Computing, Information Systems, Development Informatics & Allied Research Journal
ISBN 978-2257-44-7(Print) ISSN 2167-1710 (online)
Vol. 4. No. 2, 2013 – www.cisdijournal.net

www.iiste.org

CULTURAL FACTORS AS PREDICTORS OF COGNITIVE TEST PERFORMANCE IN INFORMATION SYSTEMS AND TECHNOLOGY EDUCATION

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ABSTRACT
A scan of the international literature suggests the existence in various countries of a persistent culture-based academic performance gap across various subjects, including computer science, and at different levels of education. Almost two decades after the formal demise of Apartheid, this study seeks to investigate whether a culture-based academic achievement gap similarly persists in the South African university classroom in the field of information and systems technology. This study sought to identify whether performance gaps exist between students of different races, home languages and genders in information systems and technology education at a South African university. Pre- and post- assessments were conducted with first year information systems and technology students at the University of KwaZulu-Natal in respect of three separate courses (Databases, Networks, Spreadsheets) attended by the same sample of students during the first semester in 2011. Multiple regression analyses were conducted to identify the extent to which the various independent variables (such as race, home language and gender) contributed to the variance of the dependent variables (improvement (gain) score and post test score). The findings when using post-test scores as the dependent variable suggested that there were significant culture-based differences in cognitive performance among first year South African university students in information systems and technology education. However, there were no significant differences in performance improvement (gain) scores on cognitive testing for the same sample. While Black students were significantly out-performed in terms of test scores, there were no significant differences in the extent to which students improved their marks over the period of the study (one entire semester). In fact, Black students improved by a slightly better margin than the Indian students, despite their raw test scores being lower than those for their Indian counterparts. This suggests that despite their disadvantaged educational background, Black students are able to respond as effectively as more advantaged students to an equalised educational context once the 'playing fields are levelled at university.

1. INTRODUCTION

Culture defined

Definitions of culture abound and are as varied as the concept they attempt to define. Markus (2008) identifies the many divergent views and opinions in the literature of various academic disciplines in attempting to define and distinguish concepts such as 'race', 'ethnicity' and 'culture'. It is certainly beyond the scope of this discussion to argue the merits of one definition over another and indeed that will not be attempted here. For the purposes of this study and in the interests of ensuring clear interpretation of the data present herein, it is worth clarifying at the outset that, with due respect to the complex definitions presented by social and differential psychologists, any reference made to 'culture' in this discussion is limited in meaning to any combination of race (used interchangeably and synonymously herein with 'ethnicity'), home language and gender. Takooshian (2010) supports this inclusion of gender, race and home language as legitimate parts of a definition of culture and refers to seminal authors in the field of differential psychology who included these and many other aspects of the human condition in their definitions of what constitutes 'culture' (Anastasi, 1954; Cohen, 2009).

1.1 A scan of international literature

A review of international research reveals that there is no shortage of evidence of a culture-based performance gap in academic performance. This performance gap appears to persist across a variety of levels of education and subjects. For example, Sheehan and Marcus (1977) point out that research into differences in academic performance among ethnic groups in the American elementary school system consistently shows ethnicity-based disparities in achievement results. Dunn et al. (1990) identified culture-based variations in both learning preference and achievement among African-American, Chinese-American, Greek-American and Mexican-American fourth, fifth and sixth grade pupils in the United States on the Group Embedded Figures Test. However, this disparity in the United States is not limited to school students. A study conducted at the University of Davis, California, compared 6,720 Physics students and identified statistically significant performance differences between various ethnic and gender groupings (Calder & Ashbaugh, 2005). In this study, males scored higher than females across all ethnicities.

Similarly, Stockly (2009) investigated performance data for more than 5,000 University of Texas Economics students and found significant variance along racial lines. Other studies find a similar trend in the Texas school system and note that since desegregation in the 1960s, the race based performance gap in the classroom has not improved significantly (Hanushek & Rivkin, 2009; Neal, 2006). Demonstrating how prolific research has been on this subject, Wiggan (2008) refers to the 'achievement gap narrative' in the literature and cites various studies in the United States that identify a performance deficit between various ethnic groups. Wiggan goes on to consider the experiences of higher achieving minority students with the objective of providing some useful insights into what can be done to close the performance gap. Like many other researchers in this field, Wiggan refers briefly to 'nature' based theories that attempt to explain the race based differences in performance levels , but then focuses on environmental issues such as discrimination in the classroom, socio-economic differences between ethnicities in America and on what he refers to as 'oppositional identity', which he defines as the tendency of minority students to perceive the educational institution as a means of perpetuating the status quo for the dominant majority.

