Educator Student Cultural Congruence as a Predictor of Academic Performance in Information Systems and Technology Education

Peter Denny
Manoj Maharaj

Abstract

The South African ICT educational landscape is as fluid and complex as the broader society it serves. Improving the quality of ICT education and skills development is critical. However, the challenges related to race and culture-based performance gaps continue to be an unavoidable characteristic of the South African educational landscape. This paper investigates the cultural factors that impact and predict ICT students' academic achievement in the context of a multicultural South African classroom. The results show that congruence factors do impact academic performance. A recommendation is for a review of teacher education with a view to ensuring that specific programmes are included that enhance teachers' abilities to relate appropriately to students of various cultures, counter the influences of deep seated prejudices and the expression of these via discriminatory teaching practices, assist educators to cultivate and nurture immediacy behaviours that are shown by research to appeal to the various students they teach, and which generally assist educators to create and maintain a higher level of affinity with their students.

Keywords: Academic performance, congruence, culture, education, gender, home language, information systems and technology, race, student, teacher

Introduction

The study investigates the cultural factors that impact and predict ICT students' academic achievement in the context of a multicultural South African classroom. The research aims to contribute significantly to better understanding and closing the culture-based academic performance gap, and to improving the returns on investment that technology education and skills development stakeholders in South Africa are able to realise.

The research conducted as part of this study investigates the impact on cognitive learning of matching educators and students in terms of race, home language and gender among first year IS&T (Information Systems and Technology) students at both a public university and a private provider of higher education in South Africa.

Research Problem

The South African ICT educational landscape is as fluid and complex as the broader society it serves. Off the back of one of the most dramatic economic meltdowns in history, ICT, like most other sectors, is facing a prolonged, slow path to recovery. The outlook is one of slow, but steady growth over the next decade and there will clearly be a need for appropriate skills to fuel the recovery of the sector (ISETT SETA, 2010). Ironically, the recent recession (and agonisingly slow recovery) has taken its toll in terms of commitment and allocation of resources to this much needed development of skills. Training budgets have been the first items to be cut as organisations struggle to traverse the financial instabilities of the times. There has arguably never been a more appropriate time for research focused entirely on improving the quality of ICT education and skills development and that does not shy away from the challenges related to race and culture-based performance gaps that continue to be an unavoidable characteristic of the South African educational landscape (ISETT SETA, 2010).

Identifying the heart of the problem, the ISETT SETA Sector Skills Plan 2011-2016 points out the real challenge South Africa has with the quality of people entering the ICT workforce, listing as some of the key weaknesses and threats to the sector the following (ISETT SETA, 2010: 60):

- “Incompetent practitioners entering the profession with worthless degrees”;
- “The exceedingly poor education system available to the vast majority of young people”;
- “The literacy and educational base in the country is very weak and skewed”;

- "The demand for competent ICT staff will outstrip the supply".

Commenting on the ICT skills supply issues, the report laments in particular the poor quality of Black entrants to the ICT workforce from the university system, citing poor English literacy, poor life skills and a weak technical skills base (ISETT SETA, 2010).

Given the government's 85% Black employment profile target, there is a clear sense of urgency around the need to address the issues pertaining to quality ICT education and skills development and in particular those that relate to the culture-based academic performance gap. The combination of recession related skills development budget pressures, the industry's frustration with skills supply quality and demand for better quality ICT professionals makes a compelling case for ensuring that precious skills development budgets and efforts in general are focused on achieving appropriate returns on education and training investment.

The findings in this paper and the related research do not assume to provide a 'silver bullet', nor an obvious set of practical suggestions, for educators faced with these challenges of multicultural education. However, the insights gleaned contribute significantly and uniquely to a growing body of academic knowledge on this subject from which it is hoped workable solutions will emerge in time.

Research Objectives

In view of the foregoing, the study reported on in this paper is both timeous and relevant in terms of investigating the factors that impact and predict ICT students' race, home language and gender related academic performance.

The study's objective is the identification of predictable (and therefore 'controllable') ways to improve the learning experience (in particular, cognitive test performance) of IS&T students in the classroom, with a special emphasis on race, home language and gender related factors.

While there are potentially a multitude of culture related factors that could be explored with a view to maximising the returns on training investment achieved in multicultural classrooms, this study focuses on the impact on student cognitive test performance of educator student congruence (in respect of race, gender and home language specifically) in information systems and technology education.

The following research questions arise from the foregoing:

- Research question 1 (RQ1): “Does matching educator and student in respect of cultural factors impact student cognitive test performance in information systems and technology education?”
    - Sub-question 1.1 (SQ1.1): “Does matching educator and student in respect of race impact student cognitive test performance in information systems and technology education?”
    - Sub-question 1.2 (SQ1.2): “Does matching educator and student in respect of home language impact student cognitive test performance in information systems and technology education?”
    - Sub-question 1.3 (SQ1.3): “Does matching educator and student in respect of gender impact student cognitive test performance in information systems and technology education?”

