, linear regressions were used for every subject (Table 11).

Table 11: Results of a Linear Regression between the ART and Academic Results

Subject	N	R	R ²	p	B (Unstandardised coefficients)
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	390	.12	.01	.01	39.80 .31
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	292	.11	.01	.04	45.13 .28
CHMT1001 Mid-Year Marks (Physics)	291	.09	.00	.10	55.54 .24
CHMT1001 End of Year Marks (Physics)	213	.09	.00	.17	57.41 .27
CHEM1031 Mid-Year Marks (Chemistry)	233	.15	.02	.02	50.51 .38
CHEM1031 End of Year Marks (Chemistry)	212	.15	.02	.02	53.19 .35
ECON1007 Mid-Year Marks (Economics)	236	.14	.02	.02	56.09 .36
ECON1007 End of Year Marks (Economics)	212	.12	.01	.07	58.11 .29

Subject	N	R	R ²	p	B (Unstandardised coefficients)
MATH1014 Mid-Year Marks (Mathematics)	246	.05	.00	.36	58.40 .19
MATH1014 End of Year Marks (Mathematics)	218	.02	.00	.66	62.61 .09

The R value shows the relationship between the ART and the academic result. All of the relationships (as described above) are weak. The R² value describes how much of the total variation of the academic results can be explained by the ART score. The highest R² value is that of CHEM1013 (end of year) where 2.5% of the variation of the academic results can be explained by the ART score. This is low and does not offer any value in predicting or understanding the relationship between the two variables. The significance column indicates the statistical significance of the regression. Thus, CHMT1000 (both sets of results), CHEM1031 (both sets of results) and ECON1007 (both sets of results) all show statistically significant results. CHMT1001 and MATH1014 are not statistically significant.

The value in the final column (the B value) contains both the constant value (the first number) and the ART unstandardised coefficient. These results can be used to create the regression equation. An example would be the equation of CHEM1031 (End of Year) = 53.19 + .35 (ART). However, as the predictive values are so low, this equation will not be of use.

In synopsis, the ART scores predict some first year engineering students' mid and end of year results, but the relationships are weak and their predictive value is extremely poor.

5.1.2 H2: The Raven's Advanced Progressive Matrices scores predict first year engineering students' mid and end of year results.

As above, correlations and regressions were run in order to examine the respective relationships between the subjects taken by the students and their scores on the Raven's Advanced Progressive Matrices (Table 12).

Table 12: Results of a Pearson Correlation between Raven's and academic results

Subject	N	Pearson Correlation	p
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	390	-.27**	.00
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	292	-.13*	.04
CHMT1001 Mid-Year Marks (Physics)	291	.08	.21
CHMT1001 End of Year Marks (Physics)	213	.19*	.01
CHEM1031 Mid-Year Marks (Chemistry)	233	.08	.27
CHEM1031 End of Year Marks (Chemistry)	212	-.01	.89
ECON1007 Mid-Year Marks (Economics)	236	-.01	.80
ECON1007 End of Year Marks (Economics)	212	-.03	.65
MATH1014 Mid-Year Marks (Mathematics)	246	-.02	.71
MATH1014 End of Year Marks (Mathematics)	218	-.05	.45

*p<.05; **p<.01

These results show three significant correlations between the Raven's and Academic Results. The first, CHMT1000 (mid-year) shows a significant correlation at the .01 level, while CHMT1000 and CHMT1001 (both end of year results) show a correlation at the .05 significance level. However, both CHMT1000 correlations show a negative relationship which suggests that as the students' Raven's score increases, so their CHMT1000 mark decreases. The positive relationship between CHMT1001 (end of year results)

and the Raven's shows that as the students Raven's score increases, so their academic result in CHMT1001 increases. However, these relationships are all weak and do not indicate a medium or strong correlation.

Regressions were then used to calculate the predictive value of the Raven's on the marks obtained by the students which can be seen in Table 13.

Table 13: Results of a Linear Regression between the Ravens and Academic Results

Subject	N	R	R²	p	B (Unstandardised coefficients)
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	390	.27	.07	.00	54.48 -.30
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	292	.13	.01	.04	55.35 -.13
CHMT1001 Mid-Year Marks (Physics)	291	.08	.00	.21	58.55 .15
CHMT1001 End of Year Marks (Physics)	213	.19	.03	.01	55.70 .38
CHEM1031 Mid-Year Marks (Chemistry)	233	.08	.00	.27	57.70 .13
CHEM1031 End of Year Marks (Chemistry)	212	.01	.00	.89	62.48 -.01

Subject	N	R	R²	p	B (Unstandardised coefficients)
ECON1007 Mid-Year Marks (Economics)	236	.01	.00	.80	66.04 -.02
ECON1007 End of Year Marks (Economics)	212	.03	.00	.65	66.88 -.05
MATH1014 Mid-Year Marks (Mathematics)	246	.02	.00	.71	65.38 -.05
MATH1014 End of Year Marks (Mathematics)	218	.05	.00	.45	68.26 -.11

As above, the R value can be used to examine the relationship between the two variables. The strongest relationship is between the Raven's and the mid-year result for CHMT1000, which shows a weak relationship. The R² values also do not add much by way of prediction, with the strongest value (CHMT1000 mid-year results) showing that 7.7% of the academic result can be explained by the Raven's score. In terms of the significance, three of the subjects show a significant relationship (namely CHMT1000 – both results and CHMT1001 – mid year results). As above, the unstandardised coefficients could be used in the regression equation, should any of the subjects be predictable by the Raven's results.

In synopsis, the Raven's scores predict some first year engineering students' mid and end of year results, but the relationships are weak and their predictive value is extremely poor.

5.1.3 H3: The Abstract Reasoning Test is a more powerful predictor for academic results than the Raven's Advanced Progressive Matrices

Table 14 summarises the significant relationships discussed in the previous two questions.

Table 14: Comparison of predictability between tests in 2014 first-year students

Subject	Strength of linear relationship		% explained by the test	
	ART	Ravens	ART	Ravens
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	Weak	Weak	1.6	7.7
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	Weak	Weak	1.3	1.7
CHMT1001 End of Year Marks (Physics)	Not significant	Weak	Not significant	3.7
CHEM1031 Mid-Year Marks (Chemistry)	Weak	Not significant	2.3	Not significant
CHEM1031 End of Year Marks (Chemistry)	Weak	Not significant	2.5	Not significant
ECON1007 Mid-Year Marks (Economics)	Weak	Not significant	2.2	Not significant
ECON1007 End of Year Marks (Economics)	Weak	Not significant	1.5	Not significant

The results for the previous hypotheses indicate that both the ART and Raven's are poor predictors of academic results for first year engineering subjects. Therefore the question about the strength of one of these tests in relation to the other becomes redundant as it can be concluded that neither the ART nor the Raven's can be used as a predictor for academic results in first year engineering subjects.

5.1.4 H4: Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices.

To examine the role that the biographical variables played in Abstract Reasoning Test and the Raven's Advanced Progressive Matrices scores, the descriptive statistics were examined for groupings based on biographical variables, followed by t-tests and ANOVAs to identify significant differences between means.

The descriptive statistics each biographical grouping are presented in Table 15.

Table 15: Descriptive Statistics for the ART scores based on biographical variables

	N	Min.	Max.	Mean	Std Dev.
Gender					
Male	216	9	35	22.94	4.92
Female	171	12	33	22.15	4.09
Age					
18	104	12	33	23.66	4.62
19	140	13	35	22.51	4.26
20+	130	9	34	21.81	4.77
First Language					
English	78	19	35	26.46	4.16
Afrikaans	3	27	30	28.33	1.52
isiZulu	66	11	32	21.85	4.28
siSwati	14	9	26	19.57	4.46
isiNdebele	5	17	29	21.80	4.76
Sepedi	72	15	30	21.76	3.62
Xitsonga	23	17	28	22.26	2.68
Setswana	41	13	31	21.32	4.44
Sesotho	28	13	33	21.82	4.52
Tshivenda	32	14	32	22.03	4.86
isiXhosa	22	14	28	20.59	4.22
Race					
African	316	9	33	21.68	4.10
White	21	21	34	27.48	3.73
Asian	48	19	35	26.50	4.32
Coloured	4	19	33	27.25	5.90

Table 15 shows some differences in means between the different biographical groupings. Based on visual inspection, the ART marginally favours males over females. Eighteen year olds performed better on the ART than older participants, with the ART score decreasing as the participants increased in age. In terms of first home language, Afrikaans students received the highest marks, with English speakers, Tshivenda and Xitsonga speakers also performing well. siSwati first language speakers scored the lowest results on the ART. The analysis of the biographical variable of race showed that White and Coloured students performed slightly better than Asian students, with African students obtaining the lowest mean score on the ART.

Table 16: Descriptive Statistics for the Raven's scores based on biographical variables

	N	Minimum	Maximum	Mean	Std. Dev
Gender					
Male	154	0	35	19.26	9.46
Female	138	0	67	18.43	11.23
Age					
18	80	0	34	23.16	6.72
19	111	0	67	19.59	10.04
20+	91	0	33	14.13	11.69
First Language					
English	53	0	35	23.07	9.93
Afrikaans	3	27	34	31.66	4.04
isiZulu	48	0	30	18.83	8.79
siSwati	11	0	25	15.54	10.36
isiNdebele	2	14	27	20.50	9.19
Sepedi	57	0	30	16.89	10.28
Xitsonga	18	0	27	13.77	10.96
Setswana	34	0	67	19.26	13.04
Sesotho	20	0	31	17.05	10.92
Tshivenda	23	0	31	19.21	7.21
isiXhosa	18	0	28	19.05	9.18

	N	Minimum	Maximum	Mean	Std. Dev
Race					
African	241	0	67	17.78	10.14
White	16	20	35	29.06	4.44
Asian	32	0	34	21.90	10.14
Coloured	4	21	34	28.75	5.73

In terms of Table 16 the Raven's Advanced Progressive Matrices, visual inspection indicates that males performed slightly better than females, with the 18 year old students performing better than their older counterparts and the Raven's score once again decreasing as the age of the participant increased. Afrikaans students far outperformed their peers in the Raven's with English students performing second best. Setswana, Tshivenda and isiXhosa students also featured in the top half of the sample in terms of their Raven's scores, with Xitsonga students scoring the lowest on average. Finally, White and Coloured students again performed better than Asian and, lastly, African counterparts. These results almost perfectly mirror the results found in terms of the ART with the only differences appearing in the home language variable as Setswana speakers did not appear in the highest scorers for the ART, and siSwati first language speakers scored the lowest on the Abstract Reasoning Test.