It is suggested in Wiggan's study that students can (as exemplified by the high achieving minority students he interviews) overcome this challenge by developing an 'engagement' paradigm in respect of their perceptions of and interaction with teachers. Moreover, Wiggan points out that 'teacher practices' are perceived to be the most influential factor affecting performance, thus suggesting that performance can be improved by varying these strategies (Wiggan, 2008). Evidence of a race based academic performance gap is not limited to the United States. Richardson (2009) researched the performance of Open University graduates in the United Kingdom and found that the attainment of ethnic minority groups tended to be lower (in terms of the class of honours attained). This trend was most pronounced in the distance learning programmes and was found to be true despite there not being disparity in terms of demographic variables (such as socio-economic factors, age or subject of study) among the students being compared. Moreover, in this particular study, it was found that the these differences in performance levels were not concomitant with a qualitatively inferior educational experience for any given group of students (Richardson, 2009).

Various other studies conducted in the United Kingdom report similar results. For example, Leslie (2005) quotes the Higher Education Statistics Agency (HESA) for the period 1998-2000 and points out that minority ethnic groups lagged significantly behind other groups in respect of the number of students graduating with an upper second or better in universities in the United Kingdom. Connor (1996) identifies a similar trend and reports disparities in achievement among Black, Indian and Chinese students. Naylor and Smith (2004) report that the probability of ethnic minority students attaining lower results was higher than for other groupings, even after demographic variables were controlled (based on their analysis of data for 1998 in the United Kingdom).

1.2 Culture and computer science

The challenges related to multicultural education are as prevalent in the field of computer science education as in any other field. The international literature abounds with discussion around race and gender differences in academic achievement and experiences of students in information technology education (Badat, 2010; Crombie, Abarbanel, & Anderson, 2000; Crombie, Abarbanel, & Trinneer, 2002; DuBow, 2011; Fisher & Margolis, 2002; Kafai, 1998; Katz, Aronis, Allbritton, Wilson, & Soffa, 2003; Kirkup, Zalevski, Maruyama, & Batool, 2010; Moorman & Johnson, 2003; Payton, 2003). Research indicates that females and minorities continue to be under-represented in information technology related employment and programmes of study in various countries of the world, including the United States (DuBow, 2011), the United Kingdom (Kirkup, et al., 2010) and South Africa (Badat, 2010; ISETT SETA, 2010). For example in the United States, females and minority groups such as African-Americans, Hispanics and American Indians have consistently been under-represented in computer and information science degrees (Margolis, 2001).

This has inevitably led to under-representation of these same groups in the information technology (IT) workforce. According to the U.S. Bureau of Labor Statistics, there are projected to be about 1.4 million jobs related to computer and information technologies in America by 2018, which represents a growth of 22% over 2008 figures and is higher than for any other occupation (DuBow, 2011). Women and minority groups are currently poorly represented in this growing computing-related workforce and there is no evidence that this state of affairs is projected to change for the better in the near future. Table 1, for example, shows the dramatic downward trend of percentages of women employed in computing related occupations in the United States since 2000. The most recent figures available show that of the 897,000 women employed in computing related occupations in the United States, 69% are White, 16% are African-American, 9% are Asian/Pacific Islander and 6% are Latina/Hispanic (DuBow, 2011).

Table 1 Female percentage employed in computing-related occupations in the United States, 2000-2009

Occupation	2000	2005	2009
Operations research analysts	51%	50%	47%
Database administrators	43%	33%	35%
Computer support specialists	35%	33%	27%
Computer scientists and systems analysts	34%	30%	27%
Network systems and data communications analysts	25%	25%	25%
Computer programmers	26%	26%	20%
Network and computer systems administrators	23%	19%	22%
Computer software engineers	24%	22%	20%
Computer hardware engineers	22%	11%	9%

Source: (DuBow 2011)

This decline in diversity in the IT workforce is ironic, since reports suggest that technology companies with the highest representation of women in their senior management teams showed a higher return on equity than did those with fewer or no women in these roles. A recent study showed that diversity (both in terms of gender and race) was associated with increases in sales revenue, customers and profits (Herring, 2009). Despite the increasing demand for more skilled IT professionals in the United States, the number of graduates in related degrees is decreasing. Moreover, not only has the total number of university graduates in the field of computer or information sciences in the United States steadily declining, female and minority representation in this field of study remains disproportionately low (DuBow, 2011). For example, in 2009, while women earned 57% of all undergraduate degrees in the United States, only 18% of all computer and information sciences undergraduate degrees were earned by women. Of these 6,966 women, 48% were White, 19% were African-American, and the remainder was made up various other ethnic minorities (DuBow, 2011).