Theoretical Framework

Social Cognitive Theory has its roots in Social Learning Theory, which, as a documented theory of learning, dates back to the late 1800’s. Albert Bandura, starting in the 1960’s, has written extensively on SLT and launched the SCT in 1960 with his book “Social Foundations of Thought and Action: A Social Cognitive Theory” (Bandura, 1986).

As per Table 1, Bandura’s Social Cognitive Theory (SCT) has been referred to by a number of authors as a theoretical framework for analysis of information systems and technology education research (Marakas et al., 1989, Compeau and Higgins, 1995, Alavi et al., 2002, Yi and Davis, 2003, Santhanam et al., 2008, Arcy et al., 2009, Grant et al., 2009, Saleem et al., 2011).

According to Bandura, learning has a strong social component (Social Cognitive Theory is also known as Social Learning Theory (SLT) and Observational Learning Theory (OLT)). The educator is an important player in Bandura’s theory of ‘observational learning’ which he describes as occurring through a process he terms ‘social modeling’. SCT suggests that ‘observers’ (students) learn from ‘models’ (teachers) through observation or verbal instruction, and that model characteristics and the relationship between model and observer are factors that can impact the effectiveness of the learning experience. For example, Bandura claims that the perceived credibility of the model in the eyes of the observer can influence the extent to which the observer pays attention and therefore impacts learning, either negatively or positively. Similarly, Bandura posits that the greater the degree of perceived similarity of observer to model, the more effective the learning experience (Bandura, 1977a, 1989).

Table 1 Information Systems Research Articles Using Social Learning Theory as a Theoretical Framework

Marakas, GM, MY Yi & RD Johnson 1989. The Multilevel and Multifaceted Character of Computer Self-Efficacy: Toward Clarification of the Construct and an Integrative Framework for Research. *Information Systems Research* 9: 126-163.
Compeau, D & C Higgins 1995. Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly* 19: 189-211.
Alavi, M, GM Marakas & Y Yoo 2002. A Comparative Study of Distributed Learning Environments on Learning Outcomes. *Information Systems Research* 13: 404-415.
Yi, MY & FD Davis 2003. Developing and Validating an Observational Learning Model of Computer Software Training and Skill Acquisition. *Information Systems Research* 14: 146-169.
Santhanam, R, S Sasidharan & J Webster 2008. Using Self-Regulatory Learning to Enhance E-Learning-Based Information Technology Training. *Information Systems Research* 19: 26-47.
Grant, DM, AD Malloy & MC Murphy 2009. A Comparison of Student Perceptions of their Computer Skills to their Actual Abilities. *Journal of Information Technology and Education* 8: 141-160.
Arcy, JD, A Hovav & D Galletta 2009. User Awareness of Security Countermeasures and Its Impact on Information Systems Misuse: A Deterrence Approach. *Information Systems Research* 20: 79-98.

The research conducted as part of this study seeks to answer the research questions in the light of Albert Bandura's Social Cognitive Theory and the related constructs of observational learning, observer-model similarity, model credibility and collective self-efficacy. Figure 1 presents the research model for the study:

Figure 1 Research Model

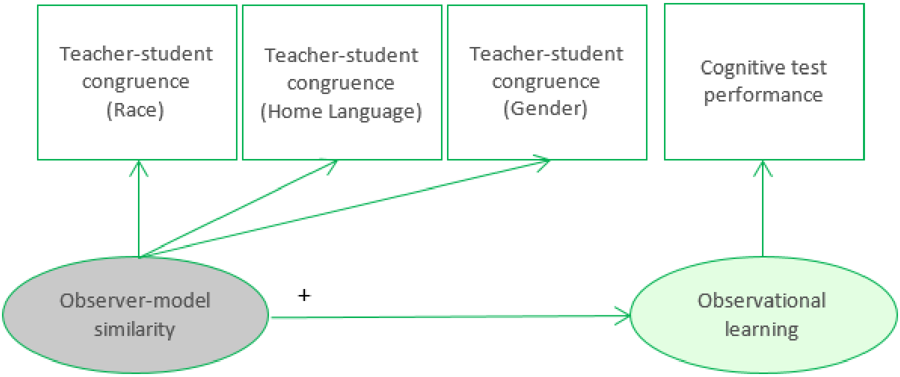

Figure 1 presents the research model for the study and describes the relationships that exist between the theoretical constructs and the respective measured variables. According to Bandura, observational learning is enhanced both when the model is similar to the observer and when the model has credibility in the eyes of the observer. As per Figure 1, the research model for this study posits that observer-model similarity as a construct affects observational learning. Observer-model similarity links to the dichotomous independent variables of educator student congruence in terms of race, home language and gender respectively, while 'observational learning' is measured in terms of the dependent variable, 'cognitive test performance'. The construct referred to as 'cultural factors' in Figure 1 links to the measurable variables 'student race', 'student home language' and 'student gender'.

Research Design

Research Sample

The research for this study was conducted using samples of ICT (information and communications technology) students from both a public and a private tertiary institution in South Africa.

Tables 2 and 3 provide the student and educator demographic descriptives for cohorts one and two:

Table 2 Student Demographics for Cohorts One and Two

	Cohort one (Institution 1)			**Cohort two (Institution 2)**	
	N	%		N	%
Total Students	4825	100.00		1278	100.00
Age	4825	100.00		1278	100.00
Race					
Black	2537	52.66		1003	78.48
White	175	3.63		154	12.05
Indian	2021	41.95		83	6.50
Coloured	85	1.76		35	2.74
Other	7	0.10		3	0.23
Home Language					
English	2376	49.24		476	37.25
Afrikaans	13	0.27		81	6.34
Zulu	2011	41.68		86	6.73
Other African:	425	8.81		635	49.69
Gender					
Male	2396	49.66		671	52.50
Female	2429	50.34		607	47.50

Table 3 Educator Demographics for Cohorts One and Two

	Cohort one (Institution 1)		**Cohort two (Institution 2)**	
	N	%	N	%
Total Teachers	20	100.0	56	100.0

Race				
Black	2	10.00	15	26.79
White	5	25.00	31	55.36
Indian	12	60.00	10	17.86
Coloured	1	5.00	0	0.00
Other	0	0.00	0	0.00
Home Language				
English	18	90.00	31	55.36
Afrikaans	0	0.00	12	21.43
Zulu	0	0.00	2	3.57
Other African:	2	10.00	11	19.64
Gender				
Male	14	70.00	30	53.57
Female	6	30.00	26	46.43

Table 4 describes the sample, which comprised two cohorts across two higher education institutions (one public, the other private):

Table 4 Cohort Comparison

	Cohort one	**Cohort two**
Institution	1	2
Institution type	Public Tertiary	Private Tertiary
Students (Participants in match/mismatch study)	4825	1278
Teachers (Participants in match/mismatch study)	20	56
Student respondents to S-CTSE survey	737	636
Educator respondents to T-CTSE survey	15	37
Different Modules/ Courses	48	118
Test scores (Unique student test scores in dataset)	12013	6358
Measures and instruments		
Match/mismatch effect		

Dependent variable	Student test scores
	• Raw test score • Raw test score converted to z-score (deviation of student score from class mean, divided by standard deviation) • Raw test score converted to simple deviation of student score from class mean
Independent variable	Educator student match mismatch (Race, Home Language, Gender)
Data source/instrument	Student records (class marks)
Statistical methods and models	• Generalized Estimating Equations (GEE)

Measures of Academic Performance

For both cohorts, raw student test scores for modules (courses) attended over a two-year period (2011 and 2012) were used. Thus the datasets for both cohorts comprised a number of test score, module and educator combinations per student. To standardize the data and to control for varying class difficulty levels (student scores were spread across a variety of modules and teachers), raw scores were converted to z-scores (deviation of student score from class mean, divided by the standard deviation).

Measures of Teacher/Student Congruence

A match in a given demographic is where the student and educator share the same demographic (e.g. a Black student and Black educator would be a match, an Indian student and Black educator would be a mismatch).

Data Analysis Models

Given the highly correlated nature of the datasets, the analyses of the educator student match mismatch effect on student test scores apply a Generalized Estimating Equations (GEE) model to the datasets representing cohorts one and two (Institutions 1 and 2 respectively). GEE is considered appropriate for analysing highly correlated data in a robust way, particularly where there are dependent (response) variables (in this case the student z-score) and a number of factors and covariates that need to be tested for significant effect on the dependent variable (Cengiz et al., 2010). GEE is therefore appropriate for this analysis as there are correlations between the outcomes (i.e. the values of the student score for a student are probably correlated, as is usually the case with repeated measures).

Data Collection

For the academic performance data, the study drew on institutional records of each student's assessment results for each module for which the student had received educator led instruction during the academic years 2011/2012.

Results and Data Analysis

Educator Student Congruence as a Predictor of Cognitive Test Performance

The following analyses (Tables 5-13) present the results of applying a Generalized Estimating Equations (GEE) model to the datasets representing cohorts one and two (Institutions 1 and 2 respectively). Combined institution analyses are performed in some cases and are made possible by the standardization of student test scores using z-scores (deviations of student tests scores from class averages), allowing not only cross module comparison, but also comparison of scores across institutions for IS&T modules.

Table 5 Educator Student Match Effect on Student Test Scores (Institution 1, Race Match)

Parameter Estimates[a]							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.046	.0135	-.073	-.019	11.525	1	.001
Match (Race)	.119	.0219	.076	.162	29.693	1	.000***
(Scale)	.980						

Dependent Variable: Student Test Score (z-Score), Institution 1 *** p = significant at p<.001

Table 6 Educator Student Match Effect on Student Test Scores (Institution 2, Race Match)

Parameter Estimates[a]							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.057	.0194	-.095	-.019	8.687	1	.003
Match (Race)	.112	.0286	.056	.168	15.368	1	.000***
(Scale)	.979						
Dependent Variable: Student Test Score (z-Score), Institution 2 *** p = significant at p<.001							

Table 7 Educator Student Match Effect on Student Test Scores (Combined Institutions, Race Match)

Parameter Estimates							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.049	.0111	-.071	-.028	19.781	1	.000
Match (Race)	.115	.0173	.081	.149	44.318	1	.000***
(Scale)	.980						
Dependent Variable: Student Test Score (z-Score) *** p = significant at p<.001							

Table 8 Educator Student Match Effect on Student Test Scores (Institution 1, Home Language Match)

Parameter Estimates[a]							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.119	.0138	-.146	-.092	74.389	1	.000
Match (Home Language)	.293	.0214	.251	.335	187.388	1	.000***
(Scale)	.963						
Dependent Variable: Student Test Score (z-Score), Institution 1							
*** p = significant at p<.001							

Table 9 Educator Student Match Effect on Student Test Scores (Institution 2, Home Language Match)

Parameter Estimates[a]							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.018	.0159	-.050	.013	1.347	1	.246
Match (Home Language)	.075	.0362	.004	.146	4.334	1	.037*
(Scale)	.981						
Dependent Variable: Student Test Score (z-Score), Institution 2							
* p = significant at p<.05							

Table 10 Educator Student Match Effect on Student Test Scores (Combined Institutions, Home Language Match)

Parameter Estimates							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.077	.0104	-.098	-.057	54.962	1	.000
Match (Home Language)	.226	.0179	.191	.261	158.339	1	.000***
(Scale)	.971						
Dependent Variable: Student Test Score (z-Score) *** p = significant at p<.001							

Table 11 Educator Student Match Effect on Student Test Scores (Institution 1, Gender Match)

Parameter Estimates[a]							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.009	.0158	-.040	.022	.312	1	.576
Match (Gender)	.018	.0214	-.024	.060	.683	1	.408[ns]
(Scale)	.983						
Dependent Variable: Student Test Score (z-Score), Institution 1 ns = not significant at p=.05							

Table 12 Educator Student Match Effect on Student Test Scores (Institution 2, Gender Match)

Parameter Estimates[a]							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.029	.0226	-.016	.073	1.586	1	.208
Match (Gender)	-.052	.0292	-.109	.005	3.206	1	.073[ns]
(Scale)	.981						
Dependent Variable: Student Test Score (z-Score), Institution 2, ns = not significant at p=.05							

Table 13 Educator Student Match Effect on Student Test Scores (Combined Institutions, Gender Match)

Parameter Estimates							
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.003	.0130	-.023	.028	.050	1	.823
Match (Gender)	-.006	.0172	-.040	.028	.131	1	.718[ns]
(Scale)	.983						
Dependent Variable: Student Test Score (z-Score), ns = not significant at p=.05							

Clearly, Tables 5-13 show significant match/mismatch effects for both cohorts one and two in respect of race and home language. The results for gender are not significant.

Figures 2-4 show the match effects from Tables 5-13 in the form of path diagrams.

Figure 2 Educator Student Match Effects on Student Test Scores (Institution 1)

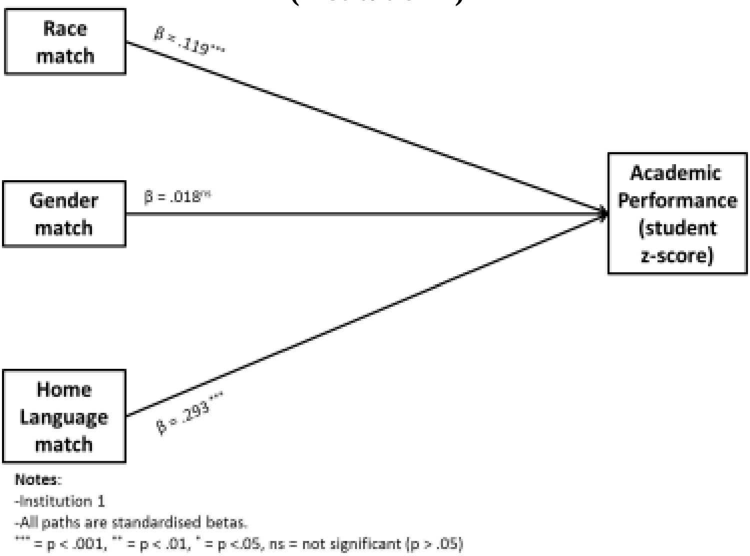

Figure 3 Educator Student Match Effects on Student Test Scores (Institution 2)

