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Learning potential and academic literacy tests as predictors of academic performance for engineering students

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Students who obtain senior certificates in the South African schooling system cannot be assumed to be adequately prepared to meet the demands of tertiary education. This study aims to determine the criterion-related validity of a mathematical proficiency test from the Academic Aptitude Test Battery (AAT-maths), an English language proficiency test (ELSA) and a learning potential test (LPCAT) as predictors of the academic performance of engineering bursary students at tertiary institutions. The findings indicate that these tests have significant criterion-related validity and can improve the likelihood of selecting the most promising bursary students. However, the findings point towards the possibility that the tests or the criterion measure are differentially valid for different race groups.

Leerpotensiaal en akademiese geletterdheidstoetse as voorspellers van ingenieurstudente se akademiese prestasie

Daar kan nie bloot aangeneem word dat studente wat in die Suid-Afrikaanse skolestelsel senior sertifikate verwerf het voldoende voorbereid is om aan die eise van tersiêre onderwys te voldoen nie. Die doel van hierdie studie is om die kriteriumverwante geldigheid van 'n wiskundige vaardigheidstoets wat deel vorm van die Akademiese Aanleg Toets battery (AAT-maths), 'n Engelse taalvaardigheidstoets (ELSA) en 'n leerpotensiaaltoets (LPCAT) as voorspellers van die akademiese prestasie van ingenieursbeursstudente aan tersiêre instellings te bepaal. Daar is bevind dat die toetse beduidende kriteriumverwante geldigheid toon en die kanse verbeter om die mees belowende beursstudente te keur. Die bevindinge dui egter ook op die moontlikheid dat die toetse of die kriteriummaatstaf differensieel geldig is vir verskillende rasgroepe.

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SUN MEDIA BLOEMFONTEIN

Various experts in the field have questioned the success of government interventions in the education system designed to transform education.[1] National results for the senior certificate examination have not been very promising to date. The unadapted figures for 2011 reflect a shocking reality about the South African educational system (Media24-Ondersoeke 2012). Based on the Department of Education's criteria, only 9% of learners who wrote mathematics in 2011 demonstrated adequate knowledge of the subject. Only 10% of physical sciences learners displayed a basic understanding of the subject. The average marks for mathematics and physical sciences were 29% and 32%, respectively (Media24-Ondersoeke 2012).

The inadequate achievement levels in mathematics and physical sciences at school subsequently lead to low university throughput rates in the natural sciences. Nearly 40% of all first-year students in these fields fail their first year of study. It is particularly historically disadvantaged students who live in socio-economically less privileged areas who fall victim to the inadequacies of the schooling system. Schools in such areas tend to have insufficient resources and lack the infrastructure to facilitate effective learning. For example, historically disadvantaged Black learners studying in the natural sciences at the University of Pretoria generally stand a lower chance of passing than other students do (Maree et al. 2011). According to Maree et al. (2011: 1126), the Outcomes-Based Education system (OBE), introduced in 1994, failed to deliver the desired results, due to inadequate implementation strategies at ground level.

In the past, matriculation results were an excellent indicator of academic performance at university, in particular for the first-year student intake (Badenhorst et al. 1990: 34-45; Jawitz 1995: 101-8; Potter & Van der Merwe 1993: 33-40). At present, the inadequate OBE system, coupled with differences in educational opportunities and standards at school level, problematises the use of Grade 12 (matriculation) results as a reliable predictor of academic performance at universities. These factors raise questions about fair and effective selection mechanisms (Zaaiman et al. 2000: 1-21). Therefore, more evidence

1 See Engelbrecht et al. 2009: 288-302; Huntley 2009; Maree et al. 2011: 1126; Zaaiman et al. 2000: 1-21.

is needed on the validity of the new Grade 12 results in predicting academic performance. Against this background, it seems vital that additional measures be implemented that are valid and reliable predictors of academic performance (see Maree et al. 2011). Although academics have attempted to identify valid and reliable criteria to be used alongside school results to predict academic performance, little progress has been made in making available broadly accepted and standardised selection measures that can be used to meet the specific needs of entities such as companies that invest in bursaries for engineering students in South Africa.

This research was undertaken to address the need of a petrochemical company, which provides bursaries to engineering students, to determine the criterion-related validity of a battery of tests used alongside school results in the selection of bursary students in engineering. The specific aim of this research was to explore the validity of the Learning Potential Computer Adaptive Test (LPCAT), the English Literacy Skills Assessment (ELSA) and the Mathematics subtest of the Academic Aptitude Tests (AAT-maths) in predicting engineering students' academic performance (the average academic year mark).

The remaining sections of this article will discuss the pressing need for qualified engineers in South Africa, predictors of success in higher learning institutions and related measures. More specifically, school performance as an entrance requirement to tertiary institutions, current practices regarding academic literacy tests as a predictor of academic performance at tertiary institutions, and the need for additional tests for selecting bursary students will also be examined. This will be followed by the research method, the results of the study and the conclusions.

1. Need for engineers

Since 2005, the number and size of engineering projects have increased considerably, in particular the number of government-led infrastructure improvements such as road improvement projects, and reconstruction and development programmes. As a result of these trends, the market demand for skilled workers in the field of engineering is set to increase substantially. In addition, the increasing

global demand for infrastructure creates a vast worldwide demand for engineers. This, in turn, affects the supply of engineers in South Africa, because some skilled South African engineers leave the country to work abroad. With the current skills shortages in South Africa, the number of graduates must increase substantially in order to make up the shortfall (Nyathi 2007).

The development of essential skills in human capital is a key driver for competing successfully in a modern global economy. The term 'human capital' encompasses relevant skills, knowledge and wisdom as important determinants of production that have a direct impact on firms' competitiveness (Kleynhans 2006: 55-62). There is a particular shortage of human capital in the petrochemical industry, which continues to grow in stature as a major regional force in Southern Africa. The latter is rapidly becoming an international competitor in select areas of fuel and chemical production. Thus, attracting and developing top talent, especially in the field of science and engineering, are key factors to ensure the continued success of the industry (Le Roux 2006).

The demand in the labour force for students graduating in the fields of science, engineering and technology has contributed to the fact that it is a key objective of the South African National Plan for Higher Education to shift the balance of enrolment in tertiary studies from the humanities to business and commerce, and most of all to science, engineering and technology (DHET 2010).