However, as these results do not give any definitive findings (and the differences found are small), ANOVAs and t-tests were conducted to test for significant differences between the two groupings.

The following ANOVA tables were produced:

Table 17: ANOVA table between gender and psychometric tests

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	1.05	2	.52	1.33	.264
	Within Groups	154.29	390	.39		
	Total	155.34	392			
Raven's Grouping	Between Groups	1.07	2	.53	.78	.45
	Within Groups	265.22	390	.68		
	Total	266.29	392			

Table 17 displays that no significant differences were found between gender and the ART and Raven's.

Table18: ANOVA table between age and psychometric tests

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	5.41	3	1.80	4.68	.00
	Within Groups	149.93	389	.38		
	Total	155.34	392			
Raven's Grouping	Between Groups	17.12	3	5.70	8.91	.00
	Within Groups	249.17	389	.64		
	Total	266.29	392			

Table 18 shows a significant difference between age and the psychometric assessments. In order to discover where the difference lies, an LSD post-hoc test was conducted. Table 19 shows the significant mean differences between groups at the .05 level.

Table 19: Post-hoc LSD significant differences table between the ART and age

(I) Age	(J) Age	Mean Difference (I-J)	p
18 and younger	19 years old	.17*	.02
	20 years old	.30*	.00

There were two significant differences in age for the ART, namely the difference between students of 18 years and younger and 19 year old students, and students of 18 and younger and the 20 year old students. Inspection of the means indicated that the 18 years and younger group performed significantly better than the 19 and 20 year olds. In terms of the Raven's assessments, the following biographical variables were found to show significant differences (Table 20).

Table 20: Post-hoc LSD significant differences between the Raven's and age

(I) Age	(J) Age	Mean Difference (I-J)	p
18 and younger	20 years old	.54*	.000
19 years old	20 years old	.36*	.000

The Raven's shows significant differences between the students who are 18 and younger and the students of 20 years of age, and the second significant relationship was between the students who are 19 years old and those that are 20 years old. There were no other significant differences found.

Table 21: ANOVA table between home language and psychometric tests

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	32.87	11	2.98	9.27	.00
	Within Groups	122.46	380	.32		
	Total	155.34	391			
Raven's Grouping	Between Groups	12.39	11	1.12	1.69	.07
	Within Groups	252.67	380	.66		
	Total	265.06	391			

The Raven's shows no significant differences between home language and psychometric tests (Table 21). As the ART does show significant differences, a post-hoc test was conducted (Table 22).

Table22: Post-hoc LSD differences between ART and home language

(I) Home Language	(J) Home Language	Mean Difference (I-J)	p
English	isiZulu	.60	.00
	siSwati	.84	.00
	isiNdebele	.84	.00
	Sepedi	.56	.00
	Xitsonga	.74	.00
	Setswana	.61	.00
	Sesotho	.68	.00
	Tshivenda	.65	.00
	isiXhosa	.68	.00
	Other	1.00	.02
Afrikaans	isiZulu	1.04	.00
	siSwati	1.28	.00
	isiNdebele	1.28	.00
	Sepedi	1.00	.00
	Xitsonga	1.18	.00
	Setswana	1.05	.00
	Sesotho	1.12	.00
	Tshivenda	1.08	.00
	isiXhosa	1.11	.00
	Other	1.00	.02
isiNdebele	Sepedi	-.28	.02

The ART shows significant differences between English and the African languages, while Afrikaans also shows a difference with the African languages, as well as the 'Other' category. The only difference found in ART scores between the African languages was between isiNdebele and Sepedi and this was the only negative mean difference. The negative difference in this case means that the Sepedi students achieved higher ART scores than did the isiNdebele students. The mean differences

found between Afrikaans and the African languages were much bigger than those found between English and the African languages. This indicates that where the Afrikaans students are scoring highly, the African language students are achieving low scores. English and Afrikaans students performed similarly on the ART.

Finally, race was examined via an ANOVA for both the ART and the Raven's (Table 23).

Table 23: ANOVA table between the psychometric tests and race

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	28.45	4	7.11	21.74	.00
	Within Groups	126.89	388	.32		
	Total	155.34	392			
Raven's Grouping	Between Groups	10.93	4	2.73	4.15	.00
	Within Groups	255.36	388	.65		
	Total	266.29	392			

Significant differences were found for both the ART and the Raven's in terms of race. Post hoc tests were run to see where the significant differences lay (Table 24).

Table 24: Post-hoc LSD significant differences between the ART and race

(I) Race	(J) Race	Mean Difference (I-J)	p
African	White	-.70	.00
	Asian	-.67	.00
	Coloured	-.83	.00

The significant differences within the race of the students are between African students and all the remaining students (with the exception of the 'Other' category). As the mean difference is negative, this shows that the African students' marks are, on average, lower than the mean marks obtained by the other students.

Table 25: Post-hoc LSD differences between the Raven's and race

(I) Race	(J) Race	Mean Difference (I-J)	p
African	White	-.59	.00
	Coloured	-.92	.00
White	Asian	.42	.04

Table 25 shows the significant differences on the Raven's assessment are seen between the African students and the White and Coloured students and between the White and Asian students. The African students, on average are performing worse than the White and Coloured students on the Raven's, while the White students are performing marginally, yet significantly, better than the Asian students on the assessment. Although this difference is significant, the Asian students' scores are closer to the White students scores than are the other groups.

The ANOVAs display in more detail the various differences between the biographical groups in terms of both the Ravens and the ART. The biggest difference was in the home language category between the Afrikaans students and the African language students.

5.2 Phase 2: Results separated into 2013 and 2014 first year students

In order to further understand any differences between the years, T-Tests were run to see the significant difference between the mean scores achieved each year on the psychometric tests. The Art was examined for each year and the results obtained are displayed in Table 26.

Table 26: Mean difference between years on the ART

Year	N	Mean	p
2013 students	114	21.31	.00
2014 students	278	23.17	.00

Although the means are both significant, the difference is not meaningful between these two groups. However, the Table 27 shows the mean scores from the Raven's between the different years. The means are both significant and the difference between the two is huge. This can lead one to believe that there are differences in the data and it would be worthwhile to examine the years independently in order to

analyse whether there are any substantial differences to the outcomes discovered in Phase One.

Table 27: Mean differences between years on the Raven's

Year	N	Mean	p
2013 students	115	11.73	.00
2014 students	180	23.58	.00

Table 28 shows the differences in university subjects between the two years.

Table28: T-Test results examining the difference between academic results for the 2013 and 2014 first year students

Subject	N (2013)	N (2014)	Mean (2013)	Mean (2014)	p
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	114	277	56.80	42.82	.00
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	115	178	59.17	46.70	.00
CHMT1001 Mid-Year Marks (Physics)	66	225	63.87	60.39	.00
CHMT1001 End of Year Marks(Physics)	69	144	66.84	62.35	.00
CHEM1031 Mid-Year Marks (Chemistry)	70	163	65.23	56.69	.00
CHEM1031 End of Year Marks (Chemistry)	70	142	67.26	58.25	.00
ECON1007 Mid-Year Marks(Economics)	69	167	70.38	61.96	.00
ECON1007 End of Year Marks (Economics)	71	141	70.39	62.01	.00
MATH1014 Mid-Year Marks (Mathematics)	72	174	65.87	61.78	.00
MATH1014 End of Year Marks (Mathematics)	72	146	70.21	62.22	.00

The mean scores for the 2014 students are consistently lower than those achieved by the 2013 class. These results are all significant.

Due to these differences, in Phase two of this chapter, the results for the different academic years were analysed separately (namely the 2013 first year students and the 2014 first year students). The emergent hypotheses that arose were:

1. The Abstract Reasoning Test scores predict first year engineering students' mid and end of year results for 2013 and 2014.
2. The Raven's Advanced Progressive Matrices scores predict first year engineering students' mid and end of year results for 2013 and 2014.
3. The Abstract Reasoning Test is a more powerful predictor for academic results than the Raven's Advanced Progressive Matrices for 2013 and 2014.
4. Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices for 2013 and 2014.

5.2.1 2013 First Year Students

In order to gain a clearer overall understanding of the sample before answering the research questions, the descriptive statistics were calculated. As the size of each class differs, the sample size differs for each grouping in the below table.

Table29: Descriptive Statistics for Academic Results (2013 First Year Students)

Subject	N	Min	Max	Mean	Std. Dev.	Skewness		Kurtosis	
						Statistic	Std. Error	Statistic	Std. Error
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	114	36.32	79.68	56.80	9.32	.07	.22	-.46	.44
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	115	31	90	59.17	8.43	.51	.22	2.56	.44
CHMT1001 Mid-Year Marks (Physics)	66	38.83	92.13	63.87	12.42	.26	.29	-.11	.58
CHMT1001 End of Year Marks (Physics)	69	0	91	66.84	15.01	-2.38	.28	10.08	.57
CHEM1031 Mid-Year Marks (Chemistry)	70	40.41	95.65	65.23	10.11	.35	.28	.39	.56
CHEM1031 End of Year Marks (Chemistry)	70	51	93	67.25	8.78	.51	.28	.24	.56
ECON1007 Mid-Year Marks (Economics)	69	42	96	70.37	9.61	-.28	.28	.79	.57
ECON1007 End of Year Marks (Economics)	71	42	96	70.39	9.61	-.24	.28	.59	.56
MATH1014 Mid-Year Marks (Mathematics)	72	37.33	95.33	65.87	13.47	.07	.28	-.40	.55
MATH1014 End of Year Marks (Mathematics)	72	48	97	70.20	11.04	.47	.28	-.16	.55

Table 29 contrasts to the descriptive statistics in Phase One as the number of students in each class from the mid-year to end of year results either stay the same or increase. This may be due to students from the previous year having failed the second half of the course and returning the following year to attain their pass.

