UNIVERSITY OF KWAZULU-NATAL

MAXIMISING RETURN ON INVESTMENT IN I.T. TRAINING: A SOUTH AFRICAN PERSPECTIVE

By

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Glossary of Acronyms

AsgiSA	Accelerated and Shared Growth Initiative for South Africa
ASTD	American Society for Training and Development
BII	Behavioural Indicants of Immediacy
CFA	Confirmatory Factor Analysis
CHE	Council on Higher Education
CSE	Computer Self Efficacy
CTSE	Collective Teaching Self Efficacy
DoE	Department of Education
DoL	Department of Labour
FET	Further Education and Training
GDP	Gross Domestic Product
GEE	Generalized Estimating Equation
GLM	Generalized Linear Modelling
HESA	Higher Education Statistics Agency
ICT	Information and Communications Technology
IDV	Individualist-Collectivist
IQ	Intelligence Quotient
ISETT	Information Systems Electronics and Telecommunication Technologies
IST&T	Information Systems and Technology
IT	Information Technology
Jipsa	Joint Initiative on Priority Skills Acquisition
LSM	Living Standards Measure
MAS	Masculinity-Femininity
MDG	Millennium Development Goal
MICT	Media, Advertising, Information and Communication Technologies
MMRI	Multidimensional Model of Racial Identity
NSDS	National Skills Development Strategy
OBE	Outcomes Based Education
OLT	Observational Learning Theory

PDI	Power Distance
ROI	Return on Investment
SAS	Statistical Analysis System
SCT	Social Cognitive Theory
SE	Self-Efficacy
SEM	Structural Equation Modelling
SLT	Social Learning Theory
SETA	Sector Education and Training Authority
STEM	Science, Technology, Engineering and Mathematics
UAI	Uncertainty Avoidance
UK	United Kingdom
UKZN	University of KwaZulu-Natal
USA	United States of America

Abstract

This thesis explores the impact of teacher student cultural congruence, specifically in respect of race, home language and gender, on cognitive learning in the information systems and technology discipline. The study is conducted in the South African context and investigates the cultural factors that impact and predict information systems and technology students' academic achievement. The research aims to contribute significantly to closing the culture-based academic performance gaps, and to improving the returns on investment that technology education and skills development stakeholders in South Africa are able to realise.

A thorough review is undertaken of international studies that explore culture and teacher student congruence as significant factors in cognitive learning. Culture-based performance gaps are explored and the theories presented by international researchers to explain these gaps are considered. A review of the results of these international studies shows that different ethnic, language and gender groups perform differently on cognitive testing, suggesting that these groupings do indeed learn differently and that certain pedagogical strategies may favour some groups over others. This appears to be true across various age groups and across various subjects.

Teacher student congruence as a predictor of performance is considered in detail in terms of learning style, home language, gender and ethnicity. International findings are reviewed which suggest significant relationships between teacher student cultural consonance and cognitive learning performance, as well as the role of teacher and student perceptions and racial identity as factors influencing the student learning experience and academic performance.

The unique South African context for this research is discussed, including the history of inequality in education, the unusually diverse cultural landscape, the culture-based academic performance gap and the factors that account for this.

The research conducted as part of this study investigates culture-based academic performance disparities and the impact on cognitive learning of matching teachers and students in terms of race, home language and gender among first year Information Systems and Technology students at a public university in South Africa. In addition, culture-based differences in student perceptions of collective self-efficacy in respect of teacher effectiveness are considered, as well as the relationship between these perceptions and student academic performance.

The study finds that cultural factors are significant predictors of cognitive test performance and that matching teacher and student in respect of cultural factors significantly improves student cognitive test performance in information systems and technology education and training. The study further finds that both student and teacher perceptions of collective teaching self-efficacy vary among cultural groupings and are significantly related to higher student test scores for students who are matched with their teachers in terms of cultural factors.

The findings are considered in the light of Bandura's Social Cognitive Theory and Phillips' five level framework for return on investment in training analysis.

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Chapter 1: Introduction

1.1 Context and relevance of study

The South African ICT (information and communications technology) skills development 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).

According to the ISETT SETA[1] Sector Skills Plan 2011-2016, South African IT (information technology) market revenue is likely to grow from approximately R60 billion in 2010 to at least R83 billion by 2014. If communications are included, total annual market revenue for ICT in South Africa will be R400 billion by 2014. With this growth comes demand for more skilled employees. In 2009 there were 141,929 employees in the ICT sector and it is estimated that by 2014, 152,214 will be required. Of the total number of employees in the ICT sector in 2009, 32% (44,801) were African, about 10% (14,448) were Indian, 12% (17,702) were Coloured and 46% (64,978) were White. The DoL (Department of Labour) continues to strive for a target of 85% Black (which includes African, Indian and Coloured employees). Similarly, the DoL is aiming for 54% of employees to be female. In 2009 there were 50,231 females (35%) and 91,698 males (65%), so there is room for improvement (ISETT SETA, 2010).

Clearly, therefore, there will continue to be a growing demand for more skilled Black and female ICT professionals over the next few years. From a supply of skills perspective, it is encouraging to note that from 2006 to 2014 the number of learners writing Matric will have increased by 34% and the number of learners choosing ICT as a career by enrolling for ICT studies at a university will increase

[1] The ISETT SETA (Information Systems Electronics and Telecommunication Technologies Sector Education and Training Authority) was renamed MICT SETA (Media, Advertising, Information and Communication Technologies Sector Education and Training Authority) on 1 April, 2011 (MICT SETA, 2011).

by 39%. Moreover, the percentage of African ICT graduates has risen over recent years and will continue to do so to 2014 at least. More concerning is the fact that there is a steady decline of Indian, White and Coloured ICT graduates and the total number of ICT university graduates will fall between 2006 and 2014 by 12% (ISETT SETA, 2010).

1.2 Research problem

In view of the huge amounts of money invested annually in skills development and education in South Africa, it would seem to be reasonable to expect that the various stakeholders responsible for this spend would be interested in measuring the impact and returns of the educational and skills development initiatives being invested in. The ICT sector alone spent in excess of R800 million on training and skills development in 2010 (with the figure expected to increase dramatically over the next five years to approximately R1.1 billion per annum in 2014) and the government spends no less than 5.8% of GDP (R165 billion) on education each year (ISETT SETA, 2010, National Planning Commission, 2011). Yet, despite corporate South Africa continuing to spend significant amounts of money on training and skills development, there is very little effort being put into measuring the benefits of the interventions and programmes that are being invested in. For example, Clementz (2005) reports an extremely limited level of training evaluation among South African companies and points out that while a number of organisations measure learning immediately after training interventions, very little effort is made to determine the impact of training on the organisation. Similarly, there is no evidence of a credible and coordinated effort on the part of government to measure, in tangible terms, the impact of the money spent on skills development in the various sectors, let alone ways to maximise return on this investment. Indeed, the signs are not encouraging- the race based academic achievement gap persists at all levels of education, there are fewer graduates from universities each year and it is clear that these graduates do not have the skills levels required by industry (ISETT SETA, 2010).

Perhaps it is appropriate to start thinking in terms of managing public education expenditure as any responsible commercial enterprise would in terms of ensuring that skills development budgets are accounted for and return on investment is measured to ensure that precious education and skills development budgets are not wasted. As per the foregoing, it is clear how much money is being spent on skills development and education annually by government and the private sector. What is less clear is the impact of this spend in tangible terms per sector and on the economy as a whole.

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 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.

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 alternative cannot be accepted, viz. wasting money on education and skills development strategies that do not specifically and credibly address the real issues that prevent Black South Africans from performing to their potential and taking their rightful place as ICT professionals in the sector.

In view of the foregoing, this study is both timeous and relevant in terms of investigating the factors that impact and predict IS&T (information systems and technology) students’ race, home language and gender related academic performance, with a view to contributing significantly to:

1. Closing the culture (and particularly ‘race’) based academic performance gaps which continue to plague the South African educational system and which hamstring the ICT sector’s ability to meet its own demands for quality employees who meet the government’s equity requirements;
2. Improving the returns on education and training investment that IS&T skills development stakeholders in South Africa are able to realise.

1.3 Objectives and research questions

The study's over-arching 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. The research is focused upon the impact on student cognitive test performance of teacher student congruence (in respect of race, gender and home language specifically) in information systems and technology education.

Secondary objectives that relate to the above-mentioned primary objective and which enhance the study include the following:

- Identify whether performance gaps exist between students of different races, home languages and genders in the field of IS&T.
- Identify demographic differences in the impact of congruence factors.
- Investigate variations among race, home language and gender groupings of student perceptions of collective self-efficacy (in respect of teacher capability specifically), and how these variations relate to culture-based differences in the impact of teacher student congruence on learning outcomes.

A number of related research questions arise from these objectives:

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 question 2(RQ2): *"Does matching teacher and student in respect of cultural factors impact student cognitive test performance in information systems and technology education?"*

> Sub-question 2.1(SQ2.1): *"Does matching teacher and student in respect of race impact student cognitive test performance in information systems and technology education?"*

Sub-question 2.2(SQ2.2): *"Does matching teacher and student in respect of home language impact student cognitive test performance in information systems and technology education?"*

Sub-question 2.3(SQ2.3): *"Does matching teacher and student in respect of gender impact student cognitive test performance in information systems and technology education?"*

Research question 3(RQ3): *"Do student perceptions of collective self-efficacy (in respect of teacher capability), vary among cultural groupings?"*

Sub-question 3.1(SQ3.1): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among race groupings?"*

Sub-question 3.2(SQ3.2): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among home language groupings?"*

Sub-question 3.3(SQ3.3): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among gender groupings?"*

Sub-question 3.4(SQ3.4): *"How does culture-based variation in student perceptions of collective self-efficacy (in respect of teacher capability) relate to culture-based differences in the impact of teacher student congruence on student cognitive test performance in information systems and technology education?"*

1.4 Overview of research approach

At the heart of this research, and in line with the research questions outlined above, is the analysis of the impact of teacher student congruence in terms of race, home language and gender on cognitive test performance. However, two other related studies are conducted to clarify and enhance the congruence discussion; viz. an investigation of the nature of the race, home language and gender based academic performance gap, and a consideration of student perceptions as they relate to teacher student congruence factors.

The study endeavors to answer the research questions stated above by drawing on the cognitive test results and perception survey responses of a sample of first year IS&T students at a public university in South Africa. The study is conducted within the framework of Phillip's 5 level ROI analysis model, with a specific focus on impact at level 2 ('Learning') (Phillips, 1997, Phillips and Stone, 2002). The cognitive test results are analysed using a variety of regression and correlation models to identify significant differences in academic performance that relate to race, home language or gender factors and an investigation conducted into the impact on performance of matching teachers and students in respect of race, home language and gender. Furthermore, student perceptions of the impact of matching teachers and students are considered with a view to providing insights that explain the test performance results.

Bandura's Social Cognitive Theory provides the theoretical framework for analysis and interpretation of results, with a special focus on the construct of 'social modeling' and its role in observational learning. The impact of 'model-observer similarity' on observational learning and the moderating effects of 'model credibility' and 'collective self-efficacy' provide the theoretical context for the study (Bandura, 1977a, 1977b, 1978, 1994, 1995).

In summary, the research comprises three related components (in line with the three research questions referred to above):

1. An investigation of race, home language and gender as predictors of cognitive test performance in information systems and technology education;
2. An investigation into the impact of matching teacher and student in respect of race, home language and gender on student cognitive test performance in information systems and technology education;
3. An investigation of variations among race, home language and gender groupings of student perceptions of collective self-efficacy (in respect of teacher capability specifically), and how these variations relate to culture-based differences in the impact of teacher student congruence on learning outcomes.

1.5 Structure of thesis

Chapter 1: Introduction

The introduction provides a brief overview of the background to the study and the broader South African education context within which the research is conducted. The importance of the outputs of the study are considered in the light of trends in South African educational policy and the ICT sector's stated strategy on skills development for the period 2011-2016. The overall objectives of the study are outlined as well as the research questions that the study will endeavor to address, and an overview is provided of the research approach adopted.

Chapter 2: Literature review

The literature review scans the international body of literature that refers to the topic of this study and related themes. Various international studies pertaining to race, home language and gender factors as they relate to education, with an emphasis on teacher student congruence as a predictor of academic performance, are reviewed. A range of countries are included in the scan, including the United States, China, the United Kingdom, Europe and other parts of the world to demonstrate the global nature of the challenge of multicultural education and to glean potentially useful insights into successful international strategies that might inform positive change in the South African context.

The literature review explores three major themes:

1. Evidence in international studies of a culture-based academic achievement gap;
2. Insights gleaned from international research regarding the possible reasons for race, home language and gender based academic performance gaps;
3. The specific South African context, including similarities with the experiences of other countries and the factors which make the South African situation unique, with special emphasis on the legacy of apartheid as it pertains to education.

Chapter 3: Research design and methodology

The chapter on research design and methodology begins by re-articulating the research problem and related research questions, followed by a presentation of the theoretical framework for the study and a detailed description of the research model, design, methodology and data analysis models.