2. School results as a predictor of academic performance

In the past, high-school results were widely accepted to be a good predictor of performance at tertiary institutions. Institutions of higher learning still rely strongly on Grades 11 and 12 results as entry requirement to universities. However, cognisance should be taken of the fact that research evidence on the predictive validity of Grade 12 results as a sole selection criterion is not conclusive. Research reported by Foxcroft & Stumpf (2005: 8-20) suggests that school results are not a convincing predictor of academic performance for disadvantaged students. Shochet (1994) argues that results obtained in a disadvantaged social and educational system cannot accurately reflect academic

potential. However, Van der Merwe & De Beer (2006: 548) point out that the findings of at least three studies, done between 1996 and 2003, showed that the Grade 12 performance of disadvantaged students did indeed correlate statistically significantly with tertiary performance.[2] Similar results reported in research conducted by Badenhorst et al. (1990: 34-45) and Van der Merwe & De Beer (2006: 547-62) indicate that the predictive validity of the matriculation results appears to vary from one tertiary institution to another and, according to Foxcroft & Stumpf (2005: 20), between race groups and language groups.

3. Academic literacy tests as predictors of academic performance

Given the differences in the standards in individual schools, there is no conclusive evidence that all students who have obtained their senior certificates are prepared and able to meet the demands and challenges of tertiary education. In that light, academic literacy tests that display content and criterion-related validity should be deemed essential for providing insight into the intellectual profile and academic readiness of students (Scholtz & Allen-Ile 2007: 919-39). Suitable and timely interventions based on the results and analysis of selection tests could have far-reaching positive and financial implications for individual students (in enabling them to become economically productive), for institutions (in improving throughput rates and gaining subsidies), and for the country as a whole (in contributing to economic advancement in South Africa).

The majority of tertiary institutions in South Africa have introduced some form of diagnostic or selection test in reaction to concern about the academic literacy levels of first-year students. A lack of academic literacy could put students at risk of not completing their courses in the minimum time, with serious cost implications for the institution, as well as for each student and for those supporting the student financially (Weideman 2003, cited by Scholtz & Allen-Ile 2007: 920). Hence, academic literacy tests for selection and placement purposes have become an accepted practice at most tertiary institutions

2 See Samkin 1996: 117-22; Huysamen & Raubenheimer 1999: 171-7; Lourens & Smit 2003: 169-76. These results were based on students who had written the 'old' Grade 12 examinations.

in South Africa (Scholtz & Allen-lle 2007: 919-39). For example, the Standardised Assessment Test for Access and Placement (SATAP) is used by the Cape Peninsula University of Technology (CPUT); the University of Cape Town has established the Alternative Admission Research Project (AARP) responsible for developing the Placement Test in English for Educational Purposes (PTEEP), and the University of Pretoria uses the Test of Academic Literacy Levels (TALL).

It is indicative of the urgency and importance of determining the academic preparedness of entry-level students that Higher Education South Africa (HESA) (the former South African Universities Vice-Chancellors Association [SAUVCA] and the Committee of Technikon Principals [CTP]) approved the proposal to institute the National Benchmark Tests (NBTs) (Scholtz & Allen-lle 2007: 922). Benchmarks are an indication of the expected level of academic literacy that students should attain, and they imply that all learners should reach certain grade levels for tertiary entry (Foxcroft 2006). Since 2009, universities have been systematically introducing the NBT as the preferred test for benchmarking and the placement of students in appropriate curricular routes.

Testing and assessments are synonymous with determining advancement in education. The aim of testing is to determine a test-taker's ability to perform at a particular level in a particular discipline (Scholtz & Allen-Ile 2007: 919). The first consideration in selecting assessment measures is that a measure should differentiate between those students who currently show academic excellence and those who display less significant accomplishments, but have the potential to develop academic excellence (Lohman 2005: 130). For that reason, valid learning potential measures should be considered for inclusion in a selection battery for predicting academic performance.

In order to determine which characteristics in a measure are important when assessing a candidate with the help of a selection test, the knowledge, skills, motivation and other personal attributes that are required for success in a particular academic programme should be carefully considered (Lohman 2005: 111).

This article focuses on academic literacy and learning potential tests that provide a range of information which is not easily and reliably assessed in other ways. Three academic literacy areas were

identified as predictors for academic success for the purposes of this study, namely language proficiency, mathematical proficiency and learning potential.

3.1 Language proficiency

Bachman (1990) provides some insight into the possible meanings and connotations of the term 'language proficiency'. Bachman (1990: 16) indicates that, traditionally, language proficiency refers to a person's competence in using a language, and his/her knowledge of, or the ability to use a language. However, Bachman (1990: 4) proposes that the broader term "communicative language ability" provides a more appropriate view of language proficiency in academic contexts, as the term implies that communicative language use involves "dynamic interaction between the situation, the language user and the discourse and entails more than simply transferring information".

Webb (2002) argues that inadequate language proficiency is an obstacle to meaningful participation in class and note-taking. Language proficiency can thus be described as a fundamental skill required in academic training, as it can either facilitate academic development, or serve as a barrier.

Lemmer (1993: 169) points out the consequences of inadequate proficiency in a student's language of learning and training at tertiary level. Minority language groups often suffer serious effects such as poor academic achievement, as well as a poor foundation for cognitive development and academic progress. Webb (2002: 52-3) maintains that language is fundamental to educational development in at least two ways: first, it is a fundamental instrument in students' cognitive, affective and social development and, secondly, it is an essential object of teaching, in the sense that becoming academically trained implies learning to use the language of the particular science appropriately in professional contexts, as well as learning to use language for general purposes.

The theoretical complexity and problem-solving environment of science and mathematics makes a wide range of demands on the reasoning, interpretive and strategic skills of students, especially when these skills are practised in a language that is not the student's first language. As early as 1987, Dale & Cuevas (1987) pointed out

that a candidate's proficiency in the language in which mathematics is taught, especially reading proficiency, is a prerequisite for mathematics achievement. More recent research by Bohlmann & Pretorius (2002: 196-206) shows a robust relationship between reading ability and mathematics performance.

Studies by Webb (2002: 49-61) and Zaaiman et al. (2000: 1-21) show that language proficiency tests can be considered valid predictors of the academic performance of students studying at tertiary institutions. According to Van Dyk & Weideman (2004), the traditional view of language proficiency must be considered limited, as it focuses only on skills related to sound, form, grammar and meaning. More recently developed tests (the NBT, SATAP, PTEEP and TALL) used in higher education institutions focus on language ability as a social instrument to mediate and negotiate human interaction in specific contexts, and are considered important for successful academic discourse. These tests are mostly used for placing at-risk students in appropriate language development courses; the tests are not intended to be used as admission or selection tests. Van Dyk & Weideman (2004) suggest that the ELSA test, which is often used in corporate environments for benchmarking, placement, selection and development purposes, represents a traditional view of language skills and has limited application regarding what is required for successful academic discourse.