The lowest mark obtained was 31% for CHMT1000² (End of Year) and the highest mark for MATH1014 (End of Year) with a percentage of 97. The highest average mark is 70.39% for ECON1007 (End of Year results). The biggest discrepancy between the marks achieved by the students is for CHMT1001 (End of Year). The skewness statistic displays the normality of the results. All of the results are normally distributed with the exception of CHMT1001 (End of Year). CHMT1001 (End of Year) will be analysed using non-parametric tests, while the rest of the results can be analysed using parametric tests.

Table 30: The descriptive statistics for the ART and Raven's (2013 intake)

Psychometric Test	N	Min	Max	Mean	Std. Dev.	Skewness		Kurtosis	
						Statistic	Std. Error	Statistic	Std. Error
Abstract Reasoning Test	114	13	30	21.31	4.05	.14	.22	-.89	.44
Raven's Advanced Progressive Matrices	115	0	35	11.73	11.81	.21	.22	-1.59	.44

Table 30 shows the descriptive statistics for the ART and the Raven's in the 2013 intake group. The lowest score on the ART is 13, with a maximum score of 30, while the lowest score on the Ravens' is 0 with a high score of 35. The mean score is 30 for the ART and 35 for the Raven's. The Raven's shows the greatest standard deviation out of the two tests (due to such a low minimum score). The data was also found to be normally distributed.

² This is excluding the mark of 0 obtained in CHMT1001 (End of Year) as it indicates a lack of participation in the course

The remainder of the 2013 section of Phase Two presents the analyses conducted in order to answer each research question.

5.2.2 H1: The Abstract Reasoning Test scores predict first year engineering students' mid and end of year results (2013 intake).

Pearson's correlations were conducted between the ART and academic results (Table 31). Throughout this section, N differs according to the varying sizes of the class.

Table 31: Results of a Pearson Correlation between the ART and academic results (2013 students)

Subject	N	Pearson Correlation	p
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	113	.13	.16
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	114	.29**	.00
CHMT1001 Mid-Year Marks (Physics)	66	.27*	.02
CHEM1031 Mid-Year Marks (Chemistry)	70	.26*	.02
CHEM1031 End of Year Marks (Chemistry)	70	.31**	.00
ECON1007 Mid-Year Marks (Economics)	69	.32**	.00
ECON1007 End of Year Marks (Economics)	71	.30*	.01
MATH1014 Mid-Year Marks (Mathematics)	72	.11	.32
MATH1014 End of Year Marks (Mathematics)	72	.07	.53

*p<.05, **p<.01

As CHMT1001 (End of Year) requires a non-parametric test, these results were analysed using a Spearman's Correlation. The results show a significant but weak correlation coefficient of .25* (N=69).

CHMT1000 (End of Year) results, CHEM1031 (End of Year) results and ECON1007 (Mid-Year) results were all significant at the .01 level. CHMT1001 (Mid-Year) results, CHEM1031 (Mid-Year) and ECON1007 (Mid-Year) results were all significant at the .05 level. This translates to a significant correlation found between these results and the ART scores. However, the strongest of these relationships is between ECON1007 (Mid-Year) results and the ART and this relationship is weak. As such, the significant relationships found in this correlation analysis are weak.

In order to test the predictive value of the Abstract Reasoning Test, linear regressions were used for every subject (Table 32).

Table32: Results of a Linear Regression between the ART and academic results (2013 students)

Subject	N	R value	R ² value	p	B (Unstandardised coefficients)
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	113	.13	.01	.16	50.29 .30
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	114	.29	.08	.00	46.32 .60
CHMT1001 Mid-Year Marks (Physics)	66	.27	.07	.02	45.48 .83
CHMT1001 End of Year Marks (Physics)	69	.16	.02	.16	53.17 .61
CHEM1031 Mid-Year Marks (Chemistry)	70	.26	.07	.02	50.90 .65

Subject	N	R value	R ² value	p	B (Unstandardised coefficients)
CHEM1031 End of Year Marks (Chemistry	70	.31	.09	.00	52.57 .66
ECON1007 Mid-Year Marks (Economics)	69	.32	.10	.00	53.47 .76
ECON1007 End of Year Marks (Economics)	71	.30	.09	.01	54.87 .70
MATH1014 Mid-Year Marks (Mathematics)	72	.11	.01	.32	57.27 .38
MATH1014 End of Year Marks (Mathematics)	72	.07	.00	.53	65.761 .20

As discussed above, the R value shows the correlation between the ART and the academic result. The strongest relationship is ECON1007 (Mid-Year) results and the ART. However, this relationship is weak, which means the other relationships are even weaker.

The R² value describes how much of the total variation of the academic results can be explained by the ART score. The highest R² value is .10 for ECON1007 (Mid-Year) results. This means that 10% of the total variation in the Economics Mid-Year marks can be explained by the ART. This value is also low, which again indicates that not much can be deduced from these results in terms of applicability.

The final value in the column (the B value) contains both the constant value (the first number) and the ART unstandardised coefficient. These results can be used to create the regression equation. However, due to the low results, this equation will not be useful as the regression shows an inability to predict students' marks from their ART scores.

5.2.3 H2: The Raven's Advanced Progressive Matrices scores predict first year engineering students mid and end of year results (2013 intake).

A Pearson's correlation and a linear regression were run in order to examine the respective relationships between the subjects taken by the students and their scores on the Raven's Advanced Progressive Matrices (Table 33).

Table 33: Results of a Pearson's correlation between academic results and Ravens (2013 students)

Subject	N	Pearson Correlation	p
CHMT1000 Mid-Year (Chemical and Metallurgical Engineering)	114	-.14	.12
CHMT1000 End of Year (Chemical and Metallurgical Engineering)	115	.19*	.04
CHMT1001 Mid-Year (Physics)	69	.28*	.01
CHEM1031 Mid-Year (Chemistry)	70	.12	.29
CHEM1031 End of Year (Chemistry)	70	.10	.39
ECON1007 Mid-Year (Economics)	69	-.01	.90
ECON1007 End of Year (Economics)	71	-.02	.86
MATH1014 Mid-Year (Mathematics)	72	-.13	.27
MATH1014 End of Year (Mathematics)	72	-.04	.68

*p<.05; **p<.01

A non-parametric Spearman's Correlation was run for the CHMT1001 end of year results. The result was a statistically insignificant correlation of .07 (N=66).

There were only two statistically significant results given in the correlation – CHMT1000 (End of Year) and CHMT1001 (Mid-Year). However, both of these results show very weak relationships.

In order to calculate the predictive value of the Raven's Advanced Progressive Matrices for the Academic Results, a linear regression was run for which the results are displayed in Table 34.

Table 34: Results of a Linear Regression between the Ravens and academic results

Subject	N	R value	R ² value	p	B (Unstandardised coefficients)
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	114	.14	.02	.12	58.15 -.11
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	115	.19	.03	.04	57.56 .13
CHMT1001 Mid-Year Marks (Physics)	69	.04	.00	.72	65.28 -.06
CHMT1001 End of Year Marks (Physics)	66	.28	.07	.01	57.52 .47
CHEM1031 Mid-Year Marks (Chemistry)	70	.12	.01	.29	62.49 .14
CHEM1031 End of Year Marks (Chemistry)	70	.10	.01	.39	65.32 .10
ECON1007 Mid-Year Marks (Economics)	69	.01	.00	.90	70.65 -.01
ECON1007 End of Year Marks (Economics)	71	.02	.00	.86	70.79 -.02
MATH1014 Mid-Year Marks (Mathematics)	72	.13	.01	.27	69.31 -.18
MATH1014 End of Year Marks (Mathematics)	72	.04	.00	.68	71.27 -.05

Two of the results given in the above table are significant (namely CHMT100 End of Year results and CHMT1001 End of Year results). However, the R values are .19 and .28 respectively which show weak relationships. The R² values show a 3% and 7% ability to use the academic results to explain the Raven's score. These are both

very low percentages and show that the Raven's scores are unable to be used to predict the academic results of students.

5.2.4 H3: The Abstract Reasoning Test is a more powerful predictor for academic results than the Raven's Advanced Progressive Matrices (2013 intake).

Table 35 gives a synopsis of the relationships discussed in the previous two questions.

Table 35: Comparison of predictability between tests in 2013 first-year students

Subject	Strength of linear relationship		% explained by the test	
	ART	Ravens	ART	Ravens
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	Weak	Weak	8	3
CHMT1001 Mid-Year Marks (Physics)	Weak	Not Significant	7	Not Significant
CHMT1001 End of Year Marks (Physics)	Not Significant	Weak	Not Significant	7
CHEM1031 Mid-Year Marks (Chemistry)	Weak	Not Significant	7	Not Significant
CHEM1031 End of Year Marks (Chemistry)	Weak	Not Significant	9	Not Significant
ECON1007 Mid-Year Marks (Economics)	Weak	Not Significant	10	Not Significant
ECON1007 End of Year Marks (Economics)	Weak	Not Significant	9	Not Significant

Table 35 gives a summary of the relationships and predictability of the psychometric tests on the academic results. The relationships are all weak and the percentages of the academic results that can be explained by the test are low. This leads to the conclusion that for the 2013 results (as for the group as a whole) the tests cannot be used to predict the academic results achieved by the students.

5.2.5 H4: Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices (2013 intake).

ANOVAs have been run in order to test for significant differences between the various biographical variables on both the ART and the Raven's. The first biographical variable to be examined was that of gender, for which the results of the test are displayed in Table 36.

Table 36: ANOVA table between psychometric tests and gender

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	1.31	2	.66	1.69	.18
	Within Groups	43.72	112	.39		
	Total	45.04	114			
Raven's Grouping	Between Groups	5.52	2	2.76	4.66	.01
	Within Groups	66.42	112	.59		
	Total	71.94	114			

There were no significant differences found in the ART scores between the male and female students. However, when a post-hoc test was conducted it was discovered that the only significant differences were found in connection with the gender category of 'not provided'. As such, no significant differences between male and female can be commented on. The ANOVA run to test the significant differences between age and the psychometric tests produced the following results in Table 37.