The gender and race disparities also exist at secondary school level. This is illustrated by the demographics of students taking the Advanced Placement (AP) Computer Science exam in the United States. The College Board (The College Board, 2012) reports that of the students taking the Computer Science exam in 2011, 55.4% were White, 4.6% were African-American and the remainder represented various other ethnic minorities. In terms of gender, 19% were female and 81% were male. A considerable amount of research has been undertaken to unearth the reasons for these gender and race disparities. For example, research suggests that females tend to view the computer science field as 'male dominated' and that both the curriculum and the culture of computer science is such that women feel they would succeed in this arena only if they modeled themselves after the 'stereotypical male computer science student' (Fisher & Margolis, 2002; Moorman & Johnson, 2003).

Interestingly, various experiments with female only computer science classes to attempt to address these issues of perceived male dominance have met with some success in terms of encouraging increased participation by females and in increasing their sense of confidence on computer science courses (Crombie, et al., 2000; Crombie, et al., 2002; Moorman & Johnson, 2003). Research suggests that these findings on female disaffection from computer science courses also appear to hold true for minority groupings. For example, Payton (2003) found that, like their female compatriots, African-American students tended to avoid computer and information science majors.

Culture- based disparities (including those related to gender and race) in academic performance, which is a requisite for retention in computer and information science courses, further exacerbate this under-representation in the IT workplace. A variety of studies have explored the factors that influence academic performance in IT related education with a view to identifying ways to close the culture-based achievement gap. This research has identified a number of different factors that predict achievement in university IT courses, including experiential, affective, personality and cognitive factors. Examples of such factors include simply owning a computer (Taylor & Mounfield, 1994), having access to and using computers in high school (Kagan, 1988), some experience (even if it is informal 'playing') in computer programming (Koohang & Byrd, 1987), confidence levels, self-efficacy and aptitudes related to mathematics, spatial and verbal reasoning (Cafolla, 1987; Clement, Kurland, Mawby, & Pea, 1986; Jagacinski, LeBold, & Salvendy, 1988; Webb, 1984).

Interestingly, despite the gender disparities in representation in the IT workforce and in computer related educational programmes, the literature does not find decisively that women perform worse than males in terms of IT related academic achievement. For example, a number of studies involving gender comparisons of academic achievement in programming related courses have found that female students perform as well, if not better, than male students, both in the pre-university and undergraduate context (Kafai, 1998; Margolis, 2001; Taylor & Mounfield, 1994; Volet & Styles, 1992).

Katz et al. (2003) investigated race and gender as predictors of computer science achievement (Perl programming) among computer and information science students at a multi-cultural university in the United States. Whites and Asians were grouped in that study and identified as the 'majority', while African-American students were viewed as the 'minority'. The dependent variables used in this study were improvement (gain) score and course grade and showed significant gender and race related differences in programming performance. In respect of gender differences, Katz et al. (2003) found partial support in the findings of their study for the findings of other studies which reveal gender differences in software use and development in respect of such factors as 'experimentation' and 'programming play' (Kafai, 1998; Margolis, 2001). Race differences in performance were also found in this study. Katz et al. (2003) quote Light (2001) in arguing that simply providing minorities with access to technology is unlikely to resolve the culture-base performance disparities they found and that they believe are rooted in complex issues of social inequality, pointing out that the African-American students that participated in their study had reported adequate access to computers during pre-college years. Katz et al. (2003) suggest that the minority students entered the course ill-prepared in terms of mathematics, verbal and basic programming skills, which the study showed were predictive of performance, and that better preparation in these skills is a major part of the solution.

Turning to South Africa specifically, the ISETT SETA's Sector Skills Plan 2011-2016 suggests that the ICT sector is expected to grow significantly over the next few years by about 5% per annum. This growth is expected to coincide with a concomitant demand for more ICT professionals. This may at first glance appear encouraging. However, the demand is for highly specialised skills and, as reported in the ISETT SETA's Sector Skills Plan 2011-2016, the major employers of ICT skills continue to lament, not only the shortage of skills, but also the poor quality of ICT graduates coming from the institutions of higher learning (ISETT SETA, 2010). Given the government's stated objectives of 85% Black and 54% female representation in the ICT sector's workforce (and the fact that current employment figures are nowhere near that target), there is a need for urgent attention to be paid to addressing the issues that prevent Black and female students from achieving their full potential in the ICT classrooms and meeting the critical need for well qualified entrants to the workplace (ISETT SETA, 2010).