Chapter 4: Results and data analysis

In line with the study's research questions, the results and data analysis are presented within three main sub-headings, reflecting the research focus areas as follows:

1. Race, home language and gender as predictors of cognitive test performance.
2. Teacher student congruence as a predictor of cognitive test performance:
    - Improvement (gain) score as dependent variable;
    - Single post-test score as dependent variable.
3. Student perceptions of collective self-efficacy.

Chapter 5: Conclusions and recommendations

The thesis concludes with a summary of key findings with reference to the major concepts highlighted in the literature review. Limitations of the study are considered, including gaps in the research conducted. Finally, implications of the findings of the study are considered, along with recommendations for further research.

Chapter 2: Literature Review

2.1 Introduction

At the heart of an enquiry into how to improve returns on investment in education and training lies the fundamental question: ‘How do different people learn?’ Apart from the obvious issue of the need to define ‘different’ in this context, the assumption has to be that ‘different’ people do, in fact, learn differently. Furthermore, if this difference in how people learn can be established and described in predictable terms, it is further assumed that training interventions can be manipulated to produce desired results. By extension, if organisations are able to so manipulate the type of training provided to particular individuals or groupings of individuals based on their proven preferences, it is suggested that this provides a useful framework for proactively ensuring generally improved returns on investments in training.

A scan of the literature reveals a plethora of empirical studies that suggest that different people (in terms of such factors as ethnicity, home language and gender) learn differently and have various preferences in terms of learning environments and teacher profile. Furthermore, international studies have shown that different race, language and gender groups perform differently on cognitive testing, suggesting that these groupings do indeed learn differently and that one pedagogical strategy may favour certain groups over others. This appears to be true across various age groups and across various subjects and disciplines (Sheehan and Marcus, 1977, Dunn et al., 1990, Connor et al., 1996, Naylor and Smith, 2004, Calder and Ashbaugh, 2005, Leslie, 2005, Richardson, 2008, Wiggan, 2008, Richardson, 2009, Stockly, 2009).

This chapter reviews international literature related to culture-based disparities in academic performance and the factors that account for these. Four related themes are considered, viz. culture and cognitive learning, teacher student congruence as a predictor of performance, racial identity and the role of perception in student academic performance, and the unique South African context.

2.2 Key concepts defined

2.2.1 Return on investment

There are well evolved analysis models which are designed to facilitate the measurement of the impact and return on investment of training and education interventions. One such model is that designed by Kirkpatrick and Phillips of the American Society for Training and Development (ASTD) (Kirkpatrick, 1998, Phillips and Stone, 2002). Although designed specifically for corporate training environments, the Phillips ROI measurement framework can be used as effectively in a university classroom to measure the impact of a specific intervention aimed, for example, at addressing the poor performance of a specific group of students, or, more broadly, to measure the effectiveness of specific skills development strategies for entire sectors of the economy.

Well known training and development authors Kirkpatrick and Phillips have further recognised that both tangible and intangible results from training can be measured and are directly relevant when measuring ROI from training (Phillips, 1997, Kirkpatrick, 1998). Kirkpatrick (1998) defined a framework for evaluating ROI in training that comprised 4 levels of measurement- reaction, learning, behaviour and results. Phillips et al. (2002) expanded on Kirkpatrick's framework and added a fifth level of evaluation- ROI expressed as a cost/benefit ratio. Phillips explains this level as an evaluation of the monetary value of the business impact of the training, compared with the costs of the training. The business impact data is converted to a monetary value in order to apply it to the formula to calculate return on investment. This shows the true value of the program in terms of its contribution to the organisation's objectives. It is presented as an ROI value or cost-benefit ratio, usually expressed as a percentage. An improvement in a business impact measure as a result of training may not necessarily produce a positive ROI (e.g., if the training was very expensive in comparison with the financial benefits).

Phillips (2002) also identifies a sixth level of measurement for what he terms "intangible benefits". He defines these as "data that either cannot or should not be converted to monetary values" and adds that this definition "has nothing to do with the importance of the data; it addresses the lack of objectivity of the data and the inability to convert the data to monetary values." Phillips cites increases in customer or employee satisfaction, customer retention, reduced conflict and reduced stress as a result of training as examples of intangible benefits that 'cannot be compared with the cost of training and so which cannot be expressed as a cost-benefit ratio'. Table 2-1 outlines the various measurement levels of Phillips' model and provides a brief description of the data at each level.

Level and Type Of Data	Description of Level	Examples
1. Reaction and/or satisfaction	Level 1 measures the extent to which trainees/students were satisfied with the learning experience- the participants' reaction to the programme, the learning environment and the instructor.	Results of 'Happy Sheets' / Course Evaluations (Was the training venue comfortable? Did the trainer effectively summarise salient points? Was the catering appropriate on the day of training?)
2. Learning	Level 2 is concerned with the extent to which students/participants learnt the desired knowledge, attitudes and skills intended by the programme.	Are the participant's Excel skills improved as a result of training, as measured by a skills assessment test?
3. Job application and/or implementation	Level 3 measures the extent to which behavioural change occurs in the workplace as a result of the training programme.	Whereas an employee was unable to produce more than 5 quotes a day prior to specific application training, the employee can easily pop out 10 or more quotes of similar complexity as a result of the training intervention.
4. Business impact	Level 4 measures the impact of the training on the business. Training interventions are typically initiated to address factors that threaten the organisation's ability to perform or meet goals. Level 4 measures the extent to which a training intervention impacts (hopefully 'improves') company performance. At this level there are both 'tangible' and 'intangible results'. Tangible results include those that can be measured in objective terms, such as cost savings, increased sales, time savings or output increases. Intangible results include more subjective data, such as customer	Non-Financial: Improved Customer Satisfaction Ratings or Staff Motivation Levels Financial: Annual sales revenue improvement

Level and Type Of Data	Description of Level	Examples
	satisfaction ratings, customer retention and staff motivation.	
5. Return on Investment (ROI)	Level 5 evaluates the monetary value of the business impact of the training programme. Business impact data is converted to a monetary value and the total cost of the training programme is calculated. A formula is applied that subtracts the costs of the training programme from the calculated financial benefits, divided by the costs and produces an ROI or cost benefit ratio that is expressed as a percentage.	ROI=275% (In other words, for every Rand spent on the training intervention, R2.75 were realised to the company as a result of the training, after all costs have been considered.)

Table 2-1 Phillips' 5 levels of ROI evaluation (Source: Phillips and Stone (2002))

In the context of this study, Philips' ROI model is used as a basic framework within which cognitive test performance improvement scores are measured and compared for different student demographics in the field of IS&T studies. This research aims to identify specific ways of improving results in the classroom. Education, training and any other form of skills development involves investment of one form or another. Maximising returns on these investments should be of key concern to all skills development stake-holders. Although, Phillip's model allows for the measurement of education and training impact at five levels, this study focuses on level 2 (specifically related to learning and the transfer of skills). However, Phillip's refers to the various measurement levels in his model in terms of what he calls a 'chain of impact'. Thus, Phillips asserts that the impact of a training or education related intervention at any given level of the model is one link in the chain and is necessary in order for impact at the following level to be realised. This study, therefore, focuses on the factors that enhance the impact ('ROI') experienced specifically at level 2 of Phillip's framework, while understanding that the 'chain of impact' of maximising ROI on one level will inevitably impact the ROI achieved at higher levels. Moreover, this study focuses on one variable in particular, viz. teacher student congruence, as a potentially impactful factor in the improvement of ROI at level 2 of Phillip's model (Phillips, 1997, Phillips and Stone, 2002).

While this study focusses on maximising ROI at level 2 within the university context, the use of Phillip's multi-level model allows extension of this research to include analysis of industry training interventions. Indeed, Phillips' ROI framework has been applied extensively to industry training interventions that relate to computer and information science skills development or to measure the impact of computer assisted learning strategies, such as e-learning (Whalen and Wright, 1999, ASTD, 2000a, b, Barron, 2001, Phillips and Phillips, 2001, Peak and Berge, 2006).

Thus, the findings of studies such as this one that explore ways of maximizing the impact of level 2 learning, regardless of the specific learning context (e.g. tertiary education), may be applied to the technical and vocational education and training environments (including the impact of teacher student congruence factors at higher levels of the Phillips framework). Moreover, it is hoped that further research will follow into the impact of pedagogical strategies aimed at closing the race based performance gap for the ICT sector as a whole. It is in this context that the Philips ROI analysis model will provide a useful model for measuring the impact of the skills development related projects and initiatives that the sector as a whole invests in.

2.2.2 Culture

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).

2.3 Culture and cognitive learning

2.3.1 Culture and the performance gap-a scan of international research

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 and 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 (Neal, 2006, Hanushek and Rivkin, 2009).

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).

Although the focus of this study is on academic achievement, it is worth noting that some of the literature relating to the subject of culture-based differences in cognitive performance specifically examines differences in IQ test scores among races, genders and language groups. Rushton et al. (2005) review the body of research that examines IQ score differences among races and point out that many of these studies show a correlation between IQ test scoring and academic performance (cognitive test performance). Some useful insights are gleaned from this research (Kaufman et al., 1995, Rushton and Jensen, 2005). For example, Kaufman et al. (1995) explore the different fluid and crystallized IQ test scores for Hispanic, Black and White students in the United States and find, in line with the research findings on race based learning performance differences, that different races perform differently in IQ tests. However, two very interesting points, both relating to the impact of language, emerge from this study. Firstly, the younger Hispanic sample (educated in English in the United States) performed better than the older Hispanic participants (who had been educated primarily in Spanish before immigrating). Kaufman et al. (1995) therefore opine that the IQ scores relate to fluency in the testing language. Secondly, when the tests involved less linguistic skill (such as the 'Famous Faces' picture recognition test), the performance gap between the races was significantly reduced, further reinforcing the notion that performance on such tests is dependent upon fluency in the testing language to at least some extent. This is a significant insight when comparing the South African context where language and race are inextricably related and where certain racial groupings are generally taught in a non-English language during the formative educational years (up to grade 3) (Howie et al., 2008, De Wet and Wolhuter, 2009).

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.

2.3.2 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 (Weis, 1988, Catsambis, 1995, Kafai, 1998, Kirkpatrick and Cuban, 1998, Crombie et al., 2000, Crombie et al., 2002, Fisher and Margolis, 2002, Beyer et al., 2003, Kao and Thompson, 2003, Katz et al., 2003, Moorman and Johnson, 2003, Payton, 2003, Hale, 2005, Beyer, 2006, Gallivan, 2006, Ilias, 2006, Mead, 2006, Badat, 2010, Kirkup et al., 2010, Riegle-Crumb and King, 2010, DuBow, 2011).

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 2-2, 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).

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%

Table 2-2 Female percentage employed in computing-related occupations in the United States, 2000-2009 (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 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 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 and Margolis, 2002, Moorman and 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 and 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. (In this thesis, Bloom’s definitions of ‘cognitive’ and ‘affective’ learning are used (Bloom, 1956). ‘Cognitive’ learning refers to attainment of mental skills (‘knowledge’), while ‘affective’ learning relates to growth in emotional areas (‘attitude’) (Bloom, 1956)). Examples of such factors include simply owning a computer (Taylor and 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 and Byrd, 1987), confidence levels, self-efficacy and aptitudes related to mathematics, spatial and verbal reasoning (Webb, 1984, Clement et al., 1986, Cafolla, 1987, Jagacinski et al., 1988).

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 (Volet and Styles, 1992, Taylor and Mounfield, 1994, Kafai, 1998, Margolis, 2001).

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 their research 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.

2.3.3 Explaining the performance gap

2.3.3.1 Nature vs. Nurture

Although there are researchers in the literature who present a controversial genetics based explanation (Rushton and Jensen, 2005), the majority of studies present an environmental explanation based on such issues as socio-economic factors, discrimination and teacher student congruence (Oates, 2003, Obiakor, 2004, Stroter, 2008, Horsford, 2010).

Other authors report results from empirical studies that demonstrate race based cognitive performance gaps, and are at pains to point out that the performance gap persists despite controlling for environmental factors, such as socio-economic status, discrimination and historical disadvantage (Naylor and Smith, 2004, Richardson, 2008, 2009). Unlike Rushton et al. (Rushton and Jensen, 2005), these authors stop short of directly proposing a genetics-based explanation, but neither do they offer an alternative explanation.

2.3.3.2 Cultural learning differences- education according to Hofstede

Despite significant criticism of his theory (Spencer-Oatey, 2000, McSweeney, 2002, Signorini et al., 2009), Hofstede (1986) remains one of the most influential authors on the subject of cultural variations in behavior and learning. Hofstede (1986) contends that different cultures and ethnicities do indeed learn differently and has created a model for assessing and differentiating national and organisational cultures, defined within his cultural dimensions theory. Hofstede identifies at least four dimensions that influence behaviours in social settings, including education: Power distance dimension (PDI), Individualist-collectivist dimension (IDV), Masculinity-femininity dimension (MAS) and Uncertainty avoidance dimension (UAI) (Hofstede, 1986, Fernandez et al., 1997, Basabe and Ros, 2005).

Power distance dimension (PDI)

Hofstede uses this dimension to compare prevailing social behaviour between countries and distinguishes between small power distance (SPD) countries and those that tend towards long power distance (LPD). The United Kingdom is cited as an example of an SPD country, which means that social interaction tends to be egalitarian, whereas LPD countries, such as China, are more authoritarian. In the educational context, this means that SPD countries would incline toward less formal teacher student interactions, while LPD countries would be characterised by teaching structures and approaches that were more rigid and focus on the role of the teacher as an authority figure not to be questioned (Hofstede, 1986, Hofstede et al., 2010).

This theory has profound implications for education. For example, the implication is that LPD countries will be characterised by an educational system that relies heavily on the quality of the teacher, whereas in SPD countries learning quality relates more to student excellence (Hofstede, 1986, Harris, 1999, Lemone, 2005).

Individualist-collectivist dimension (IDV)

This dimension describes the extent to which the collective (group) interests prevail over those of the individual. In a highly individualistic culture (such as the United Kingdom), the individual's interests are the focus of interaction, whereas in collectivist societies (such as China) the interests of the group prevail over those of the individual. In the educational context, high individualist scores indicate a culture in which individual students are encouraged to think for themselves, to debate and demonstrate independent thinking ability. Collectivist cultures do not encourage independence, but rather focus on the role of teacher as controller of all that happens in the classroom- the individual defers to the group (Hofstede, 1986, Hofstede et al., 2010).

Masculinity-femininity dimension (MAS)

Hofstede associates masculinity with assertiveness, materialism, ambition and competitiveness, while femininity is associated with greater value being placed on relationships and quality of life. In the education context, this means that groups scoring high on the masculinity index will be characterised by high levels of competition, a desire among students to shine as individuals and would value teachers on the basis of academic ability. The feminine juxtaposition would value the social skills of teacher and underplay competition in the classroom. Hofstede suggests that masculinity is particularly low in Nordic countries, while Japan and Germanic cultures are the most masculine in terms of his model (Hofstede, 1986, Hofstede et al., 2010).

Uncertainty avoidance dimension (UAI)

This dimension describes the tendency of a nation to avoid or embrace uncertainty and ambiguity. Thus, a country with a high UAI score would be characterised by a tendency to manage change via regulation and rule-setting. The low UAI scoring nation is more pragmatic and willing to function without high levels of clarity or structure. From an educational perspective, this means that high UAI scores are associated with 'not rocking the boat' in the classroom and a more structured learning environment. Low UAI scores are linked to a willingness to challenge the teacher and tolerate less structure. Interestingly, the highest UAI scores are in Latin American countries, Southern and Eastern Europe, Germanic countries and Japan. The lowest scores are associated with Anglo, Nordic and Chinese culture countries (Hofstede, 1986, Fernandez et al., 1997, Basabe and Ros, 2005, Hofstede et al., 2010).

Hofstede's theories have been the basis for numerous research studies related to cultural differences and their influence in various information and computer technology related fields. These include the implication of cultural preferences and influence on the design of websites (Ahmed et al., 2009), culture-based differences in end-user computing attitudes and learning styles (Harris, 1999), and cross cultural blended teaching and learning (Cronjé, 2011).

Despite widespread reference in the literature to Hofstede's framework, significant criticism has been leveled at his theory. Signorini et al. (2009), for example, quote Spencer-Oatey (2000) in challenging Hofstede on a variety of issues. One of these is Hofstede's definition of culture. Hofstede's explanation that a person has multiple independent cultures for each group sub-system he/she is a part of is criticised in favour of a more complex concept that describes people within a sub-system as sharing many, but not all, characteristics in common with the other members of the sub-system. Moreover, Hofstede's definition of culture suggests it is a static concept, whereas Spencer-Oatey (2000) proposes that culture is a more fluid, mutable concept. Additionally, Signorini et al. (2009) point out that Hofstede's focus on defining culture in terms of countries or nations does not take cognisance of the variety that exists within these groupings, referred to by Signorini et al. (2009) as 'micro-cultures'.

This is particularly relevant in the highly heterogeneous South African context where any attempt to define the 'culture' of South Africa without acknowledgement of the high levels of variance among the sub-groups would simply not represent accurately the complexities and diversity of the people being described. For example, as at March, 2012, Hofstede rated South Africa against the various dimensions of his model as follows: PDI: 49, IDV: 65, MAS: 63, UAI: 49 (Hofstede, 2012). The score of 49 on the PDI dimension suggests that South Africans generally accept a hierarchical structure in which each individual has their place in society (and in the workforce) and subordinates expect to be told what to do by 'benevolent autocrats' (Hofstede, 2012). In terms of the IDV dimension, South Africa is, in Hofstede's opinion, an 'individualistic' society. This implies a preference for a 'loosely-knit social framework' in which individuals tend to focus on 'taking care of their own needs and those of their immediate families only, and in which employer/employee relationships are based upon mutual advantage' (Hofstede, 2012). South Africa scores 63 on the MAS dimension and is thus a masculine society in which the emphasis is on competition, decisiveness and assertion (Hofstede, 2012). Finally, Hofstede is of the view that South Africa has a preference for avoiding uncertainty (UAI: 49). This implies that South Africans generally have a rigid set of beliefs and rules and are intolerant of 'unorthodox' behavior. High UAI cultures are characterized by high levels of punctuality, precision and work ethic, while innovation is not encouraged (Hofstede, 2012).

Hofstede's generalisations in respect of South Africa have drawn criticism from various authors who point out that Hofstede fails to reflect the diversity of sub-cultures that differ significantly in respect of the dimensions he refers to (Coldwell and Moerdyk, 1981, Godsell, 1981, 1982, Smith, 2002a, Ndletyana, 2003) . For example, it is difficult to reconcile the African concept of 'Ubuntu' (which emphasises the spirit of collective concern and support in Black African society, and the related emphasis among African cultures on caring for the 'extended family'), with the above-mentioned rating of South Africans as highly 'individualistic' (Human, 1996, Ndletyana, 2003, Cronjé, 2011). Human (1996) further points out that Hofstede fails to address intra-cultural differences, such as those that distinguish urban and rural Black South Africans (Human, 1996).

In view of these flaws in Hofstede's framework, Signorini et al. (2009) suggest an approach to evaluating culture and intercultural learning that recognises that sources of culture vary, that language and culture are related and that takes cognisance of the specific characteristics of the learning setting. Moreover, they suggest a model that examines micro-cultures first before expanding into larger models of culture or nationality (Signorini et al., 2009).

Despite these shortcomings, Hofstede provides a useful framework for describing the different learning preferences of various cultures and sub-cultures, including those based on ethnicity.

2.3.3.3 The influence of culture on learning- a scan of international research

The literature is replete with examples of research in recent decades indicating that different cultures and ethnicities learn differently, and in many cases Hofstede's model provides an appropriate framework to explain these differences.

Dunn et al. (1990) examined learning style differences among African-American, Chinese-American, Greek-American and Mexican-American elementary school pupils and identified clear differences in learning preferences in terms of environmental, emotional, sociological and physiological factors.

Using the Learning Styles Inventory instrument developed by Canfield (1988), Matthews (1991) explored learning preferences among English and Biology students at various southern state colleges and universities. Significant gender related differences were found, with females preferring higher levels of detail and organisation than their male counterparts. In addition, it was found that females had a stronger affinity than males for language related learning. Race related differences were also found, with Black students having a stronger preference for an authoritarian teaching approach than their White counterparts. Studies related to computer and information science reflect similar race and gender differences in learning preferences (Catsambis, 1995, Kirkpatrick and Cuban, 1998, Beyer et al., 2003, Beyer, 2006, Gallivan, 2006, Ilias, 2006).

In their report on a case study designed to explore the influence of cultural diversity on the learning experiences of online MBA students at a large mid-western university in the United States, Xiaojing et al. (2010) identified that different cultures (cultural differences 'originating from ethnicity') had different preferences in terms of the online learning experience. For instance, Russian students favoured an exam-oriented culture whereas their American counterparts leaned toward a process-oriented, continuous assessment approach. Chinese students were used to a memory based assessment strategy, while those in the United States were more application oriented, and expressed a desire for the instructors to be considerate of these cultural differences when preparing future assessments. In terms of instructional differences, Russian, Indian and Chinese students tended to favour one-way lectures whereas the American style of teaching was more conversational and interactive. Chinese students were also used to a more structured teaching method while the American approach was more case study oriented with a looser link between instruction and textbook. A variety of other dimensions, such as communication style, collaboration and case learning approach, were analysed in this study and significant cultural differences identified. Interestingly, however, Xiaojing et al. (2010) comment on the fact that students in this particular study did not express negativity about the cultural differences in learning that were identified. Although performance comparisons were not considered in the report, it is specifically noted that the 'cultural differences did not negatively impact communication or collaboration in learning' (Xiaojing et al., 2010).

The findings of this study reflect some of the results reported by Hofstede (1986). Hofstede suggests in his four dimension culture model that Eastern cultures display strong collectivism and femininity attributes, while Western cultures display individualism and masculinity, consistent with the study's report that the Eastern students preferred group work and American students were more independent and competitive in this context. Similarly, the preference for a structured learning approach on the part of Chinese students versus American students is consistent with Hofstede's model which ascribes strong Uncertainty Avoidance attributes to the Eastern culture. Hofstede's Power Distance dimension is high in Asian cultures and explains the strong reliance these students had for textbooks and instructors in comparison with their Western counterparts who score lower on this dimension and prefer the case study approach (Hofstede, 1986, Hofstede et al., 2010).

In a similar study, Woodrow et al. (2001) compared the learning preferences of British-Chinese and British-European pupils at Greater Manchester schools in the United Kingdom. Clear differences were found in terms of how each of the groups chose to be taught. For example, British-Chinese pupils expressed a strong preference for working alone, avoided questioning as a learning technique, favoured memorising as a learning method and did not appreciate peer discussion. British-European pupils, on the other hand, showed a preference for problem solving, 'thinking for oneself' and group learning. The results of this study align with Hofstede's framework and reflect the high collectivism, femininity, Uncertainty Avoidance and Power Distance scores of East Asian cultures (Hofstede, 1986). Interestingly, in the study conducted by Woodrow et al. (2001), the influence of the Chinese culture was still profoundly evident despite the British-Chinese pupils having generally been born and raised in the United Kingdom.

The foregoing provides enough evidence of culture-based differences on the way people learn to justify a response from educators who have to grapple with the inevitable consequence- a culture-based achievement gap. Globalisation exacerbates the challenge by throwing students of various cultures into the same educational context. In many countries, this is mainly due to rampant immigration. In South Africa, the changing political landscape has impacted education by bringing students of various races and home languages into the same classroom. Multicultural classrooms are now no longer the exception, but the norm in most parts of the world. Indeed, this sociological phenomenon has spawned a wave of research internationally to examine the related challenges under the banner of 'Multicultural Pedagogy'.

2.3.4 Multicultural pedagogy

Tong and her associates (Tong et al., 2006) refer to the "acculturation stress" that immigrant students to the United States experience in their new educational settings and proposes a number of strategies that can be employed by educators to help immigrant students cope. The point is made that the coordination of two disparate cultures and languages is anything but straightforward. Apart from the complex socialisation issues that students experience, they are likely to experience culture shock in terms of the educational culture they are now exposed to (and expected to perform in) versus that of their home country. Moreover, it is generally true that linguistic factors come into play and immigrant students are required to learn in a language they are not fluent in. Tong et al. (2006) recommend the development of what they term a 'cross cultural identity' that melds the culture of the old country with that of the new. To facilitate this process, educators are encouraged to become familiar with the cultures of the students they teach and to adapt their teaching approach and style where possible to be more culturally sensitive and consistent with the learning styles preferred by the immigrant students. Moreover, Tong et al. (2006) emphasise the need for teachers to create a sense of affinity with the immigrant students through positive personal relationships and opine that this sense of 'affinity' contributes positively to the student's perception of self, the teacher and the educational environment as a whole. In a similar vein, the teacher is encouraged to be conscious of linguistic challenges and consider these when assessing students.

These suggestions by Tong et al. (2006) that the multicultural learning environment is enhanced by teachers proactively adopting culturally sensitive teaching strategies echo the sentiments of a variety of researchers in the field of critical pedagogy. For example, Milner (2003) encourages 'reflection' by pre-service teachers on race issues and recommends culture sensitive teaching strategies which he calls 'critically engaged dialogue' and 'race reflective journaling'. Allen (2004) offers a historical narrative on 'Whiteness and Critical Pedagogy' in the United States and presents a somewhat militant argument against what he perceives as a failure amongst educators in the United States to adequately address the needs of various cultures within the American education system. Picower (2009) also examines the concept of 'Whiteness' in education as a means of preserving White supremacy and points out that about 90% of all teachers and at least 80% of teacher education students in America are White, thus emphasising the need for educationalists to make an effort to be more proficient in the art of multicultural education. Picower (2009) refers to some successes in this regard, but notes too that there is significant evidence of resistance among White teachers in the United States to adapting their teaching strategies to be more culturally sensitive. She therefore supports the argument made by other researchers for more teachers of colour to enter the American educational system (Sleeter, 2008, Villegas, 2008). Although this suggestion to put Black teachers in front of Black students is sensitive in that it presents an undertone of re-segregation, there is, in fact, evidence from international research that matching teacher and student in terms of race can improve academic performance (Oates, 2003, Stroter, 2008, Horsford, 2010).

However, not all authors are convinced that 'cultural sensitivity' in education has been (or can be) as effective in practical implementation as the theory suggests. Kauffman et al. (2008) lament the fact that after decades of research and discourse on this subject, culturally and linguistically diverse students generally continue to perform comparatively poorly in the United States. They challenge whether the subject has been researched adequately and set out to interrogate the body of research conducted to date for evidence of responsiveness to culturally sensitive interventions. Kauffman et al. (2008) conclude that 'direct instruction' (strategies targeted at and adapted specifically for a particular culture) is less advantageous than 'superior instruction' (teaching strategies that are not culture specific, but rather address culturally neutral factors demonstrated empirically to improve academic performance for all learners, such as 'active student responding, corrective feedback, stimulus control and functional analysis').

Although studies based on the American experience dominate the literature on critical pedagogy, the challenge of multicultural education, along with globalisation, is a worldwide phenomenon and a number of related studies have been conducted in various countries where ethnic heterogeneity is now a reality due in large measure to immigration. For example, Tomlinson (2003) reviews educational policy in the United Kingdom related to addressing the needs of ethnic minorities and notes that despite such efforts the race based academic performance gap continues to grow. Rijkschroeff (2005) conducts a similar study in respect of the Netherlands where more than 50% of the students in secondary education are first or second generation immigrants. Unlike the experience of the United Kingdom, Dutch educational integration policies aimed at addressing multicultural challenges in education have shown signs of success and minority ethnic groups are closing the academic performance gap slowly but surely. Showing the truly international scope of the challenge of multicultural education, Gallagher et al. (2004) review multiculturalism in Canada's educational history and point out that the early part of that history included an attempt by the colonialists of the time to use education to assimilate indigenous groups and eliminate diversity. Like the United States and South Africa, Gallagher et al. (2004) paint a picture of Canada's educational history that is fraught with ethnic and cultural tensions. Unfortunately, since the early 1990s, Canada's interest in tackling ethno cultural equity in the education system has waned and it is left to the educators themselves to find ways to do their best to apply the strategies of critical pedagogy that may contribute to a more culturally equitable education system (Gallagher and Riviere, 2004).

2.4 Teacher student congruence as a predictor of performance

2.4.1 Congruence and academic performance- a scan of international research

Zhang (2006) notes that there has been a resurgence of interest among researchers in recent decades in studying the match/mismatch hypothesis, with more than one hundred research articles and dissertations appearing in a scan of international literature on the subject. Interest in the subject is motivated by the belief that matching teacher and student in terms of various characteristics such as thinking and learning style enhances the learning experience and produces performance improvements. Zhang distinguishes between two themes in this literature, viz. the effects of match/mismatch on student performance and the effect of match/mismatch on interpersonal attraction (or affinity) between teacher and student. An alternative view, however, is that these are variations of the same theme, since improvement in the sense of affinity between teacher and student has been shown to lead to improved performance (Alexander et al., 1987, Jussim et al., 1996, Ferguson, 1998).

As Zhang points out, results for this type of research relating to the impact of matching thinking styles for teachers and students are somewhat contradictory. A number of studies provide evidence that congruence between teacher and student thinking styles significantly improves academic performance across a variety of subjects (Block, 1981, Cafferty, 1981, Grout, 1991). Other studies, however, suggest the match/mismatch aspect is less important (or entirely insignificant) and that if any factor related to thinking style is relevant, it is the cognitive style of the teacher, regardless of whether this matches that of the student (Saracho and Dayton, 1980, Foley, 1999).

Zhang's own research at a large comprehensive university in Shanghai, China, found that results varied by subject (Zhang, 2006). Mathematics students, for example, failed to show a significant correlation between teacher student thinking style match and performance. However, for Public Administration and Physics there was evidence that teacher student match is a predictor of performance. Furthermore, Zhang showed that it was not just in terms of subject matter that variations were found, but also at the level of academic discipline (Zhang, 2006).

The value of matching teacher and student in terms of ethnicity has received considerable attention in the United States, particularly since the formal desegregation of schools. Desegregation by definition encourages a mingling of cultures and, more specifically, different races. It is interesting that in education, despite the popularity of the notion, desegregation has been seen as problematic precisely because it results in putting people with different cultures and learning preferences together. The literature reports on a number of studies conducted in the United States and elsewhere that examine the impact on learning of matching teacher and student in terms of ethnicity. The results are not conclusive, with some data suggesting that matching teacher and student in terms of ethnicity, culture and other characteristics can positively impact learning achievement (Jussim et al., 1996, Oates, 2003, Stroter, 2008, Horsford, 2010, Denny and Maharaj, 2011), while others show no significant impact (Brewer et al., 1994, Pigott and Cowen, 2000).

Much of the research on teacher student congruence focuses on student perceptions and attitudes rather than academic achievement. For example, Galguera (1998) investigated students' attitudes toward teachers' ethnicity, bilinguality and gender, finding that students appeared to prefer teachers of the same ethnicity, had partial preference for bilingual teachers, and preferred female teachers (although there was no indication of student preference for same gender teachers). African American and Latino students demonstrated a higher than expected preference for teachers of the same ethnicity and students generally preferred teachers who spoke the same language. Of the various congruence factors considered, ethnicity and language were more significant than gender. This study is particularly interesting in terms of its findings on the impact of ‘length of US residency’ among immigrant students in the sample. It was found, for example, that the longer students had been resident in the United States, the more significant their attention to race factors and the more negative their perceptions towards teachers in general. Galguera (1998) is of the opinion that the history of racial tension in the United States has created a general sense of tension around this subject and that this environment of ‘racial awareness’ in education tends to impact the attitudes of people who are part of it. Perhaps controversially, Galguera (1998) further suggests that the findings of his study argue for a review of teacher recruitment policy to accommodate teachers of specific ethnicities, languages and genders depending on the preferences of students in the schools or districts in which they are being employed.

More recently, Reid (2010) examined race and gender biases among students from a variety of liberal arts colleges in the United States in respect of their professors. The study found that Black and Asian (minority) faculty were rated lower by students on overall quality, helpfulness and clarity than White faculty and that Black or Asian professors were more likely to be rated as being 'among the very worst instructors, while their White counterparts were more likely to be rated as being 'among the very best instructors' by students. No significant differences related to gender were identified in this study.

While Galguera's study (Galguera, 1998) is similar to those of a number of other authors who focus on congruence factors as they pertain to student perceptions and attitudes (Hendriks, 1997, McCroskey, 2002, 2003, Wilson, 2006, Schrodt et al., 2009, Reid, 2010), other studies investigate the impact of teacher student congruence on academic achievement and cognitive test performance. Stroter (2008), for example, examined the effect of teacher student racial congruence among 1,576 seventh grade students in middle school Texas on mathematics test scores. The 92 teachers involved in the study spanned a variety of ethnic groups, as did the students, across 76 schools in 8 Texas regions. Most of the teachers in the study were White (76.1%) and 23.9% were Hispanic, while among the students 44.4% were Hispanic, 41.4% were White and 4.2% were African-American. Using Hierarchical Linear Modeling, Stroter found that student performance improved significantly when teacher and student were matched in terms of ethnicity. This was true in equal measure for minority and White students. Unlike other studies that attempt to explain the positive impact of teacher student racial congruence by referring to teacher perception of minority students (Oates, 2003), Stroter found no significant evidence in her study to suggest that teacher perceptions and expectations of student performance aligns with their actual performance for marginalised students when there is a match of teacher and student by ethnicity.

In Stroter's interpretation of her results, she alludes to the implications for the American educational system of identifying a significant relationship between student performance and teacher student ethnicity match and points out that despite a groundswell of empirical evidence, the United States Supreme Court has recently ruled as unconstitutional any idea of assigning students to classrooms or teachers on the basis of ethnicity (Stroter, 2008).

Interestingly, Stroter uses performance improvement (based on the difference between a post and pre-test score) as the dependent variable in her study. This is a deviation from the method adopted by a number of researchers who have done similar studies and have used a single post training test score as the dependent variable. Stroter's use of performance improvement as the dependent variable for analysis (rather than a single test score) allows for isolation of the impact of teacher training on student performance and the elimination of potentially confounding variables, such as student educational history prior to the training intervention being investigated.

Horsford (2010) refers to the false sense of optimism that prevailed following the landmark *Brown vs. Board of Education* court case of 1954 which served as a catalyst for school desegregation in the United States. This case was intended to uphold the 14th Amendment and ensure equal education for all races in America. This would be achieved through eliminating legislated inequities among races in education, such as ensuring that traditionally Black schools received the same attention in terms of government investment in teacher training and infrastructure as the more affluent state schools, but it also led naturally to a conscious effort to desegregate. Horsford points out that educational research in the United States has subsequently presented a case to suggest that the very desegregation that was achieved created problems of its own, related in main to teacher student mismatch in terms of culture. Simply put: Black students were taught by White teachers who did not share a sense of affinity with the Black students or were downright discriminatory. Importantly, although Horsford believes the insights provided by her research into the positives of the 'valued segregated schools' can help educators improve the quality of the educational services they provide, she is at pains to point out that she is not suggesting a return to segregation or excusing the deplorable inequities that prevailed during periods of legislated segregation in the United States. Horsford's (2010) objective is for the positive aspects of segregated schools to inform the reform of currently desegregated schools with a view to closing the racial performance gap.

Obiakor (2004) similarly explores the Brown case and the subsequent failures of the American education system to bring the ideals of that case to fruition and refers to 'the new racism' that has prevailed in education since then. Both Obiakor and Horsford refer to the fact that the majority of teachers in the United States are Anglo American and that in a desegregated educational environment there is still a sense of cultural disconnection between White teacher and Black student. Obiakor quotes Diaz (1992) to make the point that learning is affected by cultural issues and so this mismatch in teacher and student culture threatens to perpetuate the racial performance gap- an unfortunate side effect of mismanaged desegregation. Obiakor suggests a variety of strategies to counter the effects of cultural mismatch in desegregated schools, such as cultural sensitivity training for urban teachers and continuous re-assessment of educational programmes to address multicultural requirements. Horsford takes it a step further and cites numerous researchers who endorse her findings (largely qualitative in nature and based on narratives of African Americans who attended pre-Brown segregated schools) that good segregated schools were remembered fondly by alumni for their 'community support, cultural affirmation, community, caring, and interdependency among African American constituencies', rather than the poor resources (Dempsey and Noblit, 1993, Foster, 1997, Bell, 2004). Horsford therefore suggests that recreating that sense of affinity, community and cultural affirmation that characterised segregated schools will contribute to addressing the challenge of the racial performance gap that seems to be perpetuated in the desegregated systems, but is not definite on how that might be achieved.

The relevance of the foregoing research by the likes of Obiakor and Horsford for this thesis is twofold:

1. culture and ethnicity related issues are shown to be relevant in terms of student learning and performance;
2. it is demonstrated that improvements in learning based performance can be achieved by considering cultural issues (such a teacher student ethnicity match) in learning strategies.

In attempting to explain the impact on learning of culture and ethnicity factors discussed above, including teacher student ethnicity match, various authors refer to the concepts of 'immediacy' and 'affinity' (Rucker and Gendrin (2003), Jussim et al., 1996, Sanders and Wiseman, 1990). The following section explores the role of immediacy and affinity in teacher student interaction and academic performance, with specific reference to the influence of cultural factors.

2.4.2 Immediacy, affinity and cultural consonance

2.4.2.1 The role of immediacy

Immediacy has been defined by Burgoon et al. (1980) as a "combination of verbal and nonverbal behaviours working together as a system to increase or decrease the degree of physical, temporal, and psychological closeness between individuals". Immediacy is therefore one strategy to achieve affinity, which in turn enhances learning and consequently performance. In fact, various studies have shown that immediacy is related positively to affective, behavioural and cognitive learning (Christophel, 1990, Rodriguez et al., 1996).

Janis Andersen is recognised as having engaged in the seminal research effort on immediacy. Her Behavioural Indicants of Immediacy (BII) scale has been used extensively since her research in this field began in the 1970s (Andersen, 1979, Andersen et al., 1981, McCroskey and Richmond, 1992). Using this low inference, high validity instrument, Andersen was able to demonstrate that 20% of variance in student affect toward the subject matter and 46% of the variance in affect toward the teacher were predictable from teachers' scores on immediacy (McCroskey and Richmond, 1992). Kearney (1980) similarly found a positive correlation between teacher responsiveness (immediacy) and student affect for teacher and subject matter.

Since Andersen, various studies have explored the impact of immediacy on cognitive learning. Richmond, Gorham and McCroskey (1987) slightly adapted Andersen's BII scale and used a student self-report approach to demonstrate a positive relationship between immediacy scores and cognitive learning. An interesting caveat to this research is that it suggested a non-linear relationship between immediacy and cognitive learning. Moderately high immediacy scores in this study were found to correlate with moderately high cognitive learning performance, whereas high immediacy was not significantly related to high cognitive learning scores, suggesting the possibility that immediacy may have a threshold at which it becomes ‘unpalatable’ for the student and ineffective as a learning enabler. Gorham (1988) expanded on this study and was able to replicate the findings of earlier studies which showed a significant and positive relationship between non-verbal immediacy and affective learning. To overcome certain limitations inherent in the self-reporting approach, Kelley and Gorham (1988) conducted a study that involved ‘novel learning’ (i.e. the content being tested was not known to participants prior to the study). Once again, a strong and significant relationship was shown to exist between immediacy and cognitive learning. In this case, for example, certain immediacy behaviours were demonstrated to account for more than 11% of total learning variance.

Clearly, then, there is a positive relationship between immediacy (both verbal and non-verbal) and learning (both cognitive and affective). Why is this? Attempts at explanation have tended toward one of two theories. The first is that suggested by Kelley and Gorham (1988) and relates to what they call ‘arousal-attention’ to explain how immediacy enhances cognitive learning. They propound a theory that involves a chain of impact-immediacy, they claim, is likely to stimulate arousal in students, which in turn is necessary for and encourages attention, which is a pre-requisite for memory recall and ultimately, therefore, results in improved cognitive learning.

Other researchers have proposed an alternative theory based on ‘motivation’ (Christophel, 1990, Richmond, 1990). In terms of this explanation, students learn best when they want to learn. Thus, higher levels of immediate behaviour on the part of the teacher are seen to improve motivation levels among students and in turn result in enhanced learning. Christophel (1990) was able to provide evidence that convincingly related immediacy to motivation levels among students in her study.

2.4.2.2 The role of affinity

The concept of ‘immediacy’ is closely related to that of affinity. Thus, an alternative explanation for the impact of immediacy is that it improves affinity between teacher and student and this contributes to a more conducive learning environment for students, which in turn enhances learning. Involving affinity in the chain of impact leading from immediacy to performance improvement in the classroom means that the relationship between immediacy and learning is indirect, but nevertheless consequential.

McCroskey and Richmond (1992) relate ‘affinity’ to the amount of power an individual grants another and synonymises the expression with ‘liking, loving, admiring and respecting’. With reference to their research on ‘power’ in various contexts, including the classroom, McCroskey et al. identify the teacher as being able to influence students to engage in the behaviours necessary to achieve the desired learning outcomes and point out that students will tend to be less resistant to instructions from a teacher with whom the student shares a strong sense of affinity. Bell and Daly (1984) suggest a variety of ‘affinity seeking’ strategies, implying that affinity is not necessarily simply the result of innate characteristics, but can be cultivated and learned. Assuming that affinity is a positive factor in enhancing learning and performance in the classroom, the implication is that any strategy that can enhance affinity (such as racial congruence or immediacy) between teacher and student can positively contribute to improving academic performance.

Wilson (2006) makes a similar point about the importance of a strong sense of affinity between student and teacher and expresses the opinion that immediacy behaviours are simply a subset of all those actions that demonstrate affinity between teacher and student (or, put simply, that a teacher ‘likes’ the student). Demonstrating the ‘chain of impact’, Wilson further reports that student perceptions of the extent to which they are ‘liked’ by their lecturer can be correlated with student levels of motivation and performance in the classroom (Wilson and Taylor, 2001). In particular, communicating genuine concern for students was identified as being one of the most significant expressions of teacher student affinity in terms of impact on the motivation and attitude of the student. Wilson opines that it may be misguided, therefore, to focus exclusively on the impact of immediacy as a predictor of student attitudes and performance and that the more important factor is the student’s perception of teacher affinity (Wilson, 2006).

The foregoing, therefore, suggests that while immediacy is undoubtedly a factor that contributes to enhanced learning, the impact is indirect and is a subset of the various factors that contribute jointly to a sense of affinity between student and teacher, which is the most important predictor of student learning outcomes.

2.4.2.3 Race and immediacy

It would be naïve to assume that immediacy would be experienced in the same way across various cultures and ethnicities. McCroskey et al. (1992) point out that it is well established that non-verbal behaviours vary across cultures in terms of norms and impact. Various studies have shown that immediacy is a factor in cognitive and affective learning across cultures, but varies in terms of both level of impact and the specific immediacy items being considered (Powell and Harville, 1990, Sanders and Wiseman, 1990, Neuliep, 1995). Thus, specific ethnic subgroups may respond more intensely to certain immediacy behaviours than others. Black students in Sanders and Wiseman's study, in particular, showed evidence of responding very differently to certain items than other groups (Sanders and Wiseman, 1990).

It is possible that this variety in items and impact of immediacy across cultures explains the findings of researchers who demonstrate a relationship between teacher student racial congruence and performance. In this respect, it could be that racial congruence results in 'natural immediacy' whereby the teacher's immediate behaviours are consonant with student expectations due to a shared culture and communication style.

Rucker and Gendrin (2003) explored the aspect of racial identity in their study on immediacy and its impact on cognitive learning in a historically Black university in the United States. Rucker et al. used Gorham's 20 item verbal immediacy tool and Richmond, Gorham and McCroskey's 14 item nonverbal immediacy measure with 239 students (Richmond et al., 1987, Gorham, 1988). However, the added dimension of 'Black identity' was included in this study by asking students to respond to the centrality and ideology dimensions of the Multidimensional Model of Racial Identity developed by Sellers et al. (1998). These elements were included on the premise that students with strong Black identity would be assumed to prefer an ethnically congruent learning environment and that this may influence their scores for teacher immediacy based on the ethnicity of the teacher. The results of this study suggested that Black students who had a strong sense of ethnic identity identified more strongly with the immediacy behaviours of Black teachers and therefore cognitive learning was improved in these racially congruent contexts. In summary, Black students' performance was shown to be positively related to teacher student racial consonance, particularly where the student had a strong sense of ethnic identity.

The research into cultural aspects of immediacy indicate that at least some immediacy behaviour is based on innate factors, such as personality or culture (Sanders and Wiseman, 1990). However, a number of studies have shown that immediacy behaviours can also be taught and that these taught behaviours, when implemented in the classroom, are impactful as enhancers of affect on the part of students for both teachers and subject matter (Richmond et al., 1986). The implication is that teachers can be trained to become more immediate (in respect of specific immediacy items that are culturally relevant for the particular group of students) and therefore more effective.

2.5 Racial identity and the role of perception in student academic performance

Much of the literature relating to ethnic congruence makes reference to the impact of racial identity and teacher and student perceptions of each other.

For example, Oates (2003) examined the relationship between teacher student racial congruence, teacher perceptions (defined in this study as the combination of a teacher's expectations and assessment of a student's diligence) and test performance using a multistage cluster sample of 24,599 eighth, ninth and tenth grade students in the United States and found that ethnic 'consonance' (i.e. teacher student match in terms of ethnicity) had a positive impact on student academic performance. The discussion around the possible reasons for this is interesting. Oates refers to studies by Jussim, Eccles and Madon (Jussim et al., 1996) which suggest that unfavourable teacher perceptions tend to negatively impact student performance and conversely, favourable teacher student relations tend to positively affect student test performance. Racial consonance between teachers and students is seen to foster favourable teacher perceptions and thus create a learning environment that is more conducive to improved academic performance. In short, a chain of impact is proposed whereby racial congruence results in improved teacher perceptions, which in turn results in improved student performance.

Jussim, et al. (1996) further explore why racial consonance or dissonance impacts teacher perceptions, which leads in turn to an impact on student performance, and identify two possible theories. The first is the 'self-concept' theory which postulates that racial incongruity tends to depress the relevance to the student of teacher perceptions and opinions. So, for example, a Black student will not be as impacted by the opinions of a teacher whose ethnicity does not match that of the student. The second is the 'self-fulfilling prophecy' theory which suggests that racial consonance results in teachers behaving more favourably toward students of the same race with whom they have a greater sense of affinity. Thus students in racially dissonant contexts tend to perform in a way that validates negative teacher perceptions.

Oates' study showed that White teachers had significantly higher levels of negative perception toward Black students than Black teachers had toward White students. Oates favours the 'self-fulfilling prophecy' theory as an explanation for his findings that racial dissonance results in poorer results than when students and teachers are racially matched, pointing out that the highest levels of perceptual bias (along with lowest student performance) occurred in White teacher, Black student pairings. In terms of the 'self-concept' theory, these Black students would have been less inclined to allow themselves to be impacted by White teachers' perceptions than was actually shown to be the case.

Interestingly, although Oates finds high levels of anti-Black bias among White teachers, he finds that Black teachers in his study were race neutral. White teacher perceptions were not only shown to be biased, they were shown to be consequential as a predictor of performance among both Black and White students. Significantly, positive perceptions among White teachers were more consequential as a predictor of improved performance across both White and Black students than were those of Black teachers.

In a similar study conducted by Chang et al. (2007) on a sample of education students at the University of California, teachers of all races were shown to hold stereotypes about students of other races, whether positive or negative. For example, Asian students were generally viewed by teachers of all races as diligent, more intelligent and industrious. Unlike Oates' findings, however, Chang et al. found that the stereotypes of Black and White students, although they clearly existed, did not differ greatly between teachers of different races, suggesting that teacher perceptions are potentially impactful regardless of the race of the teacher.

The findings of Oates and other researchers suggest that teacher perceptions are significantly related to teacher student racial congruence and that these perceptions impact student learning and performance. Oates opines that it is appropriate to conclude, therefore, that the predominantly negative perceptions of White teachers perpetuate the Black-White student performance gap in the United States. By implication, performance can be enhanced by pedagogical strategies that either encourage race neutrality among White teachers or match Black students with Black teachers, assuming that other factors, such as teacher quality, are effectively neutralised. Regarding the latter (and potentially controversial) implication, Oates makes specific commentary in his report on the findings of his research that cautions against concluding with finality that Black teacher, Black student matches predict performance improvement, pointing out that Black teachers' perceptions were less consequential than those of White teachers (Oates, 2003).

However, it is not only teacher perceptions that appear to make a difference in multicultural classrooms. Studies have shown that student perceptions and their own sense of racial identity not only vary among students of different races, but also impact their learning experience and academic attainment (Chavous et al., 2003, Rucker and Gendrin, 2003, Wilson, 2006). For example, Rucker and Gendrin's (2003) investigation on the impact of immediacy on the academic achievement of students of various races revealed that students' perceptions of racial identity influenced the way in which they responded to teachers of various races and consequently their academic performance.

Chavous et al. (2003) similarly explored the relationships between racial identity factors and academic achievement among African American students. They used the MMRI (multi-dimensional model of racial identity) to distinguish between three aspects of racial identity: racial centrality, private regard and public regard (Sellers et al., 1998). Students' scores in respect of these aspects of racial identity were compared and clustered into 'profile groups' which were then related to academic performance, educational beliefs and later attainment (college attendance). The results suggested that students may hold either a positive or a negative belief about their race and that these varying senses of racial identity may influence not only their attitudes toward education, for example, but by extension also impact their potential for academic achievement.

Wilson (2006) examined the extent to which perceptions among undergraduate students at an American university predicted their attitudes and performance in the classroom. She found that student perceptions of lecturers' attitudes towards them accounted for significant variances in motivation, attitude and projected grades and that this predictive ability of lecturers' attitudes towards students was largely independent of other factors, such as immediacy.

In a more recent study involving 1,416 undergraduate students from four universities in the United States, Schrodt et al. (2009) were able to show a chain of impact between instructors' communication behaviours, instructor credibility and student learning outcomes. In their study, students' perceptions of various prosocial behaviours (confirmation, clarity, and immediacy) on the part of their teachers accounted for significant percentages in the variance in instructor credibility and learning outcomes. As with Wilson's study (Wilson, 2006), immediacy was shown to be the least important of the factors contributing to learning outcomes, while perceived teacher 'confirmation' and 'clarity' produced the strongest effects for credibility and learning. Schrodt et al. (2009) summarise these findings by pointing out that these 'confirmation' and 'clarity' behaviours on the part of professors are impactful because they "reduce perceived psychological distance with their students" and "are likely to yield fruitful dividends by increasing students' motivation, affect, and effort in the classroom" (Schrodt et al., 2009).