Table 37: ANOVA between psychometric tests and age

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	2.86	3	.95	2.51	.06
	Within Groups	42.17	111	.38		
	Total	45.04	114			
Raven's Grouping	Between Groups	16.80	3	5.60	11.27	.00
	Within Groups	55.14	111	.49		
	Total	71.94	114			

This shows a significant difference between the age groups on the Raven's, but not on the ART scores. A post-hoc test was run to discover where the significant differences lay in the age groupings (Table 38).

Table 38: Post-hoc LSD significant differences table between the Raven's and age

(I) Age	(J) Age	Mean Difference (I-J)	p
18 and younger	20 years old	.93	.00
19 years old	20 years old	.77	.00
20 years old	21-and-over	-.58	.03

Significant differences were found between the students of 20 years of age and the other groups of students. The 20 year old group scored lower on the Raven's than any of the other groups.

The results of the ANOVA run between the psychometric tests and home language can be seen in Table 39.

Table 39: ANOVA table between psychometric tests and home language

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	17.09	10	1.70	6.30	.00
	Within Groups	27.93	103	.27		
	Total	45.02	113			
Raven's Grouping	Between Groups	10.75	10	1.07	1.86	.06
	Within Groups	59.50	103	.57		
	Total	70.25	113			

Significant differences were only found between the home language biographical and the ART, the following post-hoc (Table 40) was run to discover where these differences lie.

Table 40: Post-hoc LSD differences between Home Language and ART

(I) Home Language	(J) Home Language	Mean Difference (I-J)	p
English	siSwati	1.05	.02
	Sepedi	.93	.00
	Xitsonga	.60	.04
Afrikaans	isiZulu	1.26	.02
	siSwati	2.00	.00
	isiNdebele	1.33	.00
	Sepedi	1.87	.00
	Xitsonga	1.54	.00
	Setswana	1.40	.01
	Sesotho	1.33	.03

The major differences found, as in Phase 1, were between Afrikaans and the African languages. These differences were much bigger than those found between English and siSwati, Sepedi and Xitsonga, which were still significant.

The final biographical variable under analysis is that of race, for which the following ANOVA results were calculated (Table 41).

Table 41: ANOVA table between the psychometric tests and race

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	14.32	3	4.77	17.52	.00
	Within Groups	29.95	110	.27		
	Total	44.28	113			
Raven's Grouping	Between Groups	11.34	3	3.78	6.92	.00
	Within Groups	60.10	110	.54		
	Total	71.447	113			

As both the ART and the Raven's returned significant results, post-hoc tests have been run for both psychometric tests.

Table 42: Post-hoc LSD significant differences between the ART and race

(I) Race	(J) Race	Mean Difference (I-J)	p
African	White	-.97	.00
	Asian	-.97	.00
	Coloured	-1.26	.00

As in Phase One, Table 42 shows the African students have performed more poorly on the ART than the students of White, Asian or Coloured race. This is interpreted from the negative mean difference in the above table. A negative difference means that the biographical variable in the (I) column is lower (in this case has scored lower) than the biographical variable in the (J) column. The difference between the African and Coloured students is the most prominent.

Table 43: Post-hoc LSD differences between the Raven's and race

(I) Race	(J) Race	Mean Difference (I-J)	p
African	White	-1.23	.00
White	Asian	1.28	.00

Table 43 shows the difference between the African students, in the Ravens, in comparison to the other races is less predominant, with the only significant relationship occurring between the African students and the White students, with the White students achieving better results on the Raven's. The White students also achieved significantly better results on the Raven's than did the Asian students.

As in Phase One, there are a few significant differences in the biographical variables with regard to the psychometric assessments. The strongest differences are seen in terms of language and race with African students (and those who speak African languages at home) appearing to do worse in the tests than students with other languages or race.

5.2.6 2014 First Year Students

This section has displayed the analyses run in order to prove (or disprove) the hypotheses outlined at the beginning of this section beginning with the descriptive statistics (Table 44).

Table 44: Descriptive Statistics for Academic Results for 2014 First Year Students

Subject	N	Min	Max	Mean	Std. Dev.	Skewness		Kurtosis	
						Statistic	Std. Error	Statistic	Std. Error
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	277	17.76	65.09	42.82	9.51	-.00	.14	-.22	.29
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	178	12.00	69.00	46.69	10.02	-.23	.18	.02	.36
CHMT1001 Mid-Year Marks (Physics)	225	23.71	92.13	60.39	11.60	.06	.16	.28	.32
CHMT1001 End of Year Marks (Physics)	144	32.00	90.00	62.34	12.57	-.01	.20	-.52	.40
CHEM1031 Mid-Year Marks (Chemistry)	163	30.66	85.60	56.69	11.28	.36	.19	.06	.37
CHEM1031 End of Year Marks (Chemistry)	142	38.00	83.00	58.24	9.65	.55	.20	.16	.40
ECON1007 Mid-Year Marks (Economics)	167	35.00	91.00	61.95	10.26	-.04	.18	-.03	.37
ECON1007 End of Year Marks (Economics)	141	35.00	86.00	62.00	10.11	-.03	.20	-.08	.40
MATH1014 Mid-Year Marks (Mathematics)	174	13.80	93.56	61.78	16.00	-.14	.18	-.46	.36
MATH1014 End of Year Marks (Mathematics)	146	20.00	98.00	62.21	16.14	.00	.20	-.69	.39

As with the trend found in Phase One, the number of students in each class decreases as the year progresses, possibly due to failure or leaving the university. The lowest mark is 12% for CHMT1001 (End of Year) and the highest is 98% for MATH1014 (End of Year). The lowest average is for CHMT1000 (Mid-Year), while the highest is for CHMT1001 (End of Year). The biggest discrepancy

between marks (given by the standard deviation) is for MATH1014 (End of Year). The skewness and kurtosis show the normality of the marks, which in this case shows all the groups as normally distributed.

Table 45 shows the descriptive statistics for the psychometric tests.

Table 45: Descriptive statistics for the psychometric tests (2014 students)

Subject	N	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis		
						Statistic	Std. Error	Statistic	Std. Error
Abstract Reasoning Test	278	9	35	23.17	4.69	.05	.14	-.15	.29
Raven’s Advanced Progressive Matrices	180	8	67	23.58	5.58	2.43	.18	19.44	.36

Table 45 shows the mean scores on both tests to be similar, with the skewness statistics both within the range of 1 and -1 which show they are normally distributed.

5.2.7 H1: The Abstract Reasoning Test scores predict first year engineering students' mid and end of year results (2014 intake).

Table 46: Results of a Pearson Correlation between academic results and ART (2014 students)

Subject	N	Pearson Correlation	p
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	277	.33**	.00
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	178	.27**	.00
CHMT1001 Mid-Year Marks (Physics)	225	.06	.33
CHMT1001 End of Year Marks (Physics)	144	.08	.29
CHEM1031 Mid-Year Marks (Chemistry)	163	.18*	.01
CHEM1031 End of Year Marks (Chemistry)	142	.19*	.02
ECON1007 Mid-Year Marks (Economics)	167	.17*	.02
ECON1007 End of Year Marks (Economics)	141	.13	.10
MATH1014 Mid-Year Marks (Mathematics)	174	.06	.42
MATH1014 End of Year Marks (Mathematics)	146	.05	.49

*p<.05, **p<.01

Table 46 shows both CHMT1000 groupings are significant at the .05 level, while both groupings of CHEM1031 and ECON1007 (Mid-Year) are significant at the .01 significance level. However, the majority of these relationships are weak, with the Mid Year CHMT1000 results showing a weak to moderate relationship between the academic results and the ART.

Table 47: Results of a Linear Regression between the ART and academic results (2014 students)

Subject	N	R value	R ² value	p	B (Unstandardised coefficients)
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	277	.33	.11	.00	27.18 .67
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	178	.27	.07	.00	32.74 .60
CHMT1001 Mid-Year Marks (Physics)	225	.06	.00	.33	56.71 .15
CHMT1001 End of Year Marks (Physics)	144	.08	.00	.29	56.87 .23
CHEM1031 Mid-Year Marks (Chemistry)	163	.18	.03	.01	46.33 .44
CHEM1031 End of Year Marks (Chemistry)	142	.19	.03	.02	49.15 .39
ECON1007 Mid-Year Marks (Economics)	167	.17	.03	.02	52.87 .38
ECON1007 End of Year Marks (Economics)	141	.13	.01	.10	55.00 .30

Subject	N	R value	R ² value	p	B (Unstandardised coefficients)
MATH1014 Mid-Year Marks (Mathematics)	174	.06	.00	.42	57.84 .21
MATH1014 End of Year Marks (Mathematics)	146	.05	.00	.49	57.59 .19

In Table 47, the R value shows the strongest relationships between the ART and both CHMT1000 groupings. The relationship between CHMT1000 (Mid-Year) and the ART is weak to moderate, while the remaining relationships are weak. Both CHMT1000 relationships are significant, as are both CHEM1031 results and ECON1007 (Mid-Year) results to the ART. Overall, the predictability is poor as R² shows that a great number of the results cannot be explained at all by the ART score. The strongest subject in terms of explainability is 11% for CHMT1000 Mid-Year academic results.

5.2.8 H2: The Raven's Advanced Progressive Matrices scores predict first year engineering students' mid and end of year results (2014 intake).