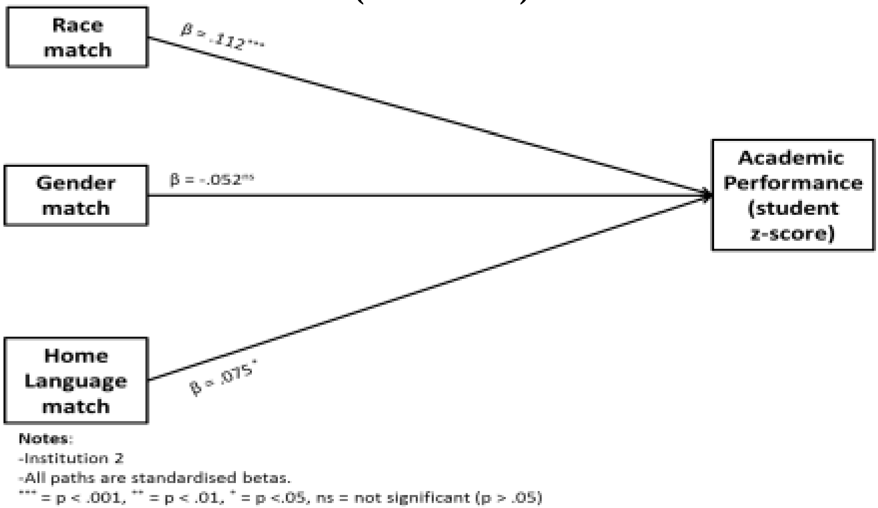

Figure 4 Educator Student Match Effects on Student Test Scores (Combined Institutions)

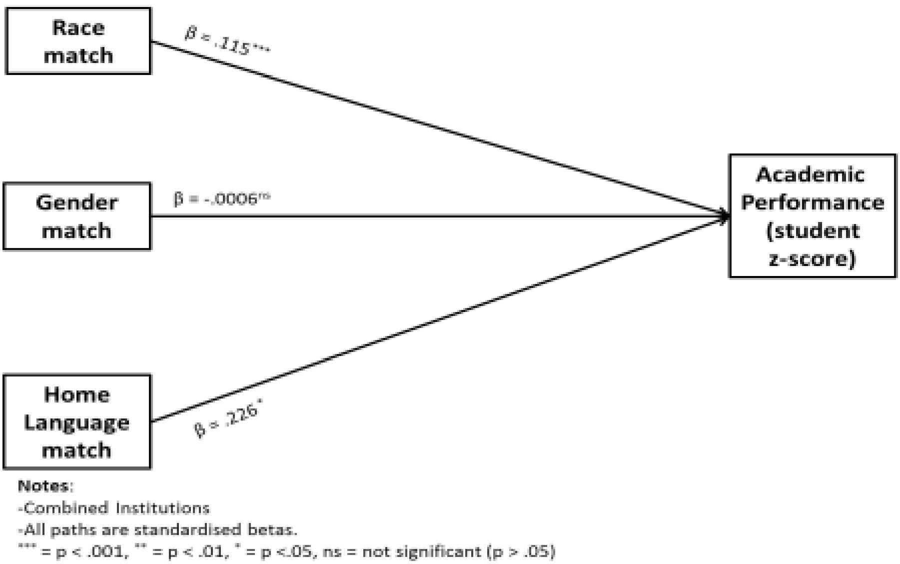

Table 14 presents a simple index of match analysis that shows the effects of various combinations of race, home language and gender match and mismatch. The results are ranked and show that generally higher levels of combined match for race, home language and gender appear to result in higher student test scores, whereas the more mismatched combinations produce lower ranking of students in terms of test scores.

Findings in Respect of the Research Questions

The following findings emerge from this study in respect of RQ1:

- Matching educator and student in terms of race, home language and gender significantly improves student cognitive test performance in information systems and technology education and training.

- There is a positive relationship between indexes of match (for race, home language and gender) and test score results.

The Generalized Estimating Equation based analyses show consistent and highly significant positive relationships between educator student match and student test performance.

In terms of research question 1, the results from cohorts one and two strongly suggest, therefore, that matching educator and student in respect of race, home language and gender positively impacts student cognitive test performance in information systems and technology education.

Moreover, the foregoing analyses on the match/mismatch effect suggest a positive relationship between indexes of match (for race, home language and gender) and test score results. In other words, the greater the level of match, the more positive the match effect on test scores.

Student Test Score (z-Scores)									
Race	Lang	Gender	Number	Rank	Med	Mean	sigma	Var	Sigma bar
MISMATCH	Mm	Mismatch	3842	25	-.047	-.091	.100	.999	.016
		Match	4201	27	-.047	-.100	.972	.945	.015
		Total	8043	26	-.047	-.096	.985	.971	.011
	M	Mismatch	1181	10	.203	.084	.993	.986	.029
		Match	1346	7	.216	.113	.967	.935	.026
		Total	2527	8	.203	.099	.979	.959	.019
	Tot	Mismatch	5023	20	.006	-.050	1.00	1.00	.014
		Match	5547	18	.000	-.049	.975	.951	.013
		Total	10570	19	.003	-.049	.987	.975	.010
MATCH	Mm	Mismatch	1547	16	.090	-.005	1.02	1.03	.026
		Match	2505	21	.052	-.062	.968	.937	.019
		Total	4052	17	.061	-.040	.988	.976	.016
	M	Mismatch	1633	3	.277	.173	.981	.962	.024
		Match	2075	1	.263	.189	.991	.982	.022
		Total	3708	2	.264	.182	.986	.973	.016
	Tot	Mismatch	3180	9	.157	.087	1.00	1.00	.018
		Match	4580	12	.130	.052	.986	.972	.015
		Total	7760	11	.129	.066	.993	.986	.011
TOTAL	Mm	Mismatch	5389	22	-.028	-.067	1.01	1.01	.014
		Match	6706	24	-.028	-.086	.970	.942	.012
		Total	12095	23	-.028	-.077	.986	.973	.009
	M	Mismatch	2814	6	.227	.136	.987	.974	.019
		Match	3421	4	.229	.159	.982	.964	.017
		Total	6235	5	.229	.148	.984	.969	.012
	Tot	Mismatch	8203	13	.058	.003	1.00	1.00	.011
		Match	10127	15	.058	-.003	.981	.963	.010
		Total	18330	14	.058	-.000	.991	.983	.010

Table 14 Ranked Index of Match Effect

The Findings in the Light of Social Cognitive Theory

Bandura's Social Cognitive Theory and its related constructs provide some useful insights when analysing the findings of this study in the South African context (Bandura, 1989).

For example, Bandura contends that observational learning is governed by four processes: attention span, retention processes, motor reproduction processes and motivational processes (Bandura, 1989). 'Attention span' describes an individual's ability to selectively observe actions and behaviours in the environment, and regulate the type, intensity and amount of observation that is experienced, thus impacting the effectiveness of the learning that takes place. In Bandura's model, an observer (such as a student) is more likely to be attentive to models (teachers) with whom the observer feels affinity or who are similar to the observer in some way. In addition, Bandura states that attractiveness, trustworthiness and perceived competence tend to enhance a model's effectiveness (Bandura, 1977a, 1989). The findings of this study in respect of research question 1 (RQ1 and the related sub-questions, SQ1.1, SQ1.2 and SQ1.3), appear to be consistent with Bandura's theory of attention span as a contributor to observational learning. Race, home language and gender matched students performed consistently better than mismatched students. In terms of Bandura's SCT, it could be argued that these students paid more attention to the model (teacher) due to their similarity (same race, home language and/or gender).

In summary, the study finds that matching educator and student in respect of cultural factors significantly improves student cognitive test performance in IS&T education.

Conclusions and Recommendations

The GEE analyses (phase 1) above consistently show highly significant results for race and home language matched students that suggest a positive relationship between educator student match and student test scores for both cohorts two and three, as well as the combined dataset. Educator student gender match effects were not significant for the GEE analyses.

Furthermore, the results show that higher match indexes (combinations of match factors) are consistently associated with higher test score rankings for both cohorts. This effect is most obvious when looking at the combined institution data (Table 14) where the top three ranked test scores are associated with the highest match indexes, while the lowest three ranked test scores are associated with the lowest match indexes.

The study has shown a significant positive relationship between matching educator and student (in terms of race and home language) and student test scores. Furthermore, it was shown that match index (‘degrees’ of match) were significant and that certain combinations of match factors were significantly related to higher test scores (in excess of 10% in some cases) for certain samples. While the literal implication that it might be better to match educator and student demographically is unlikely to be feasible in reality, it certainly does illustrate that combining a number of factors that each contribute significantly (however small the practical impact of each factor in isolation) to improved learning can result in improved return on investment (tangible or otherwise) in IS&T education and training.

Clearly, there is no lack of commitment to the cause of addressing the problems of basic education on the part of the South African government and in time the situation will improve. In the interim, the findings of studies such as this one provide useful insights that can inform current and future interventions aimed at helping university educators to more effectively work with the variety of students that are fed to them.

For example, the study suggests that certain race groups prefer to be taught by educators of the same race and that in some cases educator student racial congruence positively impacts academic performance. However, this fact does not necessarily recommend actually matching students with educators of the same race in university (or school) classrooms. Not only would this be unconstitutional, it would also be impractical. This is especially so in view of the fact that different cultures appear to respond differently to educator student congruence (for example, certain race groups may have a lower race based collective self-efficacy and therefore not react well to being taught by race matched teachers). These preferences also have to be tempered by the current reality that approximately 60% of academic staff in South Africa’s institutions of higher learning are White (Department of Basic Education, 2010).

It is not immediately clear how one would reasonably accommodate this variety in student preferences. This an important issue, since government is driving to push more Black lecturers into the system (Department of Basic Education, 2010). The findings of this study that show a significantly positive response from students to being matched racially with their educators bodes well for the future as more Black educators enter a system that comprises mainly Black students. Perhaps a more appropriate approach is to take cognisance of the international findings on immediacy and affinity (Kearney and McCroskey, 1980, Gorham, 1988, Christophel, 1990, McCroskey and Richmond, 1992, Rodriguez et al., 1996, Rucker and Gendrin, 2003). Although some of the factors influencing perceptions of immediacy and affinity relate to innate characteristics (such as race and gender), there is also evidence that immediacy behaviours that foster affinity and therefore, via a chain of impact, positively influence academic performance, can be learnt (Richmond et al., 1986, McCroskey and Richmond, 1992).