3.2 Mathematics proficiency

Mathematics is regarded as an important prerequisite for many fields of study, in particular for the physical and engineering sciences: "Mathematics provides the means to the learner to analyse, understand and describe the world and to deepen their understanding of the world while adding to the ability to solve real-world problems" (Sasman 2011: 2). Mastering mathematics can be described as the first step to a successful career in science, engineering and technology. Increasingly, the mathematical skills required in these careers require both solving problems and formulating the questions. This means that, while learners should have a strong mathematical knowledge base, they should also be developing their ability to apply that knowledge and make judgements about when to use what mathematical ideas. In fact,

engineers often have to pose their own mathematical problems in order to develop a solution to a real-world dilemma (Sproule 2011: 14).

Despite the fact that mathematics is the foundation of scientific literacy, it was reported earlier in this article that many South African students do not perform sufficiently well in this subject. According to a group of Concerned Mathematics Educators (2009), the final examination in mathematics has been watered down and has, therefore, widened the gap between school and university, even for top learners. A number of factors may have contributed to this phenomenon, but the type of education that students receive prior to entering university appears to be a key issue.

A study done at the University of Pretoria shows that first-year students lack a fundamental understanding of mathematical concepts (Du Preez et al. 2008: 49-62). In a second study conducted at the University of Pretoria, Engelbrecht et al. (2009: 288-302) report a general agreement among lecturers regarding a deterioration in general mathematical skills. Lecturers were unanimous that there had been a decrease in the specific skills of factual knowledge, algebraic manipulation and mathematical formulation. Although significantly more students were qualifying for university entrance, the first semester mathematics results for first-year students at tertiary institutions in 2009 were disturbingly poor (Huntley 2009).

Eiselen et al. (2007: 34-49) report evidence on the use of an assessment instrument (the Basix[2] questionnaire) independent of the Grade 12 results to measure the mathematical skills of students entering tertiary education. This mathematical skills test proved to be a significant predictor of success, especially in the first semester of tertiary training. Universities in South Africa are currently using the new standardised Mathematics Test (MAT) of the NBT test battery for placement purposes. However, the AAT-maths is readily available for selection purposes in industry.

3.3 Learning potential

This discussion concerns the importance of ensuring that training and education are aimed at those candidates who are potentially the most responsive and deserving. It is, therefore, important to use appropriate measures to identify the students who have the greatest

capacity to become successful learners in tertiary institutions. Many cognitive assessments can potentially cause problems, because they measure only current inherent or learned cognitive abilities, but fail to measure students' capacity to gain skills, strategies and operations in new situations (Foxcroft & Roodt 2009). The measurement of learning potential, in addition to current cognitive abilities, is increasingly used in South Africa to identify people with the capacity to become successful learners (Murphy 2002). Learning potential assessments measure individuals' current levels of ability, as well as their potential for improvement if they are given suitable assistance. These assessments focus on existing and improved levels of functioning to evaluate a person's capacity for gaining new skills or knowledge when training is provided (De Beer 2005).

In an effort to conduct more equitable cognitive assessments, non-verbal reasoning assessment has received increasing attention in the past few decades, both in South Africa and internationally (Murphy 2006). Non-verbal reasoning assessment has been intensively researched since the 1960s and 1970s and can be considered a fundamental element of learning potential tests. Research initiatives have focused, first, on providing more culture-fair assessment – this would be useful in comparing results obtained in culturally diverse populations; secondly, on designing measures appropriate for testing individuals with disadvantaged educational experiences and, lastly, on measuring learning potential as distinct from what has been learned – regardless of the culture, population, or social group of the individuals being tested (De Beer 2005: 717-47). Such research initiatives have contributed significantly to the development of the learning potential tests that form part of selection batteries for the diverse South African society. The Transfer, Automisation and Memory tests (TRAM1/2), Ability of Processing Information and Learning Battery (APIL-B) and LPCAT tests are well-known, non-verbal-based learning potential tests developed in South Africa and used in industry for selection, placement and development purposes (Foxcroft & Roodt 2009).

Specific predictors such as literacy tests and learning potential used in this study were discussed earlier. Understanding the background to these predictors provides insight into their inclusion and purpose in this research study. Studies by Zaaiman et al. (2000: 1-21) and by

Eiselen et al. (2007: 38-49) acknowledge the value of these predictors in predicting academic performance. Lohman (2005: 111-38) studied the role of non-verbal ability tests in identifying academically gifted students. His research suggests that all students should be tested for verbal, quantitative (numeric literacy) and non-verbal reasoning, which is fundamental to learning potential tests.

4. Method

4.1 Research approach

A quantitative approach was used in this study. The study was completed in 2011, based on data accumulated in a corporate environment over six consecutive years (2004-2009). More specifically, a cross-sectional design and *ex post facto* analysis were used in this study. *Ex post facto* research refers to the study of an independent variable or variables in retrospect for possible relationships to, and effects on the dependent variables or variables (Cohen et al. 2007: 264).

4.2 Sample

The sample for this study was pre-selected on the basis of more than one criterion, using panel interviews, school grades, academic literacy and potential tests. This was a convenience sample, and the researchers collected criterion data (academic performance results) from every student who was successful in the bursary selection process. The sample consisted of top-performing learners in respect of each selection criterion. The subjects of this study were 329 undergraduate students enrolled in the field of engineering at various tertiary institutions in South Africa.

The sample consisted of 73 Black, 13 Coloured, 84 Indian and 159 White respondents. The majority of the students were male (62.92% of the sample), while 37.08% were female students. The participants' ages varied from 19 to 28 years, with a mean of 20.97.

Various universities in South Africa were represented in this study. The majority of the respondents (29.48%) were at the University of Pretoria, and 22.19% of the students were at the University of KwaZulu-Natal. Other universities that were represented in this

study were the North-West University (14.29%), the University of the Witwatersrand (11.85%), the University of Cape Town (10.33%), Stellenbosch University (10.03%), and the University of Johannesburg (1.82%).