Table 48: Results of a Pearson Correlation between the Raven's and academic results (2014 students)

Subject	N	Pearson Correlation	p
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	180	.35**	.00
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	119	.34**	.00
CHMT1001 Mid-Year Marks (Physics)	146	.22**	.00
CHMT1001 End of Year Marks (Physics)	101	.22*	.02
CHEM1031 Mid-Year Marks (Chemistry)	116	.29**	.00
CHEM1031 End of Year Marks (Chemistry)	101	.19*	.04
ECON1007 Mid-Year Marks (Economics)	117	.25**	.00
ECON1007 End of Year Marks (Economics)	100	.26**	.00
MATH1014 Mid-Year Marks (Mathematics)	119	.13	.15
MATH1014 End of Year Marks (Mathematics)	100	.12	.23

*p<.05; **p<.01

Table 48 shows a number of the correlations between the academic results and the Ravens are significant. CHMT1000 (both groupings), CHMT1001 (Mid-Year), CHEM1031 (Mid-Year) and both ECON1007 groupings are significant at the .01 level of

significance. CHMT1001 (End of Year) and CHEM1031 (End of Year) are significant at the .05 level. Out of these significant relationships however, most are weak, with the CHMT1000 groupings both displaying a weak to moderate relationship

Table 49: Results of a Linear Regression between the Ravens and Academic Results

Subject	N	R value	R ² value	p	B (Unstandardised coefficients)
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	180	.35	.12	.00	29.95 .57
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	119	.34	.12	.00	32.87 .59
CHMT1001 Mid-Year Marks (Physics)	1.46	.22	.04	.00	50.72 .43
CHMT1001 End of Year Marks (Physics)	101	.22	.05	.02	46.91 .65
CHEM1031 Mid-Year Marks (Chemistry)	116	.29	.08	.00	41.20 .70
CHEM1031 End of Year Marks (Chemistry)	101	.19	.04	.04	48.56 .42
ECON1007 Mid-Year Marks (Economics)	117	.25	.06	.00	48.52 .59

Subject	N	R value	R ² value	p	B (Unstandardised coefficients)
ECON1007 End of Year Marks (Economics)	100	.26	.07	.00	48.26 .60
MATH1014 Mid-Year Marks (Mathematics)	119	.13	.01	.15	52.33 .46
MATH1014 End of Year Marks (Mathematics)	100	.12	.01	.23	52.16 .44

In Table 49, the R² values are slightly higher overall in the 2014 group of this phase than in Phase One or the 2013 sample. 12% of the CHMT1000 results can be explained by the Raven's score 8% and 7% of CHEM1031 (mid-year) and ECON1007 (End of year) respectively, can be explained through the score achieved on the Ravens. However, these scores are not sufficiently high to state that the Ravens can be used to predict the academic marks that will be achieved by students.

5.2.9 H3: The Abstract Reasoning Test is a more powerful predictor for academic results than the Raven's Advanced Progressive Matrices (2014 intake).

Table 50: Comparison of predictability between tests in 2014 first-year students

Subject	Strength of linear relationship		% explained by the test	
	ART	Ravens	ART	Ravens
CHMT1000 Mid-Year Marks (Chemical and Metallurgical Engineering)	Weak to moderate	Weak to moderate	11	12
CHMT1000 End of Year Marks (Chemical and Metallurgical Engineering)	Weak	Weak to moderate	7	12
CHMT1001 Mid-Year Marks (Physics)	Not significant	Weak	Not significant	4
CHMT1001 End of Year Marks (Physics)	Not significant	Weak	Not significant	5
CHEM1031 Mid-Year Marks (Chemistry)	Weak	Weak	3	8
CHEM1031 End of Year Marks (Chemistry)	Weak	Weak	3	4
ECON1007 Mid-Year Marks (Economics)	Weak	Weak	3	6
ECON1007 End of Year Marks (Economics)	Weak	Weak	1	7

Table 50 displays the three weak to moderate relationships are the highest scores in the two phases, yet they are still not sufficient in order to allow for unwavering decisions based on the correlations or relationships between the psychometric tests and the academic results achieved by students. The predictability of either of the psychometric tests on the academic results achieved by first year engineers is poor and will not offer any valuable input in the attempt at predicting students results for either subjects at either the mid-year or end of year mark.

5.2.10 H4: Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices (2014 intake)

ANOVAs have been run in order to test for significant differences between the various biographical variables on both the ART and the Raven's. The first biographical variable to be examined was that of gender, for which the results of the test are displayed in Table 51

Table 51: ANOVA table between psychometric tests and gender (2014 intake)

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	.31	2	.15	.41	.66
	Within Groups	105.22	275	.38		
	Total	105.54	277			
Raven's Grouping	Between Groups	4.01	2	2.00	2.98	.052
	Within Groups	184.69	275	.67		
	Total	188.70	277			

There were no significant differences found between male and female students with regards to the psychometric test results. ANOVAs were then run to test for significant differences between the psychometric tests and the age of the students in Table 52.

Table 52: ANOVA table between psychometric tests and Age

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	2.23	3	.74	1.97	.11
	Within Groups	103.30	274	.37		
	Total	105.54	277			
Raven's Grouping	Between Groups	4.46	3	1.48	2.21	.08
	Within Groups	184.24	274	.67		
	Total	188.70	277			

No significant differences were found for either the ART or the Raven's in terms of the ages of students. The results for the ANOVA analysis between the psychometric tests and home language are recorded in Table 53.

Table 53: ANOVA table between psychometric tests and home language

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	16.37	10	1.63	4.90	.00
	Within Groups	89.16	267	.33		
	Total	105.54	277			
Raven's Grouping	Between Groups	5.15	10	.51	.75	.67
	Within Groups	183.55	267	.68		
	Total	188.70	277			

The ART showed significant differences between the various home languages that the students speak. There were no significant differences between the languages with regard to the Raven's scores. A post-hoc test was conducted for the ART, where English and Afrikaans were grouped due to small sample sizes (Table 54).

Table 54: Post-hoc LSD differences between Home Language and the ART

(I) Home Language	(J) Home Language	Mean Difference (I-J)	p
English and Afrikaans	isiZulu	.50	.00
	siSwati	.82	.00
	isiNdebele	.54	.04
	Sepedi	.54	.00
	Xitsonga	.54	.00
	Setswana	.54	.00
	Sesotho	.54	.00
	Tshivenda	.54	.00
	isiXhosa	.69	.00

Significant differences were found between the English and Afrikaans group and the African languages, with the biggest difference between siSwati and the English and Afrikaans students.

Finally, an ANOVA to test for differences in race and the following results calculated.

Table 55: ANOVA table between the psychometric tests and race

		Sum of Squares	df	Mean Square	F	p
ART Grouping	Between Groups	15.03	4	3.75	11.33	.00
	Within Groups	90.50	273	.33		
	Total	105.54	277			
Raven's Grouping	Between Groups	3.89	4	.97	1.43	.22
	Within Groups	184.81	273	.67		
	Total	188.70	277			

Table 55 shows the Raven's did not produce any significant differences, but the differences with regard to the ART will be analysed through the post-hoc test shown in Table 56.

Table 56: Post-hoc LSD significant differences between the ART and race

(I) Race	(J) Race	Mean Difference (I-J)	p
African	White	-.58	.00
	Asian	-.57	.00

The African students achieved lower scores than both the White and Asian students on the ART. This follows the trend that has been seen predominantly throughout the analysis. The possible bias with regard to non-White, non-English speaking participants/students will be discussed later in this report.

5.3 Phase 3: Analysing the differences in the psychometric tests using year as a covariate

In view of the differences in results between the 2013 and 2014 intake years, the university results and the ART and Raven's scores were examined, using the intake year as a covariate. The research question for this Phase differs from the previous two phases. What has been examined are the following two questions:

1. Do engineering students with high, low and medium scores on the Abstract Reasoning Test achieve different university results when taking their intake year into account?

2. Do engineering students with high, low and medium scores on the Raven's Advanced Progressive Matrices achieve different university results when taking their intake year into account?

In order to examine these questions more effectively, the students were split into three groups for both the ART and the Raven's. They were divided into low, medium and high depending on their scores in the psychometric test. The ART groups were classified according to their raw scores, specifically 9-18 (low), 19-26 (medium) and 27-35 (high). The Raven's has been categorised in the same manner with the raw scores being grouped as follows: 0-12 (low), 13-23 (medium) and 24-35 (high).

Table 57 shows the number of students in each group.

Table 57: Number of students in low, medium and high groups for psychometric tests

	Low	Medium	High
N (ART)	70	237	86
N (Raven's)	157	122	114

Although this method of dividing the students resulted in an uneven number of students in each group, it was felt that these divisions would more accurately reflect where the candidates had scored, and as such, how well they had done in each test. Equally sized groups result in the group scores all being drawn to a very similar mean as those students who achieved a 'medium' score, far outnumber those who achieved low or high scores and as such, all three groups would reflect similar scores and not show meaningful differences.

ANCOVAs were run in order to gain clarity on these questions and the following results were obtained (Table 58).

Table 58: ANCOVAs on university results for low, medium and high ART scores with intake year as a covariate

Dependent variable	Source	R ²	df	Mean square	F	p
			model; error			
CHMT1000 (Mid-year)	Year	.36	1;387	17 083.81	205.27	.00
	ART Groups		2;387	83.21	15.61	.00
CHMT1000 (End of year)	Year	.34	1;289	12 129.29	146.27	.00
	ART Groups		2;289	903.00	10.83	.00
CHMT1001 (Mid-year)	Year	.39	1;287	689.76	5.04	.02
	ART Groups		2;287	487.09	3.56	.03
CHEM1031 (Mid-Year)	Year	.18	1;229	4 012.52	36.09	.00
	ART Groups		2;229	1 122.46	10.09	.00
CHEM1031 (End of Year)	Year	.21	1;208	4 208.09	50.25	.00
	ART Groups		2;208	527.09	6.30	.00
ECON1007 (Mid-year)	Year	.17	1;232	3 835.43	39.43	.00
	ART Groups		2;232	602.73	6.19	.00
ECON1007 (End of Year)	Year	.18	1;208	3 718.11	39.33	.00
	ART Groups		2;208	573.42	6.06	.00

The results of the ART ANCOVA show that students who are in the different (low, medium and high) groups according to their ART scores, do achieve different results (depending on their grouping) in CHMT1000 (both mid-year and end of year), CHMT1001 (mid-year), CHEM1031 (both mid-year and end of year) and ECON1007 (both mid-year and end of year).

Table 59 shows the significant results of the ANCOVA analysis to determine whether the Raven's groupings had an impact on the students' academic results.

Table 59: Significant results for ANCOVAs on university results for low, medium and high Raven's scores with intake year as a covariate

Dependent variable	Source	R²	df model; error	Mean square	F	p
CHMT1000 (Mid-year)	Year	.33	1;387	15 998.09	184.87	.00
	Raven's Groups		2;387	656.70	7.59	.00
CHMT1000 (End of year)	Year	.32	1;289	11 369.07	133.20	.00
	Raven's Groups		2;289	614.24	7.19	.00
CHEM1031 (Mid-year)	Year	.14	1;229	434.60	29.30	.00
	Raven's Groups		2;229	117.18	3.70	.02
ECON1007 (Mid-year)	Year	.14	1;232	3 529.29	35.34	.00
	Raven's Groups		2;232	303.58	3.04	.05

The high, medium and low Raven's groupings of the students will lead to a difference in their academic results in the subjects of CHMT1000 (both mid-year and end of year), CHEM1031 (mid-year) and ECON1007 (mid-year). This means that those who scored a lower score on the Raven's, are also likely to receive a lower academic result in the above subjects.