While the study by Schrodt et al. (2009) investigated the relationship between teacher credibility and student learning outcomes, gender and ethnicity factors were not explicitly considered. Glascock and Ruggiero (2006) similarly investigate university students' perceptions of professor credibility, but include an examination of the extent to which gender and ethnicity play a part in the results. Glascock et al. (2006) point out that source (teacher) credibility is one of the most important student perceptions in the higher education context. Glascock et al. (2006) cite McCroskey and Young's (1981) definition of credibility as "the attitude toward a source of a communication held at a given time by a receiver", and refer to a number of studies that relate race and gender to students' perceptions of teacher credibility (Hendriks, 1997, Rubin, 1998, Patton, 1999, Centra and Gaubatz, 2000).

It is not difficult to see how the findings referred to in the foregoing in respect of racial identity, teacher and student perceptions, immediacy and affinity and the impact thereof on student attitudes, motivation and performance in the classroom are related. Although different authors and studies have different focus areas, the nexus appears to be the resultant attitude or perception of the student and their sense of affinity with the teacher in the classroom. Racial identity issues may impact the way in which the student reacts to teachers who exhibit racially biased attitudes and behaviours. Teacher perceptions of students may be racially prejudiced or otherwise negative and discriminatory, which in turn affects the student's sense of affinity with the teacher. Teacher immediacy behaviours are only impactful in terms of student reactions to them. Thus it would appear that student perceptions are a key aspect in any discussion on factors that impact student performance in the multicultural classroom.

2.6 Social cognitive theory in computer education

2.6.1 Social modeling and observational learning

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, Compeau et al., 1999, 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 teacher 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).

Bandura's theory related to model and observer characteristics and perceptions of credibility, affinity and similarity aligns with the findings of various researchers discussed in the foregoing sections on racial identity, immediacy and affinity in the multicultural classroom (McCroskey and Richmond, 1992, Chavous et al., 2003, Rucker and Gendrin, 2003, Glascock and Ruggiero, 2006, Wilson, 2006, Schrodt et al., 2009).

2.6.2 Self-efficacy and computer education

Apart from the constructs related to models and observers, one of the most influential constructs in SCT is 'self-efficacy' (Bandura, 1977b, 1994, 1995, 2000). Bandura describes self-efficacy as an individual's perception of his or her own capability to achieve a task or learn a behaviour. Thus, a high level of self-efficacy is associated with more effective learning and the converse is also true- a low self-efficacy rating tends to impede learning. Bandura extends this concept to include the perceptions a reference group has of its own capabilities and calls this 'collective self-efficacy' (Bandura, 1995, 2000). A number of authors have referred to Bandura's construct of collective self-efficacy in explaining culture based variations in academic achievement (Oettingen, 1995, Bandura, 2000, Tschannen-Moran and Barr, 2004, Klassen et al., 2010, Moseley and Taylor, 2011). With specific reference to technology and computer science education, researchers have coined terms such as 'computer self-efficacy', 'computer anxiety' and 'technology self-efficacy' to refer to the perceptions of capability individuals or reference groups have in respect of information technology specific skills (Marakas et al., 1989, Busch, 1995, Compeau and Higgins, 1995, Saleem et al., 2011). A variety of studies have attempted to show a link between computer self-efficacy and academic performance in computer related education, with mixed results. Some of these studies have suggested that high levels of computer self-efficacy are positively related to academic achievement (Harrison and Rainer, 1997, Smith, 2002b). Other studies show no such direct link between computer self-efficacy and performance (Singh et al., 2010).

Ausburn et al. (2009) investigate the role played by what they term 'technology self-efficacy' in understanding gender effects in technology-based learning environments. These authors note that a variety of conceptual areas, including social and culturally influenced perceptions of and experiences with computer technology, provide useful insights into the differences across genders in research related to virtual environments and come together in self-efficacy theory. Ausburn and her colleagues refer to 'technological self-efficacy' as a determinant of an individual's 'performance and perception of that performance in a technology learning environment such as virtual reality (Ausburn et al., 2009). Commenting on gender differences in performance related to virtual learning environments, Ausburn et al. (2009) note the findings of various studies that have identified gender as a strong predictor of technological self- efficacy, with females consistently shown to be more likely to rate self-perception of their computer skills lower than males (Temple and Lips, 1989, Busch, 1995, Hargittai and Shafer, 2006, Hogan, 2006, Bain and Rice, 2007). Women have also frequently reported less confidence and more anxiety with usage of spatially-related materials and computer software, have displayed higher levels of ‘computer anxiety than males, and generally view technology and computers as more difficult to master and less interesting than males do (Weil and Rossen, 1995, Whitley, 1996, Schumacher and Morahan-Martin, 2001, Gilbert et al., 2003, Rainer et al., 2003, Terlecki and Newcombe, 2005, Todman and Day, 2006). Attempting to explain the technology gap between genders, the American Association of University Women Educational Foundation (2000) identified teacher attitudes, public media, software manufacturers, and curriculum as factors contributing to gender technology self-efficacy deficits and lowered self-confidence of young females about technology and computing.

Various other studies have found that gender differences in computer self-efficacy levels are related to the complexity of the task at hand. Murphy et al. (1989) found, for example, that the difference in self-efficacy rating between the genders was highest when computers were used on an advanced level. Busch (1995) found similarly in his study that at the more fundamental levels of Word Perfect and Lotus end user skills, males and females did not differ significantly in terms of self-efficacy expectations. Interestingly, Busch found not only that female students had lower self-efficacy in respect of more complex computing tasks than males, they also had less experience in programming and in paying computer games than their male counterparts. In addition, they tended to receive less positive reinforcement from friends and family and had less access than males to computers at home (Busch, 1995).

Busch (1995) makes an interesting observation regarding cultural differences in how computer self-efficacy is experienced, referring to the ‘process of socialisation’. Busch opines that gender differences in both self-efficacy and general attitudes towards computers are the result of social conditioning that begins in the home. Busch suggests that a ‘sex-role identity is formed in the first instance within the family where norms are internalized, attitudes are learned and a self-image is acquired’ (Busch, 1995). These behaviours are reinforced and developed in the school and work setting where society’s norms are imposed, including gender biases in respect of the types of career and interest areas that are ‘appropriate’ for males and females. Therefore, gender differences in attitudes toward computers and computer self-efficacy are thus the product of different social experiences and depend to a large extent on the norms of the particular culture an individual is a part of (Busch, 1995).

In line with Busch’s theory of cultural socialisation, various studies have shown that there do indeed appear to be significant differences between cultures in respect of gender disparities in computer self-efficacy and attitudes toward computers (Turkle, 1984, Collis and Williams, 1987, Elkjær, 1992, Makrakis, 1992). Collis and Williams (1987), for example, found that while both Chinese and Canadian students exhibited gender differences in computer self-efficacy and attitudes toward computers, Chinese students displayed fewer differences than their Canadian counterparts. Similarly, Makrakis (1992) compared gender differences in computer self-efficacy among Japanese and Swedish students and found that for both genders, Swedish students had higher levels of computer self-efficacy than Japanese students. Swedish male students were significantly more positive in their attitude toward computers than Swedish females, and there were no significant gender differences in attitudes for the Japanese students. Results such as these seem to support the theories of authors like Turkle (1984) who claim that gender differences are the product of socio-cultural expectations that differ from culture to culture and that determine models of ‘correct and appropriate’ behaviour for children of each gender.

Research would seem to suggest, then, that despite gains in their positive perceptions and usage of computers, females continue to lag behind males in technology and computer self-efficacy, which may continue to impact their performance in technology learning environments. Cooper (2006) reports on decades of literature related to gender disparities in computer and technology self-efficacy and suggests that it is fundamentally a problem of ‘computer anxiety rooted in gender socialization interacting with stereotype of computers as primarily a male dominated interest area’. In Cooper’s view, this computer anxiety and low technology self-efficacy rating accounts for the variations in computer related attitudes and performances that are frequently observed and reported in cross-gender computer studies (Cooper, 2006).

An interesting variation in the ‘gender difference in computer self-efficacy’ theme is explored by Saleem et al. (2011) investigate the role of personality traits as antecedents to computer self-efficacy and he role of gender as a moderating factor (see Figure 2-1). Once again, gender differences were found, with the traits of neuroticism, extraversion, openness, conscientiousness and agreeableness being shown to be significantly related to computer self-efficacy for women, but not for men. Surprisingly (given the earlier research finding that females report lower computer self-efficacy than males (McIlroy et al., 2001, Schumacher and Morahan-Martin, 2001, Chau and Hu, 2002, Durndell and Haag, 2002)), Saleem et al. (2011) found that females scored significantly higher than males on computer self-efficacy, and suggest that this may be due to the fact that the sample comprised mainly graduate students and faculty members who had previously had significant exposure to computers and technology.

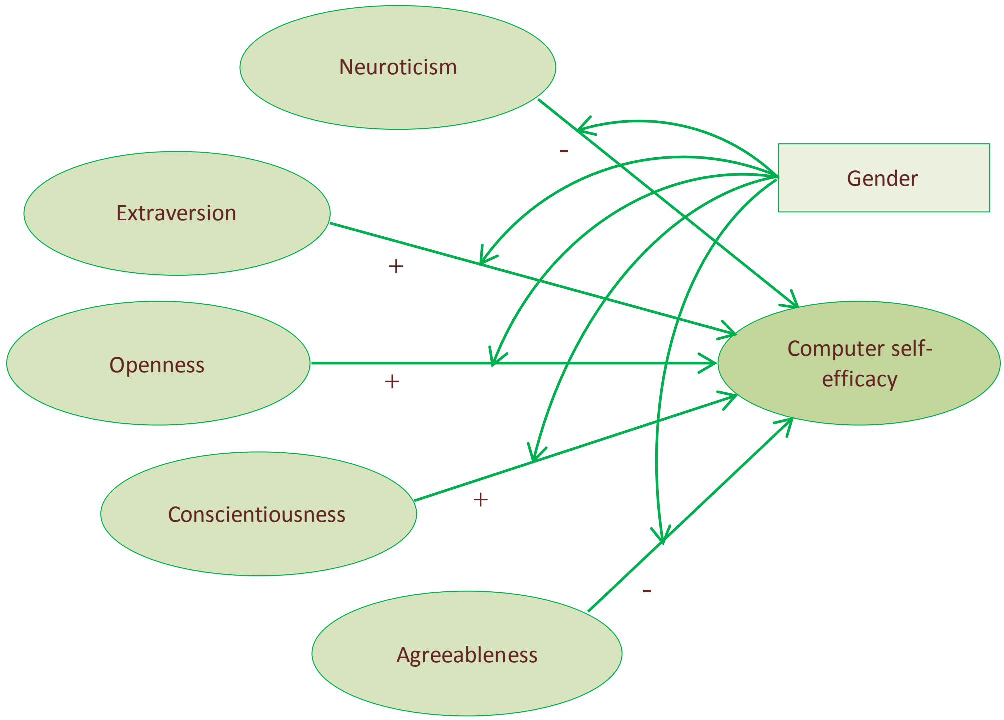


Figure 2-1 Saleem et al. research model (Source: Adapted from Saleem et al. (2011))

While the research on gender differences in computer self-efficacy consistently suggests that females tend to have lower perceptions of their own computer-related capability, the findings on race-based disparities are not as consistent. While some studies suggest that minority groups have lower computer self-efficacy (Galpin et al., 2003), other studies either find no statistically sound basis for this conclusion or find that the opposite holds true in certain instances (Johnson et al., 2008). For example, Clifford (2007) found no statistically significant differences in the levels of computer self-efficacy of African-American, Hispanic American and Caucasian-American college students, although she did find that Hispanic students tended to have higher levels of computer related anxiety than the other racial groupings. Johnson et al. (2008) investigated, inter alia, the relationship between computer self-efficacy, ethnicity and gender among African-American and Anglo-American students and found that African-American students scored higher on IT self-efficacy than their Caucasian counterparts, and that Anglo-American females had lower IT self-efficacy than any other group.

2.7 The unique South African context

2.7.1 A history of inequality in education

The review of international research provides interesting insights into the global challenge of multicultural education. The South African context, however, is unique in many respects. The value of the insights gleaned from a consideration of international studies is tempered somewhat when considered in the light of South Africa's socio-political context and an educational landscape that reflects the enormity and complexity of the challenge facing educators and politicians who attempt to redress deeply rooted historical disparities.

In comparing the journeys toward racial integration of the USA and South Africa, Tihanyi (2007) notes that South Africa's process of redressing inequalities in education has taken place within the context of broader societal reconciliation and opines that there are profound lessons to be learned from an examination of the role of race in shaping the educational landscapes of both countries. Tihanyi points out that there are a number of similarities and differences between the two countries that are worthy of consideration when investigating race related factors in education, such as the impact of teacher student racial congruence on learning and test performance.

2.7.1.1 The United States of America

Tihanyi (2007) notes that slaves in the United States of America (USA) were historically not permitted formal education and that it was not until after the Civil War that schools for former slaves were introduced. These schools were the earliest examples of segregated education in the United States and were based on the 'separate but equal' philosophy made famous by the Plessy vs. Ferguson (1896) court case. In reality, the White educational institutions were superior facilities and this was the premise for the subsequent desegregation effort that culminated (at least from a legislative point of view) in the landmark *Brown vs. Board of Education* (1954) Supreme Court decision that declared racial separation unconstitutional. White resistance to desegregation was often subtle, sometimes blatant, but effective overall in terms of delaying actual desegregation on the ground. Much like in post-apartheid South Africa, resistance to change was evident in various legal strategies, student on student race based victimisation and the establishment of expensive private schools that would predominantly be patronised by Whites who could afford it (Tihanyi, 2007).

By the mid 1970s, assisted by various further pieces of legislation, including the 1964 Civil Rights Act and the 1965 Elementary and Secondary Education Act, communities all over the USA had made significant progress toward desegregated schooling. Although some data suggest that desegregation has resulted in improved academic performance for minority students, other authors have also cautioned that desegregation has created challenges of its own, such as a racial identity disconnect for minority students who find themselves in educational environments that favour the White majority in various ways, in which most teachers are not of the same ethnicity and wherein there is not only an indifference in respect of coveted cultural values, but in many cases a sense of hostility toward minority groups on the part of the administration and teachers (Jussim et al., 1996, Oates, 2003, Obiakor, 2004).

2.7.1.2 South Africa

Since 1948 and the official advent of Apartheid as a legislated system of segregation, South Africa has been divided into four racial groupings: White, Black, Indian (typically used of anyone of West Asian origin) and Coloured (mixed race). Despite the demise of Apartheid as a legal system, race continues to be a dominant aspect of the social dynamic in South Africa and these references to people in terms of racial identity continue to be part of life for South Africans. Arguably the most devastating set of policy in terms of perpetuating White dominance in South Africa during the Apartheid era was that related to education. This is starkly illustrated using the example of per capita expenditure for education across the various race groups in pre-1994 South Africa (as per Table 2-3).

	Black	Coloured	Indian	White
1970	17	73	73	282
1980	139	253	513	913
1993	1,659	2,902	3,702	4,372

Table 2-3 Per capita government expenditure (Rands) on education in South Africa (Source: Adapted from Tihanyi (2007), Eyber et al. (1997) and Nkabinde (1997))

Not only do the figures in Table 2-3 illustrate the vast chasm between the races in terms of government input, they also show clearly that not all non-White groups were treated equally. For example, Indians generally received more than Blacks and Coloureds during the Apartheid years. In 1970, Indians received 400% what their Black compatriots received, and in 1980 they received more than either of the Black or Coloured groupings.

The South African National Planning Commission's Diagnostic Overview for 2010/11 claims that the national average allocation per learner has increased to R11,192 in 2010/11, and that equalisation of per capita government expenditure between races has been achieved (National Planning Commission, 2011). (The same report, however, points out that differences in per capita education spend per learner remain between private schools, public schools that charge school fees and no-fee schools.)

During the decade preceding the formal demise of Apartheid, South Africa experienced a period of unlegislated transition in education as one previously segregated school after the other opened its doors to all races. Unfortunately, the caveat to this account of 'transition' is that many of these former White schools, having lost the advantage of favourable government subsidy, raised their fees. The issue became, and continues to be, one of LSM (Living Standards Measure) and affordability, rather than race. As a consequence, South Africa still faces the challenge of having a relatively small group of schools being attended by more than one race- typically White, Indian and Coloured students- while former Black schools remain predominantly 'Black' and under-resourced.

The post 1994 government emphasised the role education would play in the new dispensation. In fact, education was not seen only as one of the benefactors of the new political landscape, but was seen to be a major role-player in the transformation of post-Apartheid South African society (Duvenhage, 2006). In 1995, the Department of Education's White Paper for Education and Training stated in lofty terms the special role that education would play in South Africa's evolution to a non-racial society in which all would have equal opportunity to thrive and enjoy the new 'just and peaceful society' (Department of Education, 1995). As Duvenhage (2006) points out, the ANC government of the day appeared to sincerely dedicate significant resource and effort to the task of educational transformation. Areas of focus included establishment of a truly non-racial educational system, bolstering of education management structures, improving infrastructure and updating the school curriculum.

De Wet et al. (2009) comment on the relative successes and failures in the transformation in education efforts of the middle and late 1990s. They point out that definite progress could be reported in respect of teacher qualifications and standards, per capita spending on students across the various races, access to schools and teacher to student ratios. However, De Wet et al. also refer to a number of studies done a decade after 1994 that identified serious lingering gaps, including disturbing literacy and numeracy levels, lack of interest in African culture and language in previously White schools, lack of discipline and student violence levels in previously Black schools, grossly unequal resourcing among schools, poor teacher work ethic issues, poor school administration and management and manipulation of enrolment policies to limit transformation in some higher LSM schools (Jansen, 2002, De Wet and Wolhuter, 2009).

De Wet et al. (2009) consider the reasons for the apparent failures of key aspects of the execution of the education related ideologies that inspired the political leaders of post-apartheid South Africa and suggest that ‘demographic, economic and political realities’ can sometimes get in the way of their successful implementation. Examples in the South African context include the failure of the mergers of tertiary institutions and the floundering of OBE (outcomes based education) due to the realities of poorly resourced schools and inadequately qualified teachers (Jansen, 2002, Warnich and Wolhuter, 2009). De Wet et al. (2009) refer to a number of basic factors critical to educational transformation and development that appear not to have enjoyed appropriate levels of attention in the decades following 1994, such as the fact that 16% of public schools still had no electricity in 2009 and 67% had no computers. Shockingly, the South African Institute of Race Relations reported in its South African Survey 2007/2008 that 15 years after the demise of Apartheid, only 46% of Grade 1 learners reached Grade 12 and that since 2003 the pass rate for matriculants has dropped significantly each year (The South African Institute of Race Relations, 2008).

2.7.2 The current education and skills development landscape in South Africa

2.7.2.1 Basic education

Goal 2 of the United Nations’ Millennium Development Goals is: “Achieve universal primary education” (The United Nations, 2011). South Africa’s efforts towards attainment of this objective have included a number of policies and initiatives to improve the state of basic education in the country and redress some of the issues of the past. For example, education is currently the government’s highest single expense item, with an impressive R165 billion allocated to education for 2010/11 (about 5.8% of GDP). The National Planning Commission’s Diagnostic Overview cites other examples of progressive legislation and commitment to improvement of basic education, including ‘compulsory education for children aged seven to fifteen years old or up to Grade 9; the National School Nutrition Programme, which feeds roughly 6 million learners in 18,000 primary schools throughout the country; the introduction of Grade R for children turning five (resulting in an increase in school enrolments for five year olds from 22.5% in 1996 to 80.9 percent in 2007); and exemption from school fees and a no fee policy for the poorest 40% of schools’ (National Planning Commission, 2011).

Despite the ideological will and the not insignificant resources being poured into improving the state of basic education in South Africa, the system as a whole is dramatically under-performing. Literacy and numeracy scores are extremely low compared with international (and African) standards. Of the 12 million learners in the school system, 96% are enrolled at public schools. In 2010, the matric pass rate was 67.8%. Although this seems encouraging at first glance, it is also true that only 15% of these learners achieved an average mark of 40% or more. Black learners continue to lag significantly behind White learners on literacy and numeracy ratings and enjoy vastly inferior school infrastructure. As of 2009, approximately 2,799 schools did not have electricity, 412 schools were mud structures and 706 schools had no adequate sanitation system in place (National Planning Commission, 2011).

2.7.2.2 Higher education

The situation in higher education is no more encouraging. Each year about a million learners exit the school system. Approximately 65% of these learners do not have a Grade 12 certificate (Badat, 2010, Department of Basic Education, 2010).

South Africa's higher education system comprises about 23 public universities and slightly more than 100 private higher education institutions whose offerings range from certificate courses to doctoral programmes. One of the positives of the post-1994 drive for transformation in education is the increase in student enrolments. Student enrolments have grown on average by 4.6% per year since 2000. Black student enrolments increased from 58% in 2000 to 65% in 2008, while White student enrolments dropped from 30% to 21% for the same period. In terms of gender equity, there has also been reasonable progress. Of the 473,000 enrolments in 1993, 202,000 (43%) were female, while by 2008 females made up 56.3% (450,584 of 799,388) of the total enrolments in higher education (Badat, 2010).

The increased enrolment numbers appear to be a positive trend. However, these students tend to be under-prepared for tertiary education and put added pressure on university student support systems. Moreover, despite increased Black student enrolments, Black graduates as a percentage of all graduates decreased from 58% in 2000 to 53% in 2008 (National Planning Commission, 2011). Interestingly, while Black student numbers increase rapidly, there continues to be a lag in the numbers of non-White academic staff. Whites still account for approximately 60% of academic staff at public higher education institutions. The statistics are similar in respect of gender- males make up about 56% of academic staff (Department of Basic Education, 2010). These are significant facts in the context of this study which investigates the impact of teacher student congruence in terms of race, home language and gender.

2.7.2.3 Vocational training

In 2011, about 10% of the one million school-leavers enrolled for general vocational programmes in FET (Further Education and Training) colleges. Prospects for these learners are not encouraging. Low throughput and enrolment growth rates are the hallmarks of these institutions. Furthermore, the standards of training provided are poor and thus work prospects are limited for FET graduates (National Planning Commission, 2011). Badroodien (2005) reviews the South African industrial skills development and training landscape and, while conceding that some progress has been made in terms of transformation agendas, notes that 'beneficiaries of key training initiatives, particularly in terms of high end skills, remain White and male'.

2.7.2.4 The ICT sector

One of the biggest challenges facing the ICT sector is the shortage of quality professional skills. Not only is the number of students matriculating forecast to continue its downward trend to 2016, it is also of concern that of those who qualify for technical studies at institutions of higher learning (including software development, engineering and computer science), less than 8% elect to enroll in ICT studies, and this percentage will likely continue to decline at least until 2016. Of these students that choose to enroll in ICT studies, more are electing to study at universities of technology and the number of enrolments at universities continues to drop each year. Total student numbers graduating in ICT qualifications from universities will drop by 23% leading to 2016. Encouragingly, the percentage of Black African ICT graduates has steadily increased from 48% in 2004 to 66% in 2009, while White, Indian and Coloured ICT graduates have declined over the same period and are projected to continue to do so until 2016 at least. This increase in Black graduates is no doubt contributing to the perception that the industry is slowly moving away from being a White male dominated environment (ISETT SETA, 2010).

Despite the recession, South Africa's 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).

2.7.3 A uniquely diverse cultural landscape

Any differences between South Africa and international data on the topic of culture-based academic achievement gaps and multicultural education generally relate to South Africa's unique socio-political history and current context. For example, whereas in the United States Black students are in the minority and are instructed in their home language (both in terms of curriculum and language of instruction), Black South African students are typically instructed in a second language (English) and are not in the minority. South African Black students, therefore, have to contend with historically poor education (similar to their American counterparts), but face the additional challenge of having to learn in a second language.

Moreover, if the *Brown vs. Board of Education* case (1954) is seen as the major legislative juncture in the reform of segregated education in the United States, then Black American students have the dubious honour of being 'less recently disadvantaged' (to the order of four decades) than their South African counterparts who achieved constitutional redress in 1994.

The foregoing tempers any discussion that compares the experiences of Black students in the United States with the South African situation. Table 2-4 summarises a few key differences between Black South African and Black American students:

South African Black African Students	USA Black Students
Not Minority Group	Minority Group
Second Language Basic Education	First Language Basic Education
Second Language Curriculum	First Language Curriculum
Recently Previously Disadvantaged	Less Recently Previously Disadvantaged
Mainly Black African Teachers (School)	Mainly White Teachers (School)

Table 2-4 Comparison of Black South African and Black American students

South Africa's unusually varied set of cultures, ethnicities and languages also provide a challenge for models such as that of Hoftsede (1986) that attempt to generalise on the basis of regional boundaries. Across the 1,221,037 square kilometres of South Africa exist 11 official languages (and a variety of dialects) and a variety of 'Black' and 'White' micro-cultures. The historic prejudices do not always fall neatly along racial lines-White English and Afrikaans South Africans have very distinct cultures. Some previously disadvantaged communities (such as the South African Indians) may share a history of disadvantage in education in common with their Black compatriots, but differ sharply in terms of English language skill (Indians generally have English as a first language and Blacks still speak an African language at home, while having to learn in English).

The Indian experience

Although much of the discourse related to the educational challenges related to multiculturalism in South Africa focuses on Black/White issues, the reality is that other races contribute in unique and important ways to the discussion. For example, in KwaZulu-Natal, any discussion of race based educational issues would be remiss in not referring to Indian students. More than 70% of South Africa's Indian population are found in KwaZulu-Natal and Indian students are the second largest racial grouping at the University of KwaZulu-Natal (Indians represent approximately 33% of the student population, whereas 52% are Black). Nationally, Indian students account for only 7.4% of total enrollments in higher education, but the importance of this group of students is demonstrated by considering 'participation rate' (i.e. percentage of the potential number of students from this racial grouping who are enrolled in institutions of higher education), which is about 43% for Indians, 54% for Whites and only 12% each for Coloureds and Blacks (Council on Higher Education, 2009, Department of Basic Education, 2010).

Further demonstrating South Africa's cultural diversity, Lemon (2008) describes the experiences of Indians through the process of transformation of education in South Africa, particularly in KwaZulu-Natal where most of South Africa's Indian population reside. Lemon (2008) makes the point that due to the slow pace of residential desegregation, the racial composition of schools persists to a large degree and schools that were traditionally dominated by Indians remain so to a large degree. Interestingly, he describes the resistance of Indian parents and governing bodies to the transformation process (reminiscent of the situation in previously White schools). Indian parents are opting for the best schools they can afford to send their children to, while more Black pupils are admitted into the traditionally Indian schools (which are typically better resourced than Black schools). This creates a situation in which teaching and administrative staff are predominantly Indian while the majority of pupils are Black in schools where this 'migration' occurs. While creating opportunities for 'better' education for Black pupils, the concern is that Black pupils' learning preferences are not being catered for, but rather they are being required to conform to the 'Indian' ethos in much the same way that other race groups are required to conform when enrolling in 'White' schools.

Lemon (2008) describes how the Indian racial identity has developed uniquely in South Africa. Although there has been a sense of solidarity with 'previously disadvantaged' groups, Indians have also found themselves set somewhat apart from all other races. For example, while Indians are commonly considered ‘Black’ for the purposes of ‘Black economic empowerment’ and are commonly labeled as ‘previously disadvantaged’, there has been considerable hostility directed toward them as a group, not only by Whites, but also by Black South Africans, particularly in KwaZulu-Natal where Zulu nationalism has sometimes been associated with ‘anti-Indianism’ (Lemon, 2008).

2.7.4 Culture and the performance gap-a South African perspective

There is significant evidence of a culture (specifically ‘race’) based academic performance gap in education in South Africa. South Africa’s higher education graduation rate of 15% is one of the lowest in the world. This is clearly of grave concern, given the demand for high level skills in the workplace and the government’s economic development objectives. In view of government’s employment equity targets, it is even more concerning that there are significant graduation rate disparities among races, with less than half the number of Black students graduating each year in comparison with Whites. The Department of Education has therefore identified the need to increase Black student enrolment numbers and at the same time to increase representation of Blacks in academic positions. Indeed, Black student enrolments have increased from 58% in 2000 to 77% in 2009 while White student enrolments dropped for the same period, but Whites still account for 60% of academic staff at public higher education institutions.

The improvement in respect of enrolment rates may seem to be a positive trend at first glance, but coupled with the low throughput rates, has resulted in increased numbers of learners at tertiary level and consequently greater demands for academic and financial support, further stretching the capacity of these institutions to meet the demands of previously disadvantaged learners. Furthermore, it is sobering to consider student success rates, which take into account full-time equivalent student enrolments rather than headcount enrolments. When this data is disaggregated by race, Black Africans and Coloureds are the worst affected. All role-players in higher education should be concerned that in the years since the advent of democracy, the promise of equality has yet to materialise. Black Africans and Coloureds, sections of society that bore the brunt of exclusion by apartheid education policies and legislation, continue to lag behind in education success rates. As Table 2-5 demonstrates, their performance, in particular that of Black Africans, is well below the national average.

Year	Black African	Coloured	Indian	White	Average
2001	65	75	78	85	74
2002	70	74	81	86	77
2003	70	71	80	85	76
2004	70	75	79	84	75
2009	74	78	80	85	77
Average	**70**	**75**	**80**	**85**	**76**

Table 2-5 Undergraduate success rates of students in public higher education institutions by race (Source: Adapted from Letseka et al. (2008) and Department of Basic Education (2010))

Table 2-6 shows the success rates by race in 2009 for each of a number of South Africa's leading public institutions of higher learning.

It is interesting and encouraging to note that although slow progress is being made in terms of closing the success rate gap at undergraduate level, the speed of transformation at higher levels of tertiary education is reason for optimism (Badat, 2010). Table 2-7 and Table 2-8 highlight the progress made in terms of enrollment and graduation statistics for doctoral students, both in respect of gender and race classifications.

It is clear from the foregoing that South Africa has made significant progress to date in redressing some of the culture-based disparities of the past, especially in education, but it is equally obvious that there is a need to maintain a sense of urgency in terms of closing the remaining gaps that exist.

Institution	Black African	Coloured	Indian	White	Average
Cape Peninsula University of Technology	74	81	81	88	79
University of Cape Town	76	83	84	91	84
Central University of Technology	72	70	83	78	73
Durban University of Technology	76	77	76	80	76
University of Fort Hare	78	79	67	87	79
University of the Free State	65	70	69	82	72
University of Johannesburg	73	72	76	83	75
University of KwaZulu-Natal	77	81	82	91	80
University of Limpopo	80	85	93	94	80
Nelson Mandela Metropolitan University	69	74	79	85	74
North West University	81	75	82	86	84
University of Pretoria	72	75	78	84	80
Rhodes University	78	79	87	88	83
University of South Africa	98	82	n.a.	87	85
University of Stellenbosch	72	77	84	86	84
Tshwane University of Technology	70	68	70	82	71
Vaal University of Technology	74	70	65	70	73
Walter Sisulu University	72	70	95	78	72
University of Western Cape	77	78	87	89	79
University of Witwatersrand	72	76	79	89	77
University of Zululand	77	65	69	67	77
Mangosuthu University of Technology	78	87	70	100	78
Average	**74**	**78**	**80**	**85**	**77**

Table 2-6 Student success rates by race and by institution (Source: Adapted from Department of Basic Education (2010))

Year	Enrolments				
	Males	Females	White	Black	Total
1994	3,436	1,488	4,137	787	4,924
%	69.8	30.2	84	16	100
2000	3,958	2,435	3,993	2,400	6,393
%	61.9	38.1	62.5	37.5	100
2007	5,772	4,230	4,752	5,251	10,002
%	57.7	42.3	47.5	52.5	100

Table 2-7 Doctoral enrolments by race and gender (Source: Adapted from Badat (2010))

Year	Graduates				
	Males	Females	White	Black	Total
1994	518	219	666	71	737
%	70.3	29.7	90.4	9.6	100
2000	572	400	674	298	972
%	58.8	41.2	69.3	30.7	100
2007	742	529	691	580	1,271
%	58.4	41.6	54.4	45.6	100

Table 2-8 Doctoral graduates by race and gender (Source: Adapted from Badat (2010))

2.7.5 Explaining the performance gap

Clearly, the reasons for culture-based academic performance disparities are complex and varied. The following discussion will focus on three issues that are relevant in the context of South Africa's unique and racially charged history, viz. the legacy of Apartheid (including socio-economic factors and persisting racial discrimination in education), language related issues and cultural learning differences.

2.7.5.1 The lingering legacy of Apartheid

The lingering impact of Apartheid on education continues to be felt equally acutely in terms of raw, socio-economic disparities and sociological issues that threaten to persist for far too long after the demise of legislated segregation in South Africa. The National Planning Commission, while conceding some changes since the advent of a democratic constitution and the subsequent progress made in many areas of human development in South Africa, notes that ‘social exclusion and alienation’ persist among many of the previously disadvantaged communities (National Planning Commission, 2011). It is true that there has been increased migration from the townships and previously disadvantaged areas into traditionally White areas, with the resultant attendance of ‘White’ or ‘Indian’ schools by children of this emerging Black middle class. However, the vast majority of Black Africans remains in the townships and rural areas and continues to experience poverty, extremely poor levels of education, literacy and all the other social ills that the formal end of Apartheid in 1994 promised to eradicate. As a consequence, drop-out, repetition and matriculation rates remain low among Black students. Given the deep-rooted nature of the impact of Apartheid policy and legislation, it is unlikely that Black students will perform academically on a par in the foreseeable future. What must be achieved as soon as possible, however, is the improvement of Black academic performance to a point where minimum, critical thresholds are achieved that allow Black graduates to at least be competitive in the workplace (Letseka and Maile, 2008).

As is the case with a number of studies conducted internationally (Oates, 2003, Obiakor, 2004, Stroter, 2008, Horsford, 2010), researchers in the South African context often refer to socio-economic factors to attempt to explain the race-based performance gap in education. 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. 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). Recent evidence shows that the majority (70%) of drop-outs from higher education institutions is in the ‘low economic status’ category, earning less than R1,600 per month, and that the majority of these people are Black. Students from this socio-economic grouping tend to rely on parents to fund their education. An analysis of the reasons why these students tend to drop out of their studies suggests that stress levels due to having to work part time while studying to assist in paying student fees is a large contributing factor (Letseka and Maile, 2008).

This focus on socio-economic factors is understandable, given that socio-economic disparities are typically race related. For example, in terms of median expenditure per capita, little has changed since the promising dawn of the post-Apartheid era. In 1995, median per capita expenditure for Black Africans was R333 per month as opposed to R3,443 for Whites, and in 2008 the figures were R454 per month for Black Africans and R5,668 for Whites. Poverty figures (when considered in terms of the international benchmark defining the ‘poverty line’, viz. $US2 per day per person) suggest that more than 25% of South Africans are in a state of poverty at any given time, most of whom are Black. As at September, 2011, 86% of the 4,442,000 unemployed people in South Africa were Black, 10% were Coloured, 2.7% were White and 1.3% were Indian. With an average Gini coefficient of .67 since 1995, South Africa remains one of the most unequal societies in the world, with Whites dominating the top end and Black Africans dominating the lower ends of the scale (National Planning Commission, 2011, Statistics South Africa, 2011).

The situation at South African schools and institutions of higher learning paints an equally bleak picture. As of 2009, approximately 2,799 schools (mostly ‘Black’ schools in rural areas) had no electricity, 412 schools were mud structures and 706 schools did not have appropriate sanitation and there is no evidence of this situation having improved since then. Chisholm et al. (2005) report that in ‘disadvantaged schools’ (mainly ‘Black’) less teaching occurs- average teaching time is 3.5 hours versus 6.5 hours in what were previously ‘White’ schools. Reddy et al. (2010) estimate that approximately 10% of teachers in predominantly Black schools are absent on any given day. The disparity in terms of institution quality between ‘historically White’ universities and ‘historically Black’ universities paints a similar picture. The fact that significantly more students who attended ‘historically Black’ institutions are unemployed in comparison with those who attended ‘historically White’ institutions is an indictment on the relative quality of these institutions (Letseka, 2009). Table 2-9 shows the unemployment rates of students who studied at either historically black or historically White universities by race.

Institution	Population Group			
	Black African	Coloured	Indian	White
Historically White	45	28	37	27
Historically Black	53	22	60	-

Table 2-9 Graduate unemployment rates by institution (Source: Adapted from Letseka (2009))

The National Planning Commission's Human Conditions Diagnostic (2011) comments on the profound impact socio-economic factors have on education, noting that the educational background of parents, nutrition and the availability of learning material are especially important for school pupils, and that socio-economic factors account for significant premature drop-off rates among students in higher education. It is not surprising therefore that the same report bemoans the fact that 'schools in South Africa are simply not adequately preparing young people for higher education (or the workplace, for that matter) and that higher education is failing to produce the number of appropriately skilled professionals the economy requires (National Planning Commission, 2011).

Apart from the aforementioned socio-economic disparities that persist in South Africa along racial lines, sociological issues that were born in the Apartheid era are proving disturbingly stubborn and difficult to get rid of. Arguably one of the most serious of such issues facing education in South Africa relates to persisting, deep seated racism in higher education. The so-called 'Soudien Report' (officially entitled the "Report of the Ministerial Committee on Transformation and Social Cohesion and the Elimination of Discrimination in Public Higher Education Institutions") was commissioned by the Department of Education in 2008 to "investigate discrimination in public higher education institutions, with a particular focus on racism and to make appropriate recommendations to combat discrimination and to promote social cohesion" (Department of Education, 2008). While finding that institutions had generally complied with broad transformation requirements, (such as employment equity policy), the report makes a number of alarming allegations in terms of the disjunction between institutional policy and the real-life experiences of both staff and students, finding that discrimination, particularly with regard to racism and sexism, is 'pervasive' in South Africa's institutions of higher learning.

Commenting on the impact of such 'pervasive' discrimination, the report refers to the devastating psychological and physical harm that is being done and points out that the victims of the discrimination 'are denied the opportunity to realise their full potential' and that as a consequence, the country is 'robbed of valuable, untapped human resources' (Department of Education, 2008).

In view of the findings on widespread discrimination, the Soudien report recommends the introduction of staff development programmes at institutions of higher learning with a view to sensitising faculty to the diverse learning needs of their multicultural student base. This recommendation is in line with international precedents that argue the value of such initiatives, such as the example of the Netherlands, where such interventions have been effective in helping to narrow the race based academic achievement gap (Rijkschroeff