The majority of the respondents were Grade 12 learners (60.67%) when their bursaries were awarded (60.67%), while 26.52% were first-year, 11.28% second-year, and 1.52% third-year students.

4.3 Measurement instruments

The different measurement instruments used in this study are discussed in this section. These tests were all developed in the South African context. Specifics regarding the measurement instruments in respect of their development history, purpose and measurement qualities are discussed.

4.3.1 English Literacy Skills Assessment (ELSA)

The ELSA was designed and developed locally by Brian Hough and Theunis Horn in consultation with the Human Sciences Research Council (HSRC) in the late 1980s. ELSA is a South African language, norm-based (non-syllabus-based), group measuring instrument that can be used to quantify and diagnose (Bhabha et al. 2006).

The ELSA quantifies a respondent's English language and numeracy skills performance, equating the competency input performance level to that of a South African English-mother tongue user. More specifically, English proficiency includes phonics, dictation, vocabulary, reading comprehension as well as verbal and numerical understanding. In diagnosing, it shows up an individual's strengths and areas for development in an English-language work/training environment. It is essentially a prior learning and ABET-placement guide for English and Functional Numeracy. The ELSA score levels have been compared to school grade levels (Bhabha et al 2006).

According to Bhabha et al. (2006), the ELSA is a standardised, reliable and valid assessment instrument. The ELSA has demonstrated statistically significant predictive validity in respect of academic performance – reliabilities of 0.67 and 0.86 have been reported (Bhabha et al. 2006, Van Dyk & Weideman 2004). The ELSA includes

a mix of power and speed tests. The power tests are designed to test for the depth of language skills with items that increase progressively in difficulty without imposing a strict time limit; the speed tests have a strict time limit, and focus on speed and accuracy in language skills.

The national ELSA norms were established under the direction of the HSRC, using representative groups. The ELSA is considered culturally appropriate, in that it steers clear of meta-language, colloquialisms, idiomatic expressions and dialectal usage, and it is cost-effective (Bhabha et al. 2006).

4.3.2 The Mathematical Proficiency Test (AAT-maths)

The Mathematical Proficiency Test is a subtest of the Academic Aptitude Test (AAT) battery for universities. The initial Mathematical Proficiency Test was developed and standardised by the HSRC in 1977 (Owen & De Beer 1977) and has recently been updated by Mindmuzik Media (Pty) Ltd to reflect the more recent OBE school mathematics syllabus. The test consists of a number of items which include algebraic manipulations, trigonometric functions, and geometry.

The purpose of the Mathematical Proficiency Test is to determine whether a candidate has attained such a level of proficiency in mathematics that s/he may immediately continue with the mainstream courses at university, or should rather do a bridging course first. The test consists of 30 items and has been found to be a reliable (*Alpha* = 0.71) and a useful predictor of academic success (Owen & De Beer 1977).

4.3.3 The Learning Potential Computerised Adaptive Test (LPCAT)

The Learning Potential Computerised Adaptive Test (LPCAT) (De Beer 2005: 717-47), as its name indicates, assesses learning potential. This assessment consists only of non-verbal items, in an effort to counter the effects of language ability and competency on test scores. The test includes three item types, namely figure series, figure analogies and pattern completion (Van Eeden *et al.* 2001: 171-9). The LPCAT specifically assesses the potential to develop cognitive ability, and is regarded as a culturally appropriate measure of learning potential in the general reasoning ability domain. The LPCAT (a dynamic test-train-retest computerised adaptive format) is used with standard

training provided between the pre-test and the post-test. The developer of the LPCAT defines learning potential as a combination of current performance (as measured in the pre-test) and improvement shown after relevant learning (as reflected in the difference between the post-test and pre-test scores). The LPCAT score levels have been aligned with the National Qualifications Framework (NQF) levels and can be treated as benchmarks for the level of cognition learners should demonstrate at each NQF level. A transformation table based on empirical data provides commensurate levels in respect of the typical NQF levels associated with different LPCAT score ranges. This allows the cognitive level of academic training, with which an individual would be comfortable, to be determined, given his/her LPCAT score (De Beer 2005: 717-47).

The LPCAT has internal consistency reliability values ranging from 0.92 to 0.98. It also has reliability values above 0.9 for Coloured, African and White respondents, as well as for males and females. For the low literacy adult group, correlations between the LPCAT results and training results range between 0.398 and 0.610, while for a secondary school level sample, correlations between academic results and the LPCAT performance range between 0.439 and 0.543 (De Beer 2005: 717-47).

4.4 Criterion scores

A composite criterion score per student was compiled by calculating the average academic year mark for all subjects in respect of each year of study. All subjects carried an equal weight. The data for this study represent four academic years of study. They were named Year 1 (first year of study), Year 2 (second year of study), Year 3 (third year of study), and Year 4 (fourth year of study) for analysis purposes.

Specific study-year results for the students were not gathered in the same calendar year. The students were from different universities and the syllabus varies from university to university.

According to Cascio & Aguinis (2005a), the use of a composite criterion versus multiple criteria depends on the purpose of a study. When the goal of a study is to increase psychological understanding of predictor-criterion relationships, it is best to keep the criteria separate, but when the objective is decision-making, the criteria should be

calculated into a composite score. However, composite criteria might depress the predictive validity of the predictors, due to contaminating factors that would account for considerable within-score or irrelevant variances. Contaminating factors may include differences between universities in respect of subject content and assessment practices.

4.5 Research procedure

The predictive study was conducted using the following procedure. In the first instance, top-performing learners in their final school year were invited to undergo additional testing and to participate in a panel interview (based on their Grade 11 school results). The sample group completed the LPCAT, the ELSA and the AAT-maths test for university students. The interview panel made final recommendations after integrating all the relevant information on each candidate. The candidates were eventually awarded bursaries based on the outcomes of this process and on obtaining university entrance based on their actual Grade 12 results. Information with regard to their academic results at the university where they studied was obtained, and the strength of the relationship between the predictor and the criterion was determined. All the data were gathered with the informed consent of the learners and under the supervision of a registered psychologist. All information was dealt with in a confidential manner.