Given that congruence factors do impact academic performance (albeit differently for different race groups who share the same classroom and teachers), and given that re-segregation in response to certain race groups preferring specific races of educators is both impractical and unconstitutional, a reasonable recommendation is for a review of educator education with a view to ensuring that specific programmes are included that enhance teachers' abilities to relate appropriately to students of various cultures, counter the influences of deep seated prejudices and the expression of these via discriminatory teaching practices, assist educators to cultivate and nurture immediacy behaviours that are shown by research to appeal to the various students they teach, and which generally assist educators to create and maintain a higher level of affinity with their students. A number of international studies have investigated the effectiveness of 'multicultural pedagogy' as a means of addressing culture-based performance gaps (Allen, 2004, Tong et al., 2006). Various authors have reported the successes of multicultural pedagogy and the case of the Netherlands, which has made significant in-roads over recent decades into closing the culture-based performance gap for minority immigrants, is reason for optimism among South African educators (Rijkschroeff et al., 2005, Picower, 2009).

References

Alavi, M, GM Marakas & Y Yoo 2002. A Comparative Study of Distributed Learning Environments on Learning Outcomes. *Information Systems Research* 13: 404-415.

Allen, RL 2004. Whiteness and Critical Pedagogy. *Educational Philosophy and Theory* 36: 121-136.

Angle, J & C Moseley 2009. Science Teacher Efficacy and Outcome Expectancy as Predictors of Students' End-of-Instruction (EOI) Biology I Test Scores. *School Science and Mathematics* 109: 473-483.

Arcy, JD, A Hovav & D Galletta 2009. User Awareness of Security Countermeasures and Its Impact on Information Systems Misuse: A Deterrence Approach. *Information Systems Research* 20: 79-98.

Ashton, P & R Webb 1986. *Making a Difference: Teachers' Sense of Efficacy and Student Achievement.* New York Longman.

Badat, S 2010. The Challenges of Transformation in Higher Education and Training Institutions in South Africa [Online]. Development Bank of South Africa. Available at: http://www.dbsa.org/Research/Higher%20Education%20and%20Training/The%20challenges%20of%20transformation%20in%20higher%20education%20and%20training%20institutions%20in%20South%20Africa%20by%20Saleem%20Badat.pdf. (Accessed on 11 November 2011.)

Bandura, A 1977a. *Social Learning Theory.* Englewood Cliffs, NJ: Prentice Hall.

Bandura, A 1977b. Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review* 84: 191-215.

Bandura, A 1986. *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ, Prentice Hall.

Bandura, A 1989. Social Cognitive Theory. In Vasta, R (ed): *Annals of Child Development Greenwich.* CT: Jai Press LTD.

Bandura, A 1994. Self-efficacy. In Ramachaudran, VS (ed): *Encyclopedia of Human Behavior*. New York: Academic Press.

Bandura, A 1995. Exercise of Personal and Collective Efficacy in Changing Societies. In Bandura, A (ed): *Self-Efficacy in Changing Societies.* New York: Cambridge University Press.

Bandura, A 2000. Exercise of Human Agency through Collective Efficacy. *Current Directions in Psychological Science* 9: 75-78.

Cengiz, M, T Senel, Y Terzi, N Murat & N Savas 2010. Comparing Different Sedation Medications Using Generalized Estimating

Equations Approach. *African Journal of Pharmacy and Pharmacology* 4,4: 130-134.

Christophel, DM 1990. The Relationship among Teacher Immediacy Behaviors, Student Motivation, and Learning. *Communication Education* 37: 323-340.

Compeau, D & C Higgins 1995. Computer Self-efficacy: Development of a Measure and Initial Test. *MIS Quarterly* 19: 189-211.

Department of Basic Education 2010. *Education Statistics in South Africa 2009.* Pretoria: Department of Basic Education.

De Wet, C & C Wolhuter 2009. A Transitiological Study of Some South African Educational Issues. *South African Journal of Education* 29: 359-376.

Goddard, RD, WK Hoy & A Woolfolk 2000. Collective Teacher Efficacy: Its Meaning, Measure, and Effect on Student Achievement. *American Education Research Journal* 37,2: 479-507.

Gorham, JS 1988. The Relationship between Verbal Teacher Immediacy Behaviors and Student Learning. *Communication Education* 37: 40-43.

Grant, DM, AD Malloy & MC Murphy 2009. A Comparison of Student Perceptions of their Computer Skills to their Actual Abilities. *Journal of Information Technology and Education* 8: 141-160.

ISETT SETA 2010. Sector Skills Plan 2011–2016. [Online]. Available at: http://www.isett.org.za/isett/downloads/Isett_Seta_Sector_Skills_Plan_2011_2016_Sept_2010_Version_v1p1.zip. (Accessed on 23 November 2011.)

Kearney, P & JC McCroskey 1980. Relationships among Teacher Communication Style, Trait and State Communication Apprehension, and Teacher Effectiveness. In Nimmo, D (ed): *Communication Yearbook 4.* New Brunswick, N.J.: Transaction Books.

King, K, L Shumow & S Lietz 2001. Science Education in an Urban Elementary School: Case Studies of Teacher Beliefs and Classroom Practices. *Science Education* 85: 89-110.

Koul, R & P Rubba 1999. An Analysis of the Reliability and Validity of Personal Internet Teaching Efficacy Beliefs Scale. [Online]. *Electronic Journal of Science Education.* Available at:

http://ejse.southwestern.edu/article/viewArticle/7621/5388. (Accessed on 21 February 2012.)

Letseka, M & S Maile 2008. High University Drop-out Rates: A Threat to South Africa's Future [Online]. Human Sciences Research Council. Available at: http://www.hsrc.ac.za/Document-2717.phtml. (Accessed on 11 November 2011.)

Marakas, GM, MY Yi & RD Johnson 1989. The Multilevel and Multifaceted Character of Computer Self-Efficacy: Toward Clarification of the Construct and an Integrative Framework for Research. *Information Systems Research* 9: 126-163.

Mccroskey, JC & VP Richmond 1992. Increasing Teacher Influence through Immediacy. In Richmond, VP & JC McCroskey (eds.): *Power in the Classroom: Communication, Control, and Concern.* Hillsdale, NJ: Erlbaum Associates, Inc.

Moseley, C & B Taylor 2011. Analysis of Environmental and General Science Teaching Efficacy among Instructors with Contrasting Class Ethnicity Distributions: A Four-Dimensional Assessment. *School Science & Mathematics* 111: 199-208.

Oettingen, G 1995. Cross-cultural Perspectives on Self-efficacy. In Bandura, A (ed): *Self-efficacy in Changing Societies.* New York: Cambridge University Press.

Picower, B 2009. The Unexamined Whiteness of Teaching: How White Teachers Maintain and Enact Dominant Racial Ideologies. *Race, Ethnicity & Education* 12: 197-215.

Reddy, V, CH Prinsloo, T Netshitangani, R Moletsane, A Juan & D Janse van Rensburg 2010. An Investigation into Educator Leave in the South African Ordinary Public Schooling System. Research Commissioned by UNICEF. Study undertaken for the Department of Education.

Richmond, VP, JC Mccroskey, TG Plax & P Kearney 1986. Teacher Nonverbal Immediacy Training and Student Affect. *World Communication* 15: 181-194.

Rijkschroeff, R, G ten Dam, JW Duyvendak, M de Gruijter & T Pels 2005. Educational Policies on Migrants and Minorities in the Netherlands: Success or Failure? *Journal of Education Policy* 20: 417-435.

Rodriguez, JI, TG Plax & P Kearney 1996. Clarifying the Relationship between Teacher Nonverbal Immediacy and Student Cognitive Learning: Affective Learning as the Central Causal Mediator. *Communication Education*, 45, 293-305.

Rucker, ML & DM Gendrin 2003. The Impact of Ethnic Identification on Student Learning in the HBCU Classroom. *Journal of Instructional Psychology* 30: 207-215.

Saleem, H, A Beaudry & A Croteau 2011. Antecedents of Computer Self-efficacy: A Study of the Role of Personality Traits and Gender. *Computers in Human Behavior* 27: 1922-1936.

Santhanam, R, S Sasidharan & J Webster 2008. Using Self-Regulatory Learning to Enhance E-Learning-Based Information Technology Training. *Information Systems Research* 19: 26-47.

Skaalvik, EM & S Skaalvik 2007. Dimensions of Teacher Self-Efficacy and Relations with Strain Factors; Perceived Collective Teacher Efficacy, and Teacher Burnout. *Journal of Educational Psychology* 99,3: 611–625.

Tamir, M & IB Mauss 2011. Social Cognitive Factors in Emotion Regulation: Implications for Well-Being Emotion Regulation and Well-Being. In Nyklíček, I, A Vingerhoets & M Zeelenberg (eds): *Emotion Regulation and Well-being*. New York: Springer.

Tong, VM, CW Huang & T McIntyre 2006. Promoting a Positive Cross-Cultural Identity: Reaching Immigrant Students. *Reclaiming Children & Youth* 14: 203-208.

Tschannen-Moran, M & AW Hoy 2001. Teacher Efficacy: Capturing an Elusive Construct. *Teaching and Teacher Education* 17: 783-805.

Tschannen-Moran, M & M Barr 2004. Fostering Student Learning: The Relationship of Collective Teacher Efficacy and Student Achievement. *Leadership & Policy in Schools* 3: 189-209.

Yi, MY & FD Davis 2003. Developing and Validating an Observational Learning Model of Computer Software Training and Skill Acquisition. *Information Systems Research* 14: 146-169

Peter Denny
School of Management, Information Technology and Governance,
College of Law and Management Studies
University of KwaZulu-Natal
Durban, South Africa
peter.john.denny@gmail.com

Manoj Maharaj
School of Management, Information Technology and Governance,
College of Law and Management Studies
University of KwaZulu-Natal
Durban, South Africa
maharajms@ukzn.ac.za