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 information systems and technology. This study investigated whether, almost two decades after the formal demise of Apartheid, a culture-based academic achievement gap similarly persists in the South African university classroom in the field of information and systems technology. When using post-test scores as the dependent variable the findings showed significant culture-based differences in cognitive test performance. However, there were no significant differences in performance improvement (gain) scores on cognitive testing for the same sample. This suggests that previously disadvantaged students may be capable of responding as effectively as more advantaged students to an equalised educational context once the ‘playing fields are levelled’ at university.

CULTURE DEFINED

Definitions of culture abound and are as varied as the concept they attempt to define. Markus (2008) identifies the many divergent views 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).

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 & 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 found a similar trend in the Texas school system and noted that since desegregation in the 1960s, the race-based performance gap in the classroom has not improved (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 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 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 & 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).
The challenges related to multicultural education are as prevalent in the field of information systems and technology (IS&T) 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 IS&T 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 & Batoool, 2010; Moorman & Johnson, 2003; Payton, 2003).

Research indicates that females and minorities continue to be under-represented in IS&T 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. The percentage of women employed in computing related occupations in the United States since 2000 continues to decline. 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).

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 been 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 of various other ethnic minorities (DuBow, 2011).

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 modelled 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, 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 home language, 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.

Apart from the studies referred to in the foregoing that focus on race and gender factors, much of the culture-based academic performance gap literature relates to the impact of language related factors. For example, Howie and her associates at the University of Pretoria investigated the impact of second language learning on learner performance and found that learners whose home language was one of the African languages performed worst on language tests (Howie et al., 2008). Their discussion and conclusions on the results of the study focus on socio-economic explanations. They opine that South Africa’s ‘political heritage’, the inadequacy of resources in the schools these learners attended and the severity of the socio-economic context under which learning takes place explain the poor performance results. Similarly, the
superior performance of the English and Afrikaans home language speakers is explained with reference to the ‘diversity of quality imposed historically on the education system along race and language lines’ (Howie et al., 2008). It is important when discussing reasons for the performance gap in education to note that although English is the primary language in both commerce and higher education, it is the home language of only 8.2% of the population. On this note, De Wet et al. (2009) point out that not only did Apartheid create separate educational systems with inequalities in terms of factors such as resources and infrastructure, but it also effectively used language policy to perpetuate segregated learning.

Turning to South Africa specifically, the ISETT SETA’s Sector Skills Plan 2011-2016 suggests that the ICT sector is expected to grow 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.

RESEARCH DESIGN AND METHODOLOGY

Research Objective and Questions

This study sought to determine 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 explored 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?’

Research Approach

A pilot study was first conducted to ascertain the applicability, readability, credibility and reliability of the research instrument. The data collected from the pilot study were subject to strict reliability tests. Only those constructs passing the reliability tests were included in the main study. Data collected during the primary analysis were also subject to Cronbach’s Alpha test to measure internal consistency. Chi Squared tests were also conducted to determine the nature of the data obtained, and hence apply suitable statistical analyses. The pre- and post-assessment tests used were standard internationally tested and reliable instruments.
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 a public university in South Africa, and in respect of three different courses. 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.

Ethical Considerations
Strict ethical guidelines imposed by the host institution for this study, as well as the respondent institutions, were met. All respondents were informed of their rights and responsibilities and had to provide informed consent prior to participating. Students who were not willing to accept the conditions of participation, and hence did not sign the informed consent letter, were not included in the study. Additionally, informed consent and permission to conduct the research was obtained from the institutions. Respondents were informed that their responses would be used only in aggregate and it would not be possible to identify individuals from the research presented. All data collected is securely stored at the host institution for a period of five years for audit purposes.

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 Linear 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 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. 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. Multi-collinearity (excessively high correlation) among independents was tested using the Tolerance and VIF tests.