4.6 Statistical techniques

4.6.1 Descriptive statistics

The descriptive statistics mean, standard deviation, kurtosis and skewness were calculated. The purpose was to describe the sample, to check the variables for any violation of the assumptions underlying the statistical techniques, and to address specific research questions, as recommended by Pallant (2007). Cohen's (1988) effect sizes were used as a benchmark to determine the impact (practical significance) of the statistical findings. There is general agreement that Cohen's criteria are somewhat arbitrary and should not be treated in exact terms (Durlak 2009). Cohen (1988) suggests that correlation effect sizes should be interpreted taking into consideration the correlational trends in the study domain or scientific field. Meta-analysis studies on the criterion-related validity of the instruments used for selection

purposes were used to denote more precise ranges for Cohen's criteria, as recommended by Pulakos (2005). Therefore, "low" validities were denoted as approximately 0.20 or less, "medium" validities were approximated as within the 0.20 to 0.40 range, and "high" validities as approximately 0.40 or higher. Cohen's effect size values (r=0.10: small, 0.30: medium, and 0.50: large) were treated as midpoints for these approximate ranges. The SPSS (SPSS 2010) software package was used for all statistical analyses reported in this article.

4.6.2 Inferential statistics

Correlation coefficients between the predictor variables and the criterion were calculated to determine the nature and the magnitude of relations. Stepwise regression analysis was done in this study to understand how the different predictors contribute to the prediction of academic performance. Additional regression analyses were performed for selected predictor variables to illuminate the influence of race as a moderator on the regression model (see Berenson et al. 1983).

5. Results

5.1 Descriptive statistics

Table 1 indicates the descriptive statistics for the sample. The sample sizes for the different predictors differ, due to some missing test and academic performance data. The sample sizes for Years 1 to 4 became progressively smaller, because the majority of the students in the sample had not progressed to later years of study at the time of the study. The average marks for Grade 12 mathematics, physical sciences and English second language were all above the 80% mark, signifying a pre-selected group of top-performing learners. The average mark for all engineering subjects for the respective academic years are noticeably lower than the Grade 12 marks and vary between 62% and 66%.

Table 1: Descriptive statistics for predictors and criterion measure

Variable	N	Mean	Std dev	Kurtosis	Skewness
English	95	82.586	8.985	-0.567	0.059

Variable	N	Mean	Std dev	Kurtosis	Skewness
Mathematics	160	83.213	9.979	1.257	-0.931
Physical science	159	81.513	9.591	1.500	-0.756
Grade 12	137	83.381	9.365	1.637	-0.765
ELSA	265	3.440	1.305	-.0835	-0.490
LPCAT	324	64.462	3.941	-0.205	0.191
AAT-maths	283	18.749	3.651	0.108	0.051
Academic year 1	329	66.316	9.938	-0.550	0.154
Academic year 2	229	62.330	9.596	0.110	0.444
Academic year 3	125	62.272	9.965	0.838	0.201
Academic year 4	36	65.274	9.544	-0.119	0.303

The data set is not observably skewed (exceeding a range of -1 to 1), and there are no questionable kurtoses (>3), which indicates acceptable data symmetry for the purposes of analyses using parametric statistical techniques (Fife-Schaw 2006: 409).

5.2 Correlation analysis results for criterion-related validity

Table 2 sets out the correlation statistics between the Grade 12 school results (English second language, mathematics and physical sciences), the Mathematical Proficiency Test (the AAT-maths), the ELSA, the LPCAT, and Years 1 to 4.

No statistically significant correlations ($p \leq 0.05$) between school results and academic performance were obtained. However, the ELSA ($r=0.299$), the LPCAT ($r=0.252$) and the AAT-maths ($r=0.489$) correlated statistically significantly with academic performance at the first-year level. At the second-year level, a positive and statistically significant correlation with academic performance can be reported for the ELSA ($r=0.212$), the LPCAT ($r=0.240$) and the AAT-maths ($r=0.330$). At the third-year level, a positive and statistically significant correlation with academic performance can be reported for the ELSA ($r=0.283$), the LPCAT ($r=0.206$) and the AAT-maths ($r=0.332$). At the fourth-year level, a positive and statistically significant correlation

with academic performance can be reported for the AAT-maths (r=0.316), using the distribution free Kendall's correlation coefficient.

Table 2: Correlations of predictor variables with average academic performance for each year level

Criterion variables		School Grade 12 results (senior certificate)				Predictor variables		
Academic year		English	Maths	Physical science	Grade 12	AAT-maths	ELSA	LPCAT
Year 1	Pearson correlation	.154	.019	.018	.187*	.489**	.299**	.252**
	N	95	155	154	133	270	265	312
Year 2	Pearson correlation	.085	-.032	-.107	-.076	.330**	.212**	.240**
	N	71	113	112	95	176	173	218
Year 3	Pearson correlation	.071	-.021	.033	-.031	.332**	.283**	.206*
	N	41	66	65	53	82	78	121
Year 4	Kendall's tau_b correlation	-.068	.239	.164	-.111	.316*	.206	-.171
	N	16	18	18	9	25	24	36

Note: **p<=0.01; *p<=0.05

Range restriction (see Cascio & Aguinis 2005a) would have had a significant depressing effect on the correlation coefficients, given that only selected scholastically top-ranked students were included in the study. Range restriction is most probably present for school results and for the ELSA, the LPCAT and the AAT-maths scores. Range restriction significantly depresses validity coefficients and is considered to be a restricting factor if the goal is to understand the general relationship between the variables being studied (Cascio & Aguinis 2005b). In the context of this study, the researchers had to rely on the limiting depressed correlation coefficient in order to understand the relationship between the specific predictor and criterion variables in question.

When Cohen's (1988) criteria for correlation effect sizes (r=0.10: small, 0.30: medium, and 0.50: large) were applied as midpoint benchmarks, the statistically significant correlation coefficients obtained for the respective tests were small to large. More specifically,

for the first-year level, the AAT-maths effect size was large, thereafter levelling off to a moderate effect size for the second-, third- and fourth-year levels. The effect sizes for the ELSA and LPCAT correlations were lower overall, varying from moderate in effect size to small. The LPCAT correlation effect sizes appeared to be the lowest for the predictors under investigation. According to Cascio & Aguinis (2005b), experts argue that correlation coefficients within the range of 0.30 (moderate effect size) and higher should be taken seriously and could yield significant utility value under the right conditions (for example, low testing costs and a large number of applicants). Urbina (2004: 191) indicates that validity correlations within the 0.20 to 0.30 range are not uncommon in predictive validity studies. Nunnally & Bernstein (1994) point out that the validity correlation coefficients of single tests rarely exceed the 0.30 to 0.40 range.

5.3 Regression analysis results for predictive validity

A stepwise multiple regression analysis was conducted to determine the validity of the tests in predicting academic performance at the first- and second-year levels. The sample size recommendations by Knofczynski & Mundfrom (2008) to obtain good prediction accuracy levels with multiple regression analyses were applied. The third- and fourth-year groups respectively consisted of sample sizes too small to make valid inferences using multiple regression analyses and they were, therefore, excluded from the analyses. The ELSA, the AAT-maths and the LPCAT tests were treated as the independent variables, whereas academic performance at the first- and second-year levels was used as the dependent variable. Tables 3 and 4 illustrate the results of the regression analysis performed to determine the predictive validity of the ELSA, the AAT-maths and the LPCAT at the first- and second-year levels.

The collinearity statistics suggest that no significant multi-collinearity (variance inflation factors VIF > 10) was present. This implies that the probability of invalid numerical computations for the individual predictors is reduced (Pallant 2007).

According to Table 3, in Step 1 of the regression analysis, the AAT-maths alone already explains 23% of the variance in first-year academic performance (R^2=0.235). In Step 2, the ELSA was included

and significantly increased the prediction model of first-year academic performance, with 3.9% (ΔR^2=0.039) to 27.4% (R^2=0.274). The LPCAT was excluded in this instance, as it did not make a significant contribution to the model (t=0.642, p>0.05). The LPCAT did not provide a significant improvement on the regression model when it was used in combination with the ELSA and the AAT-maths as predictors. (The correlation statistics in Table 2 show that the LPCAT on its own should have a significant prediction value, but not over and above that provided by the ELSA and the AAT-maths.)

Table 3: Regression analysis results indicating the relationship between academic performance at first-year level with the ELSA, AAT-maths and LPCAT as predictors

				Std error of the estimate	Change statistics				
					Model	R	R square	Adjusted R square	Sig. F change
1[a]	0.485	0.235	0.232	8.76862					0.000
2[b]	0.524	0.274	0.268	8.55775	0.039	13.872	1	257	0.000

a. Predictors: (Constant), AAT-maths

b. Predictors: (Constant), AAT-maths, ELSA

c. Dependent variable: Year 1

Model B		Unstandardised coefficients		Standardised coefficients	t VIF	Collinearity statistics
		Std error	*Beta*			
1	(Constant)	41.657	2.802		14.865**	
	AAT-maths	1.305	0.147	0.485	8.900**	1.000
2	(Constant)	38.427	2.869		13.393**	
	AAT-maths	1.193	0.146	0.443	8.151**	1.045
	ELSA	1.549	0.416	0.202	3.724**	1.045
2	Excluded variables: LPCAT			0.037	0.642	0.863

Note: **p<=0.01; *p<=0.05

Table 4 depicts the predictive model of the AAT-maths, the ELSA and the LPCAT at the second-year level. The total variance explained

by these variables dropped significantly to 14.4%. The LPCAT did not show significant incremental validity above what the AAT-maths and the ELSA could provide. In Step 1, the AAT-maths explained 11.5% of the variance in first-year academic performance (R^2=0.115). In Step 2 of the regression analysis, the ELSA was included, and it significantly increased the prediction model of the first-year academic performance, with 2.9% (ΔR^2=0.029) to 14.4% (R^2=0.144). Again, the LPCAT was excluded, because it did not make a significant contribution to the model at this level (t=0.383, p>0.05).

Table 4: Regression analysis results indicating the relationship between academic performance at the second-year level with the ELSA, AAT-maths and LPCAT as predictors

Model	R	R square	Adjusted R square	Std error of the estimate	Change statistics				
					R square change	F change	df1	df2	Sig F-change
1 a	0.339	0.115	0.110	8.74893	0.115	21.728	1	167	0.000
2 b	0.380	0.144	0.134	8.62939	0.029	5.659	1	166	0.019

a. Predictors: (Constant), AAT-maths

b. Predictors: (Constant), AAT-maths, ELSA

c. Dependent variable: Year 2

Model B		Unstandardised coefficients		Standardised coefficients	t VIF	Collinearity statistics
		Std error	Beta			
1	(Constant)	45.204	3.714		12.172**	
	AAT-maths	0.895	0.192	0.339	4.661**	1.000
2	(Constant)	42.044	3.896		10.790**	
	AAT-maths	0.855	0.190	0.324	4.493**	1.008
	ELSA	1.168	0.491	0.171	2.379*	1.008
2	Excluded variables: LPCAT			0.030	0.383	1.207

Note: **p<=0.01; *p<=0.05

5.4 Analysis results for adverse impact and differential predictive validity

Table 5 indicates the descriptive statistics for the different race groups in this study. The Coloured race group consisted of a sample of 13

subjects. This group was, therefore, considered too small to make valid inferences using parametric statistical analyses – small sample sizes reduce the power to detect significant effects (Pedhauzer & Schmelkin 1991). Consequently, the Coloured group was not included in the adverse impact and differential predictive validity analyses.

Overall, the sample sizes for students in their first academic year were higher than for those in their second year. The White race group was best represented in this study. There was a very distinct difference between the mean scores of the different race groups. A notable positive skewness can be reported for the LPCAT results in respect of the Black race group.

Table 5: Descriptive statistics for race groups

Race group	Variable	N	Mean	Std dev	Kurtosis	Skewness	Effect size
Black	Academic year 1	73	61.162	8.390	-0.003	0.407	-0.886
	Academic year 2	53	59.362	8.115	0.461	0.530	-0.637
	LPCAT	71	62.000	3.723	1.658	1.000	-1.058
	AAT-maths	60	16.850	3.677	-0.484	-0.241	-0.837
	ELSA	61	2.360	1.291	0.583	-0.721	-1.143
Indian	Academic year 1	84	64.892	9.956	0.471	0.554	-0.433
	Academic year 2	54	59.297	8.892	0.427	0.751	-0.617
	LPCAT	82	63.866	3.899	0.899	0.230	-0.530
	AAT-maths	71	18.338	3.779	0.300	0.607	-0.405
	ELSA	70	3.770	1.066	-0.634	-0.214	0.009
White	Academic year 1	159	69.113	9.554	-0.700	-0.188	
	Academic year 2	114	64.972	9.499	-0.036	0.478	
	LPCAT	159	65.836	3.529	-0.767	0.149	
	AAT-maths	139	19.770	3.300	0.113	0.088	
	ELSA	134	3.760	1.158	-0.788	-0.098	

The effect sizes (Cohen's d) for the differences in the mean scores between the White race group and the Black and Indian groups are set out in the last column (see Cohen 1988). According to Cohen's d criteria for effect sizes (d=0.20: small, 0.50: medium, and 0.80: large), the White group's mean scores for most of the variables differed, with a large effect size, from those of the Black group. The largest effect sizes occurred for the ELSA, followed by those for the LPCAT in the

first academic year and by those for the AAT-maths. The effect sizes for the Indian group were notably smaller when the mean scores were compared to those for the White group. On average, the effect sizes were medium, except for the ELSA's effect size, where the difference between the mean values for the White and Indian groups was very small. The results suggest a potentially adverse impact of measures for historically disadvantaged groups, particularly the Black group. An adverse impact, in this instance, refers to a substantially different rate of selection that works to the disadvantage of members of a particular race, gender or ethnic group (Cascio & Aguinis 2005b).

Table 6: Correlations (Pearson) of predictor variables with academic results in respect of race groups

		Black			Indian			White		
Academic year		LP-CAT	AAT-maths	ELSA	LP-CAT	AAT-maths	ELSA	LP-CAT	AAT-maths	ELSA
Year1	r	.183	.208	.139	.006	.513**	-.007	.209**	.476**	.338**
	N	71	60	61	82	71	70	159	139	134
Year2	r	.183	.047	.291	.056	.379*	-.254	.185*	.354**	.281**
	N	51	40	41	53	41	40	114	95	92

Note: **p<=0.01; *p<=0.05

The correlation coefficients of the predictor variables with the academic results for the race groups in Table 6 show the differential validity of the predictors. Only Years 1 and 2 were included, as samples sizes after Year 2 diminished beyond the point of acceptability for comparison purposes. The LPCAT, the AAT-Maths and the ELSA do not appear to predict academic performance to the same extent in respect of the different race groups. More specifically, the LPCAT and the ELSA do not appear to be valid predictors of academic performance for the Indian and Black groups. The correlations obtained on the LPCAT for the White group represent small effect sizes and are, therefore, also of little practical significance for prediction purposes. None of the predictor variables in Table 6 appear to predict academic performance significantly for the Black group. However, the AAT-maths appears to predict academic performance equally well in respect of the White and Indian groups at the first- and second-year levels, but not for the Black group. This finding was explored further

at the first-year level by testing for the equality of regression lines for the groups, an important prerequisite for determining the differential prediction of a test for multiple groups (Cascio & Aguinis 2005a). Young & Kobrin (2001: 4) point out that differential prediction has a more direct bearing on considerations of fairness in selection than do differences in correlation.

Table 7: Regression analysis to test for differential prediction validity in respect of race groups

Academic year 1				
Variable	DF	Unstandardised slope coefficients	Std error	t value
Intercept	1	41.748	4.411	9.46**
AAT-maths	1	1.373	0.220	6.24**
Race1[a]	1	10.675	6.825	1.56
Race2[1]	1	-2.112	6.706	-0.31
AAT-maths x Race1[2]	1	-0.884	0.374	-2.36*
AAT-maths x Race2[3]	1	0.005	0.348	0.01
Academic year 2				
Variable	DF	Unstandardised slope coefficients	Std error	t value
Intercept	1	43.880	5.572	7.875**
AAT-maths	1	1.051	0.281	3.740**
Race1 [a]	1	12.901	8.724	1.479
Race2[1]	1	-2.095	8.870	-0.236
AAT-maths x Race1[2]	1	-0.949	0.465	-2.041*
AAT-maths x Race2[3]	1	-0.131	0.457	-0.287

Note: **p<=0.01; *p<=0.05

[a] Category variable Race1; Black =1; White = 0

[1] Category variable Race2; Indian=1; White = 0

[2] AAT-maths x Race1 = Interaction Race1 and AAT-maths results

[3] AAT-maths x Race2 = Interaction Race2 and AAT-maths results

Dummy variables were used to identify race categories in the regression analysis, as recommended by Berenson et al. (1983). Race1 is the first-year scores for the Black group (Race1=1); Race2 is the first-year scores for the Indian group (Race2=1). The White group

was used as a reference group (Race1=0 and Race2=0). AAT-maths x Race1 resembles the interaction between the score for the AAT-maths test and the Black race group (Race1=1). The AAT-maths x Race2 resembles the interaction between the score for the AAT-maths test and the Indian race group (Race2=1). The White group was used as the reference group in each comparison (AAT-maths x Race1=0 & AAT-maths x Race2=0).

Table 7 reports a regression analysis for first-year and second-year levels. In respect of the first-year group, the unstandardised slope coefficients for the dummy variables for the Black group (AAT-maths x Race1) differ significantly (t-value=-2.041, $p<0.05$) in this model. It can be concluded that the regression line slope for the Black group differs significantly from the regression line slope for Whites. The intercept (Race1) for the Black group does not differ significantly (t-value=1.56, $p>0.05$) from that of the reference group (White). However, the test does have differential prediction for these groups, because the slope of the regression line differs.

For the Indian group, neither variable (Race2; AAT-maths x race2) differs significantly in this model. It can, therefore, be concluded that, with regard to Indians, neither the regression line slope nor the intercept differs significantly from those of the Whites. Thus, the test does not have differential prediction at the first-year level.

In respect of the second academic year, the findings reported in Table 7 are noticeably similar to those for the first academic year. All t-values are non-significant, except for the interaction between the Race1 and AAT-maths results, which differ significantly (t-value=-2.042, $p<0.05$). The same conclusion can be drawn, namely that the AAT-maths test does provide differential predictions when the Black and White race groups are compared, but not when the Indian and White groups are compared.

The regression analysis for differential prediction was not repeated for the LPCAT and the ELSA, because the correlation statistics (see Table 6) were only statistically significant for the White race group and represent single group validity (see Young & Kobrin 2001: 4).

6. Recapitulation and conclusions

This study aimed to investigate the criterion-related validity of three cognitive and academic literacy tests as predictors of academic performance for students in the engineering field. This research contributes to the education literature by demonstrating the importance and effectiveness of additional selection measures as entry requirements into tertiary education. The study sample consisted of top-performing learners who were pre-selected, based on their school performance in mathematics, physical sciences and English language.