An important first step in addressing this issue is describing the nature of the culture-based performance gap in information systems and technology education.

2. RESEARCH DESIGN AND METHODOLOGY

Research Objective and Questions
This study seeks to Identify whether performance gaps exist between students of different races, home languages and genders in information systems and technology education at a South African university, and explores the following research questions:

Research question 1 (RQ1):
"Are cultural factors predictors of cognitive test performance in information systems and technology education?"

Sub-question 1.1 (SQ1.1):
"Is race a predictor of cognitive test performance in information systems and technology education?

Sub-question 1.2 (SQ1.2):
"Is home language a predictor of cognitive test performance in information systems and technology education?"

Sub-question 1.3 (SQ1.3):
"Is gender a predictor of cognitive test performance in information systems and technology education?"

2.1 Research Approach

In addressing the research objective and questions described above, a census was attempted in terms of collecting data from all first year students enrolled for Information Systems and Technology at the University of KwaZulu-Natal, South Africa, and in respect of three different courses, each with a different lecturer. Each course was taught by a different lecturer with a specific demographic in terms of race, home language and gender, allowing for analysis of potential linkages between teacher student match/mismatch and performance scores. Of the 1,157 students enrolled in the first year programme, 496 chose to participate as part of the cognitive testing sample for Course A (Databases), 474 participated in the Course B (Networks) sample, and 509 participated in the Course C (Spreadsheets) sample.

To measure cognitive test performance, pre- and post- training assessment tests were developed to assess the students' cognitive learning in respect of each of the three courses' subject matter. These assessment tests took the form of multiple choice questionnaires, an assessment approach not uncommon in the field of Information Systems and Technology when assessing technical skills (Roberts, 2006). Ten multiple choice questions with mutually exclusive options were presented for each of the three subject areas, based upon the course content for the semester. Three separate pre-tests were administered to each student for each of the three courses in advance of any lectures taking place. Post-tests (the same instrument) were subsequently administered immediately after completion of the lecture period for each course (at the end of the semester in this case). For each course, each student's pre-test score was then subtracted from the post test score to obtain an 'improvement score'. Analysis of the data was conducted on two fronts:

1. Using post-test score as the dependent variable;
2. Using Improvement score as the dependent variable.

Table 2 Demographics of research sample (cognitive testing)

		Course A (Databases)		Course B (Networks)		Course C (Spreadsheets)	
		Students	**Lecturer**	**Students**	**Lecturer**	**Students**	**Lecturer**
Gender	**Male**	204	Male	195		212	Male
	Female	292		279	Female	297	
Race	**Black**	131		129	Black	136	
	Coloured	6		7		7	
	Indian	348	Indian	328		355	Indian
	White	10		9		10	
	Other	1		1		1	
Home Language	**English**	367		346		375	English
	Xhosa	6		6	Xhosa	6	
	Zulu	118		118		123	
	Swazi	2		1		2	
	Tswana	1		1		1	
	Venda	1		1		1	
	Other(Student)	1		1		1	
	Other(lecturer)		Other				

3. DATA ANALYSIS MODELS

A variety of data analysis models are used in the international studies conducted to date on the subject of culture-based performance predictors. For example, while Sheehan used multiple regression to investigate the impact of teacher student race congruence on vocabulary and mathematics achievement, Stroter favours Hierarchical Liner Modeling to address the multi-level nature of her data (Sheehan & Marcus, 1977; Stroter, 2008). Zhang uses three different models of varying levels of statistical stringency on the same data set in the form of Zero-Order Correlations, multiple regression and Hierarchical Multiple Regression in his study on learning style congruence as a predictor of cognitive performance (Zhang, 2006). In line with international studies of a similar nature (such as those referred to in the foregoing), this study uses a multiple regression model to identify the extent to which the various independent variables (such as race, home language and gender) contribute to the variance of the dependent variables (improvement and post test scores).

Multiple regression

Multiple regression is an accepted and widely used statistical method that is employed to account for (predict) the variance in an interval dependent variable, based on linear combinations of interval, dichotomous or dummy independent variables.

The model identifies which independent variables significantly contribute to the variance of the dependent variable and can also provide the relative predictive importance of the independent variables. In the case of this study, the dependent variable is improvement score – an interval scale variable. The independent variables are the dichotomous match/mismatch variables. Pre-test score is used as a covariate. While the analysis of an improvement (gain) score is a measure of the post-test score relative to the pre-test score, it does not take into account differences in pre-test scores. Clearly, a person with a low pre-test score has the potential to achieve a higher improvement score than one with a high pre-test score.

Computing, Information Systems, Development Informatics & Allied Research Journal
ISBN 978-2257-44-7(Print) ISSN 2167-1710 (online)
Vol. 4. No. 2, 2013 – www.cisdijournal.net

The interpretation of an analysis on a gain score can be problematic when differences in pre-test scores exist. Therefore, it is important to include the pre-test score as a covariate as this controls for the effect of the pre-test which co-varies with the dependent variable.

In respect of the regression process utilised in this analysis, the following assumptions were made:

- **Independence**: Keeping the classes for each course separate adequately addressed this condition.
- **Normality**: Once the outliers (all subjects with an Improvement score of -40 or less) were removed, problems relating to normality were eliminated. Checks were made by plotting histograms of the standard residuals as well as measuring Skewness and Kurtosis. These measurements all fell well within the accepted interval of [-1; +1].
- **Homoscedasticity**: Plots of the residuals were examined to ensure that the variance of the residuals was constant for all values of the independents.
- **Linearity**: The rule of thumb for regression was used for this analysis to test for linearity. i.e. the standard deviation of the dependent must be greater than the standard deviation of the residuals.
- **Proper specification of the model**: In each case, variables added to the model were checked for correlation with other independents. Multicollinearity (excessively high correlation) among independents was tested using the Tolerance and VIF tests.

4. RESULTS

The sample comprised three separate first year IS&T courses conducted in the first semester at the University of KwaZulu-Natal relating to the topics of Databases, Networks and Spreadsheets- referred to in the analysis as Course A, Course B and Course C respectively. The same students were represented across all three courses and separate analyses were conducted for each course.

Table 3 Summary of cognitive test data by race, home language and gender

		Race			**Home Language**		**Gender**	
		Black	**Indian**	**Other**	**African**	**English**	**Male**	**Female**
Course A	Pre Test Score	48.40	52.79	54.12	48.06	52.94	53.19	50.62
(Databases)	Post Test Score	66.41	70.86	69.41	65.97	70.93	71.32	68.46
	Improvement Score	18.01	18.07	15.29	17.91	17.98	18.14	17.84
Course B	Pre Test Score	51.86	67.20	66.47	51.56	67.23	65.33	61.36
(Networks)	Post Test Score	58.60	73.26	71.18	58.36	73.21	72.21	67.10
	Improvement Score	6.74	6.07	4.71	6.80	5.98	6.87	5.73
Course C	Pre Test Score	42.72	48.93	49.44	42.54	48.99	48.82	46.20
(Spreadsheets)	Post Test Score	54.41	60.23	60.00	54.25	60.24	60.38	57.44
	Improvement Score	11.69	11.30	10.56	11.72	11.25	11.56	11.25
Average	Pre Test Score	47.66	56.31	56.68	47.39	56.39	55.78	52.73
(All Courses)	Post Test Score	59.81	68.12	66.86	59.53	68.13	67.97	64.33
	Improvement Score	12.15	11.81	10.19	12.14	11.74	12.19	11.61

The following presents detailed race, home language and gender results per course:

Course A (Databases):
The tables below present the results obtained for Course A (Databases) in respect of student gender, race and home language.

Table 4 Course A: Sample statistics (student gender)

	Student Gender	N	Mean	Std. Deviation	Std. Error Mean
Pre Test Score	Male	204	53.19	18.225	1.276
	Female	292	50.62	17.556	1.027
Post Test Score	Male	204	71.32	18.852	1.320
	Female	292	68.46	18.031	1.055
Improvement Score	Male	204	18.14	22.294	1.561
	Female	292	17.84	21.293	1.246

Notes: The above scores were not significantly different for the different genders.

Table 5 Course A: Sample statistics (student race)

Student Race		Pre Test Score	Post Test Score	Improvement Score
Black	Mean	48.40	66.41	18.01
	N	131	131	131
	Std. Deviation	20.146	18.525	23.285
White	Mean	55.00	76.00	21.00
	N	10	10	10
	Std. Deviation	13.540	22.706	17.288
Indian	Mean	52.79	70.86	18.07
	N	348	348	348
	Std. Deviation	17.043	17.832	21.136
Coloured	Mean	51.67	65.00	13.33
	N	6	6	6
	Std. Deviation	11.690	28.810	20.656
Other	Mean	60.00	30.00	-30.00
	N	1	1	1
	Std. Deviation			
Total	Mean	51.67	69.64	17.96
	N	496	496	496
	Std. Deviation	17.861	18.408	21.688

Table 6 Course A: Sample statistics (student race)- grouped to exclude minor race groups

	Student Race	N	Mean	Std. Deviation
Pre Test Score	Black	131	48.40	20.146
	Indian	348	52.79	17.043
	Other	17	54.12	12.277
	Total	496	51.67	17.861
Post Test Score	Black	131	66.41	18.525
	Indian	348	70.86	17.832
	Other	17	69.41	26.094
	Total	496	69.64	18.408
Improvement Score	Black	131	18.01	23.285
	Indian	348	18.07	21.136
	Other	17	15.29	21.248
	Total	496	17.96	21.688

*Notes:*Post-test and improvement scores were not significantly different

Table 7 Course A: Sample statistics (student home language)

Student Home Language		Pre Test Score	Post Test Score	Improvement Score
English	Mean	52.94	70.93	17.98
	N	367	367	367
	Std. Deviation	16.907	18.294	21.097
Zulu	Mean	47.71	65.93	18.22
	N	118	118	118
	Std. Deviation	20.482	18.362	23.665
Xhosa	Mean	51.67	71.67	20.00
	N	6	6	6
	Std. Deviation	14.720	18.348	26.077
Swazi	Mean	55.00	65.00	10.00
	N	2	2	2
	Std. Deviation	21.213	21.213	.000
Tswana	Mean	60.00	80.00	20.00
	N	1	1	1
	Std. Deviation			
Venda	Mean	50.00	40.00	-10.00
	N	1	1	1
	Std. Deviation			
Other	Mean	40.00	50.00	10.00
	N	1	1	1
	Std. Deviation			
Total	Mean	51.67	69.64	17.96
	N	496	496	496
	Std. Deviation	17.861	18.408	21.688

Table 8 Course A: Sample statistics (student home language)- grouped to exclude minor race groups

Student Home Language		N	Mean	Std. Deviation	Std. Error Mean
Pre Test Score	African	129	48.06	19.964	1.758
	English	367	52.94	16.907	.883
Post Test Score	African	129	65.97	18.308	1.612
	English	367	70.93	18.294	.955
Improvement Score	African	129	17.91	23.374	2.058
	English	367	17.98	21.097	1.101

Notes:

- Significant differences existed between home language groups for the pre-test (p=.014) and the post-test (p=.008) with English speakers performing better in all cases.
- There were no significant differences for the improvement scores.

Computing, Information Systems, Development Informatics & Allied Research Journal
ISBN 978-2257-44-7(Print) ISSN 2167-1710 (online)
Vol. 4. No. 2, 2013 – www.cisdijournal.net

Course B (Networks):

The tables below present the results obtained for Course B (Networks) in respect of student gender, race and home language.

Table 9 Course B: Sample statistics (student gender)

	Student Gender	N	Mean	Std. Deviation	Std. Error Mean
Pre Test Score	Male	195	65.33	19.878	1.423
	Female	279	61.36	19.935	1.193
Post Test Score	Male	195	72.21	17.521	1.255
	Female	279	67.10	19.577	1.172
Improvement Score	Male	195	6.87	18.940	1.356
	Female	279	5.73	19.213	1.150

Notes:

- Significant differences existed for males and females for the pre-test (p=0.033) and post-test (p=0.004) scores with males performing better in all cases.
- There were no differences for the improvement scores.

Table 10 Course B: Sample statistics (student race)

Student Race		Pre Test Score	Post Test Score	Improvement Score
Black	Mean	51.86	58.60	6.74
	N	129	129	129
	Std. Deviation	21.678	21.677	20.848
White	Mean	71.11	73.33	2.22
	N	9	9	9
	Std. Deviation	21.473	15.000	13.944
Indian	Mean	67.20	73.26	6.07
	N	328	328	328
	Std. Deviation	17.576	16.256	18.542
Coloured	Mean	60.00	68.57	8.57
	N	7	7	7
	Std. Deviation	16.330	10.690	20.354
Other	Mean	70.00	70.00	.00
	N	1	1	1
	Std. Deviation	.	.	.
Total	Mean	63.00	69.20	6.20
	N	474	474	474
	Std. Deviation	19.987	18.908	19.089

Table 11 Course B: Sample statistics (student race)- grouped to exclude minor race groups

	Student R	N	Mean	Std. Deviation
Pre Test Score	Black	129	51.86	21.678
	Indian	328	67.20	17.576
	Other	17	66.47	19.020
	Total	474	63.00	19.987
Post Test Score	Black	129	58.60	21.677
	Indian	328	73.26	16.256
	Other	17	71.18	12.690
	Total	474	69.20	18.908
Improvement Score	Black	129	6.74	20.848
	Indian	328	6.07	18.542
	Other	17	4.71	16.247
	Total	474	6.20	19.089

Notes:

- Significant differences existed for the different races for the pre-test (p<.0005) and post-test (p<.0005) scores. For both pre- and post-scores, the Black scores were significantly less than the other race group scores.
- There were no significant differences for the improvement scores.

Table 12 Course B: Sample statistics (student home language)

Student Home Language		Pre Test Score	Post Test Score	Improvement Score
English	Mean	67.23	73.21	5.98
	N	346	346	346
	Std. Deviation	17.639	16.092	18.393
Zulu	Mean	50.76	57.03	6.27
	N	118	118	118
	Std. Deviation	20.925	21.694	20.581
Xhosa	Mean	66.67	71.67	5.00
	N	6	6	6
	Std. Deviation	17.512	14.720	16.432
Swazi	Mean	50.00	70.00	20.00
	N	1	1	1
	Std. Deviation	.	.	.
Tswana	Mean	90.00	80.00	-10.00
	N	1	1	1
	Std. Deviation	.	.	.
Venda	Mean	.00	70.00	70.00
	N	1	1	1
	Std. Deviation	.	.	.
Other	Mean	70.00	90.00	20.00
	N	1	1	1
	Std. Deviation	.	.	.
Total	Mean	63.00	69.20	6.20
	N	474	474	474
	Std. Deviation	19.987	18.908	19.089

Table 13 Course B: Sample statistics (student home language)- grouped to exclude minor race groups

Student Home Language		N	Mean	Std. Deviation	Std. Error Mean
Pre Test Score	African	128	51.56	21.497	1.900
	English	346	67.23	17.639	.948
Post Test Score	African	128	58.36	21.582	1.908
	English	346	73.21	16.092	.865
Improvement Score	African	128	6.80	20.921	1.849
	English	346	5.98	18.393	.989

Notes:

- Significant differences existed between home language groups for the pre-test ($p<.0005$) and the post-test ($p<.0005$) with English speakers performing better in all cases.
- There were no significant differences for the improvement scores.

Course C (Spreadsheets):

The tables below present the results obtained for Course C (Spreadsheets) in respect of student gender, race and home language.

Table 14 Course C: Sample statistics (student gender)

	Student Gender	N	Mean	Std. Deviation	Std. Error Mean
Pre Test Score	Male	212	48.82	15.998	1.099
	Female	297	46.20	16.275	.944
Post Test Score	Male	212	60.38	16.575	1.138
	Female	297	57.44	13.956	.810
Improvement Score	Male	212	11.56	18.827	1.293
	Female	297	11.25	18.088	1.050

Notes:

- Significant difference between male and female for the post-test score ($p = 0.036$).

Computing, Information Systems, Development Informatics & Allied Research Journal
ISBN 978-2257-44-7(Print) ISSN 2167-1710 (online)
Vol. 4. No. 2, 2013 – www.cisdijournal.net

Table 15 Course C: Sample statistics (student race)

Student Race		Pre Test Score	Post Test Score	Improvement Score
Black	Mean	42.72	54.41	11.69
	N	136	136	136
	Std. Deviation	16.396	15.385	18.199
White	Mean	51.00	64.00	13.00
	N	10	10	10
	Std. Deviation	16.633	15.776	13.375
Indian	Mean	48.93	60.23	11.30
	N	355	355	355
	Std. Deviation	15.926	14.766	18.656
Coloured	Mean	48.57	54.29	5.71
	N	7	7	7
	Std. Deviation	10.690	16.183	17.182
Other	Mean	40.00	60.00	20.00
	N	1	1	1
	Std. Deviation	.	.	.
Total	Mean	47.29	58.66	11.38
	N	509	509	509
	Std. Deviation	16.196	15.156	18.381

Table 16 Course C: Sample statistics (student race)- grouped to exclude minor race groups

	Student	N	Mean	Std. Deviation
Pre Test Score	Black	136	42.72	16.396
	Indian	355	48.93	15.926
	Other	18	49.44	13.921
	Total	509	47.29	16.196
Post Test Score	Black	136	54.41	15.385
	Indian	355	60.23	14.766
	Other	18	60.00	15.718
	Total	509	58.66	15.156
Improvement Score	Black	136	11.69	18.199
	Indian	355	11.30	18.656
	Other	18	10.56	14.742
	Total	509	11.38	18.381

Notes:

- Significant differences existed for different races for the pre-test (p=.001) and post-test (p=.001) scores. For both pre- and post-scores, the Black score was significantly less than the Indian score.
- There were no significant differences for the improvement scores.

Table 17 Course C: Sample statistics (student home language)

Student Home Language		Pre Test Score	Post Test Score	Improvement Score
English	Mean	48.99	60.24	11.25
	N	375	375	375
	Std. Deviation	15.821	14.760	18.479
Zulu	Mean	41.79	53.74	11.95
	N	123	123	123
	Std. Deviation	16.448	15.063	18.137
Xhosa	Mean	51.67	65.00	13.33
	N	6	6	6
	Std. Deviation	7.528	18.708	15.055
Swazi	Mean	55.00	65.00	10.00
	N	2	2	2
	Std. Deviation	21.213	7.071	28.284
Tswana	Mean	70.00	60.00	-10.00
	N	1	1	1
	Std. Deviation	.	.	.
Venda	Mean	30.00	60.00	30.00
	N	1	1	1
	Std. Deviation	.	.	.
Other	Mean	40.00	20.00	-20.00
	N	1	1	1
	Std. Deviation	.	.	.
Total	Mean	47.29	58.66	11.38
	N	509	509	509
	Std. Deviation	16.196	15.156	18.381

Table 18 Course C: Sample statistics (student home language)- grouped to exclude minor race groups

Student Home Language		N	Mean	Std. Deviation	Std. Error Mean
Pre Test Score	African	134	42.54	16.346	1.412
	English	375	48.99	15.821	.817
Post Test Score	African	134	54.25	15.432	1.333
	English	375	60.24	14.760	.762
Improvement Score	African	134	11.72	18.169	1.570
	English	375	11.25	18.479	.954

Notes:

- Significant differences existed between home language groups for the pre-test ($p<.0005$) and the post-test ($p<.0005$) with English speakers performing best in all cases.
- There were no significant differences for the improvement scores.

5. SUMMARY OF FINDINGS

In line with the findings of various international studies, the data presented herein suggests strongly that there are significant culture-based differences in cognitive performance among first year South African university students in the field of Information Systems and Technology (Calder & Ashbaugh, 2005; Dunn, et al., 1990; Sheehan & Marcus, 1977; Stockly, 2009; Stroter, 2008; Wiggan, 2008). The following highlights some of the salient aspects of these findings related to race, home language and gender cognitive test performance:

Pre and post-test scores:

- The performance of Black students is shown to be poorer on average than that of Indian students in respect of raw test performance across all the information systems and technology courses for which the study was conducted. Black students scored an average of 47.66% on pre-tests, while their Indian counterparts scored 56.31% (i.e. Black students scored on average 8.65% lower on pre-testing than Indian students). The scores for post-tests are similar: Black students scored on average 8.31% less than Indian students.
- The results for each of the specific courses did not vary significantly and all reflected the same finding that Indian students scored higher marks in both pre and post testing than their Black counterparts.

- For Course A (Databases), race related differences in pre and post-test scores were not statistically significant, but Indians scored on average 4.39% higher than Black students on the pre-test and 4.45% higher on post-test. The results for Course B and C were statistically significant and showed a similar trend. For Course B (Networks), Indians scored an average of 15.14% more than Black students on the pre-test and 14.66% on the post-test. For Course C (Spreadsheets), Indians scored on average 6.21% more than Black students on pre-testing and averaged 5.82% more on the post-test.

Improvement (gain) scores:

- Interestingly, improvement (gain) scores presented a significantly different picture to the raw (pre and post-test) score results. Whereas the pre and post-test score results showed a clear disparity in performance levels between races and home languages, for example, improvement scores were not significantly different across race, home language or gender groupings (none of the results pertaining to improvement scores were statistically significant).
- Black students improved by an average of 12.15% while Indian students improved by 11.81% (a statistically insignificant difference of 0.34%).
- Similarly, African language speakers improved by an average of 12.14% compared with 11.74% for the English speaking students (a difference of only 0.4%).
- Males out-performed females by 0.59% on average across all courses.

6. DISCUSSION AND CONCLUSION

The analysis of the data for this study revealed an interesting difference in the results obtained when using the *post-test score* as a dependent variable and those for *improvement score* as the dependent variable.

When using *post-test score* as the dependent variable, each of the independent, culture-related variables (race, home language and gender) were indeed shown to be significant predictors of cognitive test performance. However, no statistically significant results were achieved when using *improvement score* as the dependent variable. In other words, no significant race, home language or gender differences in improvement score were found. On the other hand, there were significant differences in performance by race, home language and gender in terms of the raw pre and post-test results. For example, Black students scored on average 8.65% less on pre-tests than Indian students and 8.31% less on post-tests. African Language speaking students scored on average 8.6% less on post-tests than their Indian counterparts. In two of the three courses analysed, males out-performed females by a statistically significant margin.

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