**RESULTS**

The sample comprised three separate first-year IS&T courses conducted in the first semester at a public university in South Africa 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 1 presents a summary of race, home language and gender performance for all courses.
Table 1:
Summary of cognitive test data by race, home language and gender

<table>
<thead>
<tr>
<th></th>
<th>Race</th>
<th></th>
<th>Home Language</th>
<th></th>
<th>Gender</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Black</td>
<td>Indian</td>
<td>Other</td>
<td>African</td>
<td>English</td>
<td>Male</td>
</tr>
<tr>
<td>Course A (Databases)</td>
<td>Pre-Test Score</td>
<td>48.40</td>
<td>52.79</td>
<td>54.12</td>
<td>48.06</td>
<td>52.94</td>
</tr>
<tr>
<td></td>
<td>Post-Test Score</td>
<td>66.41</td>
<td>70.86</td>
<td>69.41</td>
<td>65.97</td>
<td>70.93</td>
</tr>
<tr>
<td></td>
<td>Improvement Score</td>
<td>18.01</td>
<td>18.07</td>
<td>15.29</td>
<td>17.91</td>
<td>17.98</td>
</tr>
<tr>
<td>Course B (Networks)</td>
<td>Pre-Test Score</td>
<td>51.86</td>
<td>67.20</td>
<td>66.47</td>
<td>51.56</td>
<td>67.23</td>
</tr>
<tr>
<td></td>
<td>Post-Test Score</td>
<td>58.60</td>
<td>73.26</td>
<td>71.18</td>
<td>58.36</td>
<td>73.21</td>
</tr>
<tr>
<td></td>
<td>Improvement Score</td>
<td>6.74</td>
<td>6.07</td>
<td>4.71</td>
<td>6.80</td>
<td>5.98</td>
</tr>
<tr>
<td>Course C (Spreadsheets)</td>
<td>Pre-Test Score</td>
<td>42.72</td>
<td>48.93</td>
<td>49.44</td>
<td>42.54</td>
<td>48.99</td>
</tr>
<tr>
<td></td>
<td>Post-Test Score</td>
<td>54.41</td>
<td>60.23</td>
<td>60.00</td>
<td>54.25</td>
<td>60.24</td>
</tr>
<tr>
<td></td>
<td>Improvement Score</td>
<td>11.69</td>
<td>11.30</td>
<td>10.56</td>
<td>11.72</td>
<td>11.25</td>
</tr>
<tr>
<td>Average (All Courses)</td>
<td>Pre-Test Score</td>
<td>47.66</td>
<td>56.31</td>
<td>56.68</td>
<td>47.39</td>
<td>56.39</td>
</tr>
<tr>
<td></td>
<td>Post-Test Score</td>
<td>59.81</td>
<td>68.12</td>
<td>66.86</td>
<td>59.53</td>
<td>68.13</td>
</tr>
<tr>
<td></td>
<td>Improvement Score</td>
<td>12.15</td>
<td>11.81</td>
<td>10.19</td>
<td>12.14</td>
<td>11.74</td>
</tr>
</tbody>
</table>

**SUMMARY OF FINDINGS**

In line with the findings of various international studies, the data presented herein suggests strongly that there are important 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 was 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 were similar: Black students scored on average 8.31% less than Indian students.

The results for each of the specific courses did not vary much 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 posttest 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.

All of the Black students in this study spoke an African language as their home language and all of the Indian students spoke English as their home language. Given that home language and race are so closely related in the South African context, it is not surprising that the home language results closely reflected the race results. African language speakers scored an average of 47.39% on pre-testing and 59.53% on post-tests, whereas their English speaking counterparts scored 56.39% on pre-tests and an average of 68.13% on post-tests. English speaking students therefore out-performed African language speakers by an average of 9% on pre-tests and 8.6% on post-tests. All the results showing home language disparities in pre- and post-test performance for Course A, B and C were statistically significant.

There were differences in performance for males and females. Males out-performed females in every case and for every course, but only in the case of Course B and C was this by a statistically significant margin. On average, males scored 55.78% on pre-tests while females scored 52.73% (a difference of 3.05%). On post-tests males scored 67.97% and females scored 64.33% (a difference of 3.64%).

Improvement (gain) scores

Interestingly, improvement (gain) scores presented a 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 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% (the difference of 0.34% was not statistically significant). 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.

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 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.

It is interesting that while Black students were out-performed in terms of the 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 (12.15%) than the Indian students (11.81%), despite their raw test scores being more than 8% 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.

The results and outputs referred to in this paper refer specifically to race, home language and gender related gaps in academic performance in the IS&T discipline. It should be noted, however, that this represents only part of a larger study that investigates culture-based academic performance disparities and the impact on cognitive learning of various social learning strategies that address the challenges of the multicultural classroom (Denny & Maharaj, 2012). Taken in isolation, this may appear to be of limited value and even merely to reinforce stereotypes. However, when the outputs of this paper are considered in the context of the larger study that it is a part of, it becomes clear that the findings of this research have the potential for higher education practitioners to investigate new teaching and learning methods, strategies and plans to fill the cultural gaps that continue to plague the South African educational landscape (Denny & Maharaj, 2012). Unpacking notions of culture and teaching and learning is important in the context of South Africa’s inability to date to shed the demons of the past two decades after the demise of apartheid. It is sobering and important to ask and answer the question: ‘Twenty years into democracy, have we addressed the race, home language and gender-based academic performance gap?’ The fact that a study such as this that reports so starkly on the continued existence of a culture-based academic performance gap that it appears to ‘reinforce stereotypes’ should be unsettling for anyone concerned with the future of South African education.

Both the review of literature and the primary research and analysis conducted as part of this study confirm that the challenges of multicultural information systems and technology education are complex. There is no silver bullet that will quickly dispatch the culture-based academic achievement gaps that persist wherever various races, language groups and genders share classrooms and teachers. At the same time, we simply cannot afford to shy away from the complexities that characterise the challenge of multicultural education in South Africa. To a large extent, this challenge must focus on identifying effective strategies to address the race-based performance gap, and specifically the poor performance of Black students at institutions of higher learning. A plethora of studies have been, and continue to be, conducted internationally and in the South African context to identify effective ways of improving the learning experience in the multicultural classroom. These have included investigations into the impact of teacher student match (in terms of race, language and gender) on academic performance (Denny & Maharaj, 2012), the role of culture-based collective self-efficacy factors (Denny & Maharaj, 2012), the role of racial identity (Rucker and Gendrin, 2003), culturally appropriate immediacy strategies (Christophel, 1990; Rodriguez et al., 1996), and culture-sensitive multicultural pedagogy (Oates, 2003; Stroter, 2008; Horsford, 2010).

Regardless of the specific focus of investigation or particular remedial pedagogical strategy that is proposed, a critical starting point for all investigations that relate to addressing the culture-based academic performance gap is an honest description of the status quo. It is appropriate, therefore, that this paper reports candidly on the status quo in respect to the culture-based IS&T academic performance gap at one public university in South Africa. However, culture-based performance gaps in IS&T education do not have to be accepted as inevitable in view of the socio-economic challenges that plague South Africa. As noted above, many of the studies referred to in the literature review above provide reason for optimism and report varying degrees of success in enacting pedagogical strategies aimed at closing the culture-based academic performance gap (Denny & Maharaj, 2012) As South Africa slowly, but surely, unravels and redresses the disparities of the past, it is vital that intensity be maintained in respect of efforts to maximise the return on investment that all stakeholders achieve for the vast sums of money that are being spent on education and skills development annually. Moreover, with the information and communication technology sector set to grow dramatically over the next decade and demanding more skilled professionals in the workforce, identifying factors that contribute positively to and which maximise the impact of the learning
experience in the information systems and technology classroom becomes, not only a desirable, but a critical component of the development of the sector as a whole.

REFERENCES