The AAT-maths, the ELSA and the LPCAT appear to be statistically significant predictors of the future academic performance of first- to third-year engineering students. In addition, the AAT-maths predicts academic performance at a statistically significant level at fourth-year level. Irrespective of the depressing effect of range restriction, the tests can be considered practically significant predictors (moderate to large effect sizes), especially at the first-year level. More specifically, the AAT-maths proved to be a strong significant predictor of academic performance for all year levels. It is clear that additional tests of academic literacy and learning potential can add prediction value over and above what school results can provide.

It was pointed out earlier that numerous educators have questioned the standard of OBE school results as a valid indicator of scholastic levels. This may explain why AAT-maths and the ELSA tests show incremental predictive validity for learners who had high marks in Grade 12. Another possible explanation may be found in school examination-preparation practices – schools are under enormous pressure to perform well in the national senior certificate examinations, so examination coaching is a common practice in schools (drilling learners on test content and using mock examinations to help students become test-wise). However, these practices are inclined to facilitate rote learning. Moreover, problem-solving skills are not always adequately assessed (Lubisi & Murphy 2002; Popham 2001: 16-20; Volante 2004). Consequently, the reduced predictive validity of school results as predictors of university academic performance is only to be expected (Volante 2004). When learners are required to do an independently developed test such as a mathematical reasoning test or an English language test, they are then confronted with a novel

situation where learners have to rely strongly on domain-specific problem-solving and knowledge-application skills.

When the LPCAT, the ELSA and the AAT-maths tests were combined in the regression model, the AAT-maths and the ELSA appeared to make a significant and unique contribution (little variance is shared by predictors) in predicting academic performance for the study sample at the first- and second-year study levels. However, the LPCAT did not make a significantly unique contribution in predicting academic performance in the regression model. These results confirm Lohman's (2005: 19) finding that the incremental validity of figural reasoning or non-verbal tests is low when they are used in combination with verbal and quantitative reasoning tests. Figural reasoning tests are good measures of fluid ability which contribute strongly toward general cognitive ability (G-factor). Lohman (2005: 19) argues that readiness for a particular educational opportunity does not reside so much in the students' innate or fluid ability as it does in their level of knowledge, skills and crystallised ability to reason in the symbol system of particular study domains. However, Lohman (2005: 113) suggests that non-verbal tests should be considered in conjunction with verbal and quantitative abilities and achievement if the test candidates are not adequately proficient in English.

It is evident from the results of this study that the AAT-maths test is the best predictor of academic performance for engineering studies, compared to the ELSA and LPCAT. These results confirm Eiselen et al.'s (2007) finding that mathematical skill tests are the best predictors for success at the tertiary level in general.

Race differences in respect of the predictor and criterion variables were apparent with regard to the reported descriptive statistics. The differences between the mean scores on the predictors indicate that the Black population sample group is less likely to be selected if the common cut-off values for the different groups apply. In terms of academic performance, a similar trend was observable, but to a lesser extent. On average, the Black learners are less likely to perform at the same academic level as their Indian and White counterparts. These findings have significant implications for selection practices and should be dealt with in a fair, equitable and sensitive manner.

The correlation and regression analysis revealed that the LPCAT, the AAT-maths and the ELSA have possible differential predictive validity for the different race groups. This can be ascribed to differential test functioning (test bias) or criterion contamination. The AAT-maths does not predict differentially for the Indian and White groups. The students' results were obtained from different tertiary institutions, so a range of contaminating factors might have had an influence on the criterion. These may include unexplained variances that should be ascribed to differences in the course content, structure, presentation and assessment at different universities. Cascio & Aguinis (2005a) suggest that criterion contamination occurs when the operational or actual criterion includes discrepancies that are not related to the definitive criterion. In particular, the differential treatment (for example, in the form of bridging programmes, academic development programmes and course interventions) of at-risk students could depress the correlation coefficient between the predictor and criterion variables. In this instance, depressed correlation coefficients would signify the success of the interventions. Thus, the reason for differential validity may reside either with the predictor or with the criterion and should be investigated further before final conclusions can be reached.

The practical implications of these findings emphasise the relevance of including additional measures over and above school marks in the selection of engineering bursary students. Although there may be an overlap between what school examinations measure and what is conceptually measured by the tests included in this study, the overlap does not appear to be large enough to cover the unique contribution that tests make in predicting performance in engineering studies. Currently, the need for additional proficiency tests in South Africa for the purpose of bursary student selection cannot be overemphasised. Given the expense involved to the student, the tertiary institution and a company supporting the students, in terms of finance, time and effort, valid predictors of academic performance should be in place for the effective selection of promising engineering students (Scholtz & Allen-Ile 2007).

In practice, the effect of group-related differential mean scores on tests and academic performance should be dealt with appropriately in order to reduce any possible adverse impact. Provided that there is no

evidence of test differential validity, the practice of in-group rankings and/or an uncommon cut-off score for predicting academic success should be considered to counter the possible effect of the adverse impact caused by tests (Cascio & Aguinis 2005b; Lohman 2005: 111). The extent to which universities can support students at risk should be a consideration in determining uncommon cut-off scores for the groups. Test users cannot assume that tests are insensitive to group differences (differential validity), unless this is proven to be the case. In this study, the findings point towards differential validity which could be attributed to the differential functioning of the tests, or the criterion, or both.

Overall, it can be concluded that the assessment battery used in this study does have predictive validity in predicting the academic performance of engineering students at a tertiary level. The results of this study indicate that the AAT-maths test has the best predictive characteristics, compared to the ELSA and LPCAT tests. This supports the argument that the best predictors of future achievement in a domain are current achievement in that domain, and the ability to reason in the symbol system(s) used to communicate new knowledge in that domain (Lohman 2005: 111).

7. Limitations and recommendations

The limitations for this study reside first, in score range restriction and the effect thereof in depressing correlations coefficients. Range restriction resulted from the pre-selection of students based on scholastic performance and based on the AAT-maths, ELSA and LPCAT test results. Secondly, criterion contamination was evident due to the composite score calculated for academic results across the different universities, different curricula and different subjects. Thirdly, the sample sizes for the race groups were not representative of the population demographics of South Africa, thereby compromising the generalisability of the results. Finally, the reason for the differential prediction validity of the tests in respect of race groups calls for further enquiry.

Suggestions for further research include the need to do analyses per university and course module using adequate sample sizes, thereby reducing criterion contamination. If it is possible to reduce criterion

contamination that leads to irrelevant score variances, more accurate statistics can be reported. In addition, information on university remedial programmes for 'at-risk' engineering students or related interventions should be investigated in order to increase understanding of the factors that may contaminate criterion measures.

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