This section has analysed and displayed the statistics in order to answer the research questions and hypotheses. The conclusions reached in this section, and their resultant implications will be discussed in the following chapter of this report.

Chapter 6: Discussion

6. Discussion

This chapter gives an overview of the results that were found and the interpretations that were derived in terms of each hypothesis for the first two phases, with a brief discussion on the results to the research questions for phase three. A reflection on the literature and the implications of the results is followed by the limitations of the study, implications for further research and a conclusion.

This chapter discusses the findings and implications of the results. The discussion is structured around the following four hypotheses as outlined in the previous chapters.

1. The Abstract Reasoning Test scores predict first year engineering students' mid and end of year results.
2. The Raven's Advanced Progressive Matrices scores predict first year engineering students' mid and end of year results.
3. The Abstract Reasoning Test is a more powerful predictor for academic results than the Raven's Advanced Progressive Matrices.
4. Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices

The four hypotheses have been analysed in two different phases. Phase one used the sample as a whole, with both the 2013 and 2014 first year intakes incorporated. Phase two was split into two sections, separating the 2013 intake from the 2014 intake. Finally, Phase three examined the following two research questions:

1. Do engineering students with high, low and medium scores on the Abstract Reasoning Test achieve different university results when taking their intake year into account?
2. Do engineering students with high, low and medium scores on the Raven's Advanced Progressive Matrices achieve different university results when taking their intake year into account?

6.1 Phase One Discussion

This section discusses the results found for each research hypotheses for the sample group as a whole.

6.1.1 H1: The Abstract Reasoning Test scores predict first year engineering students' mid and end of year results.

Although all of the correlations between the ART and the academic results were significant, they all displayed weak relationships. In addition, the percentages of the academic results that could be explained by the ART were low. The highest R value was .15 for CHEM1031 for both the mid-year results and the end of year results. As the highest R value, this effectively displays how weak the relationships are. The highest R^2 value is that of CHEM1013 (end of year) which shows that 2.5% of the variation in academic results can be explained by the student's ART score. This is also a low percentage which again displays the weakness of the predictability of the ART overall.

The overall outcome to this hypothesis is that it is false. The Abstract Reasoning Test scores cannot be used to predict first year engineering students' mid and end of year results.

6.1.2 H2: The Raven's Advanced Progressive Matrices scores predict first year engineering students' mid and end of year results.

The Raven's regression displayed three significant correlations between the Raven's and the academic results. The subjects which showed significant correlations were CHMT1000 (both mid and end of year results) and CHMT1001 (end of year results). Out of those three significant correlations, the strongest R value was .27 for CHMT1000 (mid-year). This is a weak correlation and corresponds to a poor R^2 value of .07 (which, incidentally, was the strongest R^2 value of the 3 significant correlations). This shows that 7% of the variation in the CHMT1000 (mid-year) results can be explained by the Raven's score.

The overall outcome disproves this hypothesis. The Raven's Advanced Progressive Matrices scores cannot be used to predict first year engineering students' mid and end of year results.

6.1.3 H3: The Abstract Reasoning Test is a more powerful predictor for academic results than the Raven's Advanced Progressive Matrices.

The above results show that the ART has more significant relationships than the Raven's, but the strongest correlation and predictability value were found in the Raven's regression. However, as the conclusions for both of the previous hypotheses show that neither the Abstract Reasoning Test nor the Raven's

Advanced Progressive Matrices can be used as predictors for the academic results of students, this hypothesis is obsolete.

6.1.4 H4: Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices

The ART and the Raven's were discussed separately in this section due to the possibilities of differences within the biographical variables.

An initial observation of the means for each group showed that the ART scores had males, 18 year olds, Afrikaans home language speakers and White students attaining the highest results. ANOVAs were produced to discover whether any of the differences between the biographical variables were significant. No significant differences were found for gender in terms of the ART scores. Significant differences were found in the age variable, specifically between the 18 and younger group and both the 19 year old group and the 20 year old group. This difference indicated that the 18 and younger group scored more highly than both the 19 year old and 20 year old group, with the biggest difference between the 18 and younger group and the 20 year old group. In terms of home language, English showed significant differences to all the African languages (namely, isiZulu, siSwati, isiNdebele, Sepedi, Xitsonga, Setswana, Sesotho, Tshivenda and isiXhosa) where the English speakers attained higher scores than those who speak an African language. Significant differences were also found between those who spoke Afrikaans and all of the African language speakers, as well as the 'Other' category. The final significant difference between home languages on the ART was between isiNdebele and Sepedi where the Sepedi speakers achieved higher results. Finally, race showed significant results with African students scoring lower marks on the ART than the White, Asian and Coloured students.

The overall conclusion is that biographical variables (with the exception of gender) do contribute to the scores the students achieve in the Abstract Reasoning Test.

The Raven's, upon a visual observation of means, appeared to show differences within the biographical groups, thus ANOVAs were run to assess where the significant differences lay. As with the ART, there were no significant differences in terms of gender. In terms of age, there was a significant difference between the 20 year old and the 18 and younger and 19 year old age group where the 20 year olds

scored significantly less on the Raven's than did the younger age groups. The Raven's showed no significant differences in home language. Significant differences were found in the biographical variable of race, where African students scored lower scores on the Raven's than did White or Coloured students. The other significant difference showed that White students achieved better scores on the Raven's than did Asian students.

6.2 Phase Two Discussion

As mentioned above, Phase two is split into two sub-sections for the 2013 intake and the 2014 intake. The 2013 intake will be discussed first, after which the 2014 intake synopsis will be given.

6.2.1 H1: The Abstract Reasoning Test scores predict first year engineering students' mid and end of year results (2013 intake).

The strongest R value was found between ECON1007 (mid-year) and the ART with a score of .32. This is a weak relationship which results in the conclusion that all of the other significant relationships are even weaker. In terms of the predictive value, ECON1007 (mid-year) also shows the highest value, where 10% of the variation in ECON1007 mid-year results could be explained by the ART.

This means that the ART scores do not hold much predictive value for the students' academic results and cannot be used as a predictive measure.

6.2.2 H2: The Raven's Advanced Progressive Matrices scores predict first year engineering students' mid and end of year results (2013 intake).

The Raven's showed only two significant relationships, of which the strongest (CHMT1001 – end of year) held an R value of .28, which relates to a weak relationship. This subject also displayed the highest R^2 value of .07, which relates to a 7% ability to use the Raven's score to explain the academic results.

However, as these results are the strongest predictors, while they themselves are weak, shows that the Raven's Advanced Progressive Matrices scores cannot be used to predict first year engineering students' mid and end of year results. This could possibly be due to biased sampling as a small percentage of the 2013 students gave permission for their marks to be accessed.

6.2.3 H3: The Abstract Reasoning Test is a more powerful predictor for academic results than the Raven's Advanced Progressive Matrices (2013 intake).

The above results for the previous two hypotheses indicate that neither the Abstract Reasoning Test nor the Raven's Advanced Progressive Matrices can be used to predict the academic results in the first year engineering students. As such, the hypothesis is irrelevant.

6.2.4 H4: Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices (2013 intake)

For this hypothesis, the ART and the Raven's will be discussed separately.

The ART showed no significant differences in terms of gender or for the age biographical. Home language showed numerous significant differences. The English students scored higher on the ART than did the siSwati, Sepedi and Xitsonga speaking students. The Afrikaans students achieved higher scores than did the isiZulu, siSwati, isiNdebele, Sepedi, Xitsonga, Setswana and Sesotho students. Finally, an analysis of race showed that African students scored lower marks than did the White, Asian and Coloured students.

The Raven's did not show any significant differences between gender and the assessment. With regard to age, the 18 and younger age group scored higher on the Raven's than did the 20 year old age group, while the 19 year olds also scored higher than did the 20 year old age group. Finally, the 20 year old age group scored lower on the Raven's than did the 21-and-over age group. No significant differences were found for the home language biographical variable. Race showed a significant difference between the African and White students, where the White students scored higher results than did the African students. The White students also scored higher scores on the Raven's than did the Asian students.

The biographical variables of home language and race contribute to the scores achieved by students in the ART, while age and race contribute to the scores achieved by students in the Raven's.

6.2.5 H1: The Abstract Reasoning Test scores predict first year engineering students' mid and end of year results (2014 intake).

The strongest correlation was found between CHMT1000 (mid-year) and the ART which displays a weak to moderate relationship. This subject also displays the

highest R^2 value in terms of the ART which shows that 11% of the subject's results can be explained by the ART results.

These scores are weak and do not allow the Abstract Reasoning Test to be used as a predictor for academic results.

6.2.6 H2: The Raven's Advanced Progressive Matrices scores predict first year engineering students' mid and end of year results (2014 intake).

The highest correlation was found between the Raven's and CHMT1000 (mid-year) results. The score shows a weak to moderate correlation. There was one other weak to moderate correlation (between the Raven's and CHMT1000 (end of year) results), but all of the other significant correlations showed weak results. The highest R^2 value was 0.12 for CHMT1000 (both mid-year and end of year results).

These scores are not sufficiently high enough to allow for predictions to be made for academic results using the Raven's.

6.2.7 H3: The Abstract Reasoning Test is a more powerful predictor for academic results than the Raven's Advanced Progressive Matrices (2014 intake).

There are three weak to moderate relationships which are the highest r values in the two phases, yet these scores are not high enough to allow for predictions about academic results to be made using either the Abstract Reasoning Test or the Raven's Advanced Progressive Matrices.

As in Phase One and the 2013 intake section of Phase two, this question has become obsolete.

6.2.8 H4: Biographical variables contribute to the scores achieved by students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices (2014 intake)

As for the fourth hypothesis in the above two sections, the Abstract Reasoning Test will be analysed first, followed by the Raven's Advanced Progressive Matrices.

No significant differences were found between the ART and gender or the ART and age. English and Afrikaans were grouped for home language in this analysis due to small sample sizes. Significant differences were found between this English-Afrikaans group and isiZulu, siSwati, isiNdebele, Sepedi, Xitsonga, Setswana, Sesotho, Tshivenda and isiXhosa. The students in the English-Afrikaans group scored higher marks than the African language speakers. The African students

scored lower in the ART than did White and Asian students when race was analysed.

The Raven's analyses showed no significant differences in terms of any of the biographical variables.

In conclusion, the biographical variables of home language and race showed significant differences in terms of the ART scores. The Raven's Advanced Progressive Matrices did not display any differences in terms of the biographical variables.

6.3 Phase Three

Phase three examined the following two questions:

1. Do engineering students with high, low and medium scores on the Abstract Reasoning Test achieve different university results when taking their intake year into account?
2. Do engineering students with high, low and medium scores on the Raven's Advanced Progressive Matrices achieve different university results when taking their intake year into account?

The results displayed that the grouping the student belonged to in terms of their scores on the ART and the Raven's had an effect on the university results when the year was taken into account. These results were all significant.

6.4 Comparing the results to the literature and its corresponding implications

The main concern that arises from the literature are the issues surrounding the education system in South Africa, including the educational issues that may still remain due to unequal schooling opportunities within the Apartheid era to those of different races (Zaaiman et al., 2001, Christie, 1998, Department of Basic Education, 2013). The racial differences in this study were not examined in terms of academic results (as this was not the focus of the study), but they were analysed in terms of the students' performance on psychometric tests.

As found in a 2004 study at the University of the Witwatersrand, the Raven's shows a possible bias in terms of race (Rushton et al., 2004). This was reaffirmed in this

study where African students scored significantly lower than students of other races. In Phase One, the African students achieved lower scores in the ART than students of all other races, while in the Raven's the African students scored significantly lower than both the White and Coloured students. In the 2013 intake of Phase Two, the African students achieved significantly less on the ART than did students of all other races, and significantly less on the Raven's than White students. In the 2014 intake, African students scored significantly less on the ART than White and Asian students, but no significant differences were found in terms of race on the Raven's Advanced Progressive Matrices. Due to the above differences, the ART appears to be more racially biased than does the Raven's, which one would not expect due to the ART being a South African test, developed for use on a South African population (Psytech, retrieved on 15/08/2014).

The Raven's Progressive Matrices Test is designed to allow for the identification of Spearman's g – a factor of general, well-rounded, adaptable intelligence (Duncan, Seitz, Kolodny, Bor, Herzog, Ahmed, Newell & Emslie, 2000, Embretson & McCollam, 2000). Thus, students scoring highly in this should score highly in all other subjects as they should have the ability to problem-solve and learn in such a way that would enable them to achieve well in an academic context (Duncan, Seitz, Kolodny, Bor, Herzog, Ahmed, Newell & Emslie, 2000, Embretson & McCollam, 2000). As no correlation or predictive value was found, one should tentatively examine this concept as the Raven's may not be a fully accurate measure of this type of intelligence in this specific context. This may lead to a disinclination to use this test as a measure of general intelligence under the assumption that the students who score highly will naturally achieve well academically in a South African context.

Another cause for concern was the difference between the students' home language, and the language in which they were being taught (in cases where this varied). It is important to take into account that students who experience a difference between their home language and the language in which they are taught may struggle to grasp concepts fully that are taught in subjects such as Mathematics due to an additional difficulty, the barrier of language influencing their ability to succeed (Schaap & Luwes, 2013). Very few of the students in this study have English as a home language, yet the University of the Witwatersrand delivers its lectures in English. This will be further discussed in the limitations, but it may offer an

explanation as to why the students continuously struggle in this subject and why it did not correlate to the ART and Raven's. When analysing Phase One (the sample as a whole) it was discovered that only 19.7% of the sample were first language English speakers. In total, 77.4% of the sample were students' whose home language was an African language. This means that the vast majority of students in these courses under analysis, are not being taught in their first language, which is their primary mode of communicating and understanding (Schaap & Luwes, 2013). This poses numerous problems about whether the students' are able to grasp what is already acknowledged to be difficult content, in a language in which they may not be fully fluent (Schaap & Luwes, 2013).

These results, in addition to the lack of predictability found for the tests, add to the inability of the University to use this test as a predictive measure as this will show (incorrectly) a vast number of candidates as achieving less than desirable scores. The use of a test in a setting where the majority of the candidates/students would be discriminated against would not be able to aid one's knowledge or understanding regarding the strengths and weaknesses of the group.

A flawed or incomplete education relates to a skills shortage within the country (Chisholm, 1983). It was claimed that the education students' receive in high school, does not adequately prepare them for their tertiary education, which can lead to failure in their first year (Laidra et al., 2006). This in turn will lead to less students graduating from a particular course (in this case engineering), which will directly translate to a further skills shortage in South Africa (Schaap & Luwes, 2013). Following this train of thought, it is important to assess students results in their first year to examine whether or not they have the ability to pass their courses. An examination of the marks obtained in Phase One shows that not every student has the ability to pass the Engineering first year course. For the mid-year marks in CHMT1000, majority vast number of students failed as the mean score reflected a mark of 46.9%, with a standard deviation of 11.38. The end of year mark for this subject shows a slight increase to 51.59%, but the minimum marks displays a score of 12%. From these statistics, one can assume that a possibility for these marks is that not all the students are necessarily equipped for the learning that takes place on a tertiary level.

Romer (2001) claimed that the most important economic question was how to increase growth of output for each individual as this would enable the individual to provide for not only his/her organisation, but the economy of the country too. The aim of this research followed a similar vein, in that the engineering department hoped that if the psychometric tests showed predictive validity, it would enable them to focus on each individuals 'development areas', enabling them to provide opportunities to further enhance the learning in these areas. Following Romer's logic (2001), a small increase in the growth rate will lead to a cumulative effect on the standard of living within the country, and the enhancement of the training and developing of engineers, would enable the university to make a small difference in the skills shortage experienced in South Africa.

The subject of mathematics was presented as the most difficult subject in the engineering degree and the one with which the students struggled the most (Rylands & Coady, 2009). This theory was found to be disproven in the research as the mathematics marks displayed the highest maximum mark (98%) as well as the highest mean (64.85%) in Phase One with a standard deviation of 15.10. The 2013 intake of Phase Two also showed Mathematics as the highest average mark (70.21%), with the 2014 intake reiterating this finding with the highest mean mark of 62.22% achieved by students in mathematics.

This study aimed to find a way of predicting a students' mathematical ability at a university level that could be used as a more reliable indicator than matric results. Tests of intelligence such as the Abstract Reasoning Test and Raven's Advanced Progressive Matrices claim to test the aspect of reasoning that the students' will also make use of when solving some mathematical problems (Lam & Kirby, 2002). It was believed that abstract reasoning and problem solving skills (which are tested in both the ART and the Raven's) would enable clear correlations between the psychometric tests and the mathematics results (Lam & Kirby, 2002). However, there was no link found between either of the tests and the students' ability to perform well in Mathematics. The result is that this study is unable to contribute to a measure of predicting students' ability to succeed in the subject of Mathematics.

Another disjuncture found between the literature and the results in the study is with regard to the Economics courses. In both Phases, Economics correlated (albeit weakly) to the ART and the Raven's. These tests, as discussed above, are

measures of intelligence, abstract thinking and problem solving, while Economics is more a subject of 'book learning' which would not require any of these skills (Lubinski, 2004). Economics is the only subject out of the five that the first year engineering students are required to complete, which would fall into the 'book learning' category, but it was the subject that showed significant predictors most consistently. The directions for future research will discuss possibly furthering the inquiry as to why these results were found.

6.5 The limitations of the study

There are a number of limitations that have been identified with regard to this study which may have influenced the results in a way which could lead to the results being skewed:

1. The consent from the students to make use of their marks in this study was only attained after the test had been completed and from students who were present in lectures. Students who missed lectures may have lower marks which would mean that the data that the researchers were given permission to use in this study was skewed. The students whose consent was not gained could form a similar group of students with lower academic results which may have biased the sample.
2. Linked to the above point, consent from the 2013 first years to use their university results in this study was only gained in 2014. Every student in that class who formed part of the original database, had passed first year and were part of the upper echelons of the class in terms of academic results. This would have led to a bias in the sample and data, as the students who had failed or withdrawn from the class were not included for ethical reasons. This resulted in a restricted range for the correlations and regressions, and would have led to smaller correlation coefficients. Therefore it is not known whether the tests predicted university results for students who did not achieve well academically, or whether the predictive ability of the tests would have been better if these 2013 students had been included in the sample. However, as permission was gained from the 2014 students early in the year before any of the students had failed or left the course, it gives an opportunity to examine the differences between the two groups and analyse these differences. A brief overview shows weak correlations as the strongest relationships in the 2013

sample, but weak to moderate correlations as the strongest relationships in the 2014 sample. It is possible that the inclusion of the students who were not present in the class at the time of gaining consent, may have allowed for a small difference in the results found.

3. These tests have shown a possible bias against African students. As most of the research group comprised African students this may have led the analyses to show no prediction for academic results as opposed to showing a direct relationship that may have been found if the test was unbiased and fair.
4. The biographical variables were not analysed with regard to differences that they may have on academic results. An analysis in this area may have added valuable information to this topic and furthered understanding of why no predictability could be found between the groups and their academic results. If, for example, different groups were made in terms of biographical variables and academic results, these separate groups could have been analysed individually to assess whether the psychometric tests could be used for any particular sub group as predictors of their academic results.

6.6 Directions for future research

The results of this study stand in direct contrast to previous studies with regard to the correlation between test scores and levels of intelligence used in engineering courses (Lam & Kirby, 2002, Lubinski, 2004, Duncan et al., 2000, Embretson & McCollam, 2000, Prietual & Simon, 1989). In this case, there was a possible bias against African students in terms of both the ART and Raven's results. It may be beneficial to do this study with tests that do not show a bias towards a large percentage of the participant group.

No analysis was conducted into the extraneous variables of how successful the students' had been in adapting to their tertiary education climate. The low marks that some students received could have been due to an inability to successfully adapt from a high school framework to that of a university. As such, low marks could have been a result of personal issues, not relating to the student's level of intelligence or ability to perform. This, in turn, could have impacted on the results, showing that the psychometric tests could not be used to predict academic results. It would be useful to see whether adaption to one's new environment would play a significant role in this study.

The different biographical variables were not analysed individually to assess whether certain groups of students' may allow for accurate predictions on academic results using psychometric test scores. Although significant differences were found between the groups on the test scores, it may be useful to analyse whether these differences also exist in the academic results and (if so), whether this leads to a better overall result on the predictability of the tests.

As discussed earlier in this section, it would add to the scope of this project to examine the type of reasoning and intelligence used in each subject more fully. This would aid in understanding the complete disassociation of Mathematics with the type of problem solving ability test with which it is supposed to correlate, while Economics shows correlations to a test which measures a facet of intelligence Economics claims not to use.

Finally, the role of language in the teaching process, a reference to the type of school attended and the new National Benchmarking Tests could have all played a role in understanding the differential performance of different groups in their academic results. This would have added insight to the study and possibly acted as extraneous variables in understanding the relationship between the academic results and the psychometric assessments.

Chapter 7: Conclusion

7. Conclusion

This research project aimed to test whether the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices could be used as predictors for first year engineering students mid and end of year results. In addition, biographical variables were examined to analyse whether they contributed to the scores a student obtained on the ART or the Raven's. This theory was tested through two different Phases. Phase One used the sample as a whole, incorporating both 2013 and 2014 first year students, whereas Phase Two separated the 2013 first year students from the 2014 first year students.

Phase One showed significant relationships between every subject and the ART, yet all of these correlations were weak. The percentages of the academic results that could be explained by the scores on the ART were low.

Additionally, three significant correlations were found between the Raven's and the academic results, yet all of the relationships were weak with poor R^2 values, leading to the conclusion that for the Phase One sample, the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices cannot be used as predictors for mid-year and end of year academic results for first year engineering students.

For Phase Two, the 2013 students were analysed first. The significant relationships between the ART and the academic results were all weak, with correspondingly weak R^2 values. The regression between the Raven's and the academic results produced only two significant relationships, both of which were weak and held even weaker R^2 values than those found in the regression between the ART and the academic results. As such, the 2013 sample showed that no predictions could be made for mid-year and end of year results using the scores students obtained on either the Abstract Reasoning Test or the Raven's Advanced Progressive Matrices.

Finally, the 2014 sample was analysed and it was discovered that weak to moderate relationships existed between the Abstract Reasoning Test and the academic results of the students'. However, these relationships corresponded to weak R^2 values which showed low levels of predictability. The Raven's also produced a weak to

moderate relationship between itself and two of the academic subjects. However, the predictability scores were as low as those found for the ART. The conclusion reached was that for this sub-group the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices could not be used as predictors for the academic results of first year engineering students.

Biographical variables were analysed in order to see whether they contributed to the scores achieved by the students on the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices. Gender did not display any significant differences in either of the tests for Phase One or Two.

Phase One showed significant differences between age, home language and race on the ART. The age group of 18 years and younger scored significantly higher marks than did the 19 year old age group and the 20 year old age group. Both English and Afrikaans speakers scored significantly higher than the students' whose home language was an African language. The African students scored lower marks than did the White, Asian and Coloured students. As with the ART, the Raven's showed a significant difference in age, where the 18 years and younger students scored better than did the 19 year old or 20 year old students. No significant differences were found in terms of home language, but race displayed differences, showing that White and Asian students performed better than African students.

In Phase Two (the 2013 intake), the ART displayed a significant difference for home language, where the English speaking students scored higher than the siSwati, Sepedi and Xitsonga speaking students, while Afrikaans students scored more highly than did any of the African language speakers. White, Asian and Coloured students all achieved significantly better results than did the African students with regard to race. The Raven's showed significant differences for both age and race. The 20 year old students scored significantly less than their younger counterparts, while White students scored significantly more than either the Black or Asian students.

For the 2014 intake of Phase Two, a significant difference in both home language and race was found for the ART. The Afrikaans-English group of students scored significantly more than isiZulu, siSwati, isiNdebele, Sepedi, Xitsonga, Setswana, Sesotho, Tshivenda and Xhosa speakers, while the White and Asian students

scored higher than the African students. The Raven's did not show any significant differences in terms of the biographical variables.

In conclusion, the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices cannot be used as predictors for mid-year or end of year academic results for first year engineering students. In addition, biographical variables do contribute to the scores achieved on both the Abstract Reasoning Test and the Raven's Advanced Progressive Matrices.

Chapter 8: References

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Chapter 9: Appendices

9. Appendices

9.1 Appendix A: Consent Form

I,.....(First and last name)
.....(student number), hereby grant permission for my
Abstract Reasoning Test scores, Advanced Raven's Test scores, thinking test
scores and mid- and end-of-year results to be used for research purposes.

I understand that this information will be kept confidential and that at no point will my
scores or marks be reported individually or accessed by anyone other than the
researcher and her supervisor.

.....

(Signature)

Please also fill in the below biographical information:

1. Gender? _____
2. Age? _____
3. Matric Examination Written: IEB or GDE? _____
4. Home Language? _____
5. What degree are you studying towards? _____
6. What year of study are you in currently? _____
7. Are you currently repeating any subjects? _____

9.2 Appendix B: Letter for 2014 Participants



Psychology

School of Human & Community Development

University of the Witwatersrand

Private Bag 3, WITS, 2050

Tel: (011) 717 4500

Fax: (011) 717 4559



17 March 2014

Good day

My name is Julia Groves and I am conducting research for my Masters degree at the University of the Witwatersrand. My research focuses on using psychometric tests, specifically the Abstract Reasoning Test, Ravens Advanced Progressive Matrices and thinking tests, as predictors for student marks.

By the end of the second block, you will have completed both these tests, and I would like to ask for your permission to use the results and your university marks in the data for my study. Participation is voluntary and confidential and I will link the results of the various assessments using student numbers and not names. I will only report group trends and not individual results in the research report. You will not be advantaged or disadvantaged in any way by choosing to participate in this study. If are willing to participate, and you are interested in the results, they will be made available on a public forum within the engineering department at the end of the year.

If you are willing to participate in this study, please could you fill out the attached consent form and return it to me. If you have any further queries, I can be contacted telephonically on 082 547 8782 or via email through jules@uniclips.com and my supervisor (Fiona Donald) can be contacted on 011 717 4507 or Fiona.Donald@wits.ac.za.

Thank you for taking the time to consider taking part in this study. This research will contribute to a larger body of knowledge about psychometric testing and its predictive values.

Yours sincerely,

Julia Groves

Dr Fiona Donald

9.3 Appendix C: Letter for 2013 Participants



Psychology

School of Human & Community Development

University of the Witwatersrand

Private Bag 3, WITS, 2050

Tel: (011) 717 4500

Fax: (011) 717 4559



17 March 2014

Good day

My name is Julia Groves and I am conducting research for my Masters degree at the University of the Witwatersrand. My research focuses on using psychometric tests, specifically the Abstract Reasoning Test, Ravens Advanced Progressive Matrices and thinking tests, as predictors for student marks.

Over the last year or two, you probably completed these tests, and I would like to ask for your permission to use the results and your university marks in the data for my study. Participation is voluntary and confidential and I will link the results of the various assessments using student numbers and not names. I will only report group trends and not individual results in the research report. You will not be advantaged or disadvantaged in any way by choosing to participate in this study. If are willing to participate, and you are interested in the results, they will be made available on a public forum within the engineering department at the end of the year.

Should you be willing to participate in this study, please complete the attached consent form and return it to me. If you have any further queries, I can be contacted telephonically on 082 547 8782 or via email through jules@uniclips.com and my supervisor (Fiona Donald) can be contacted on 011 717 4507 or Fiona.Donald@wits.ac.za.

Thank you for taking the time to consider taking part in this study. This research will contribute to a larger body of knowledge about psychometric testing and its predictive values.

Yours sincerely,

Julia Groves

Dr Fiona Donald

9.4 Appendix D

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

HUMAN RESEARCH ETHICS COMMITTEE (SCHOOL OF HUMAN & COMMUNITY DEVELOPMENT)

CLEARANCE CERTIFICATE

PROTOCOL NUMBER: MORG/14/001 IH

PROJECT TITLE:

The predictive validity of the Abstract Reasoning Test and the Raven's Advanced Matrices Test for the academic results of first year Engineering students.

INVESTIGATORS

Groves Julia

DEPARTMENT

Psychology

DATE CONSIDERED

05/05/13

DECISION OF COMMITTEE*

Approved

This ethical clearance is valid for 2 years and may be renewed upon application

DATE: 19 June 2014


CHAIRPERSON
(Professor M. Nduna)

cc Supervisor:

Dr. F Donald
Psychology

DECLARATION OF INVESTIGATOR (S)

To be completed in duplicate and **one** copy returned to the Secretary, Room 100015, 10th floor, Senate House, University.

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

This ethical clearance will expire on 31 December 2016

PLEASE QUOTE THE PROTOCOL NUMBER IN ALL ENQUIRIES

9.5 Appendix E



Research Office

HUMAN RESEARCH ETHICS COMMITTEE (NON MEDICAL)

H061116 Woollacott

CLEARANCE CERTIFICATE

PROTOCOL NUMBER H061116

PROJECT TITLE

To improve the education of engineers and professionals by reforming how we teach first year.

INVESTIGATOR(S)

Mr L Woollacott

SCHOOL/DEPARTMENT

Chemical Engineering

DATE CONSIDERED

10 February 2012

DECISION OF THE COMMITTEE

Approved Unconditionally (15/02/2008)
Recertification dated 13 February 2012 extended to
29 February 2015.

EXPIRY DATE

29 February 2015

DATE

14 February 2012

CHAIRPERSON


(Professor R Thornton)

DECLARATION OF INVESTIGATOR(S)

be completed in duplicate and **ONE COPY** returned to the Secretary at Room 10005, 10th Floor, Senate House, University.

I/We fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to resubmit the protocol to the Committee. **I agree to completion of a yearly progress report.**


Signature

14, 06, 2012.
Date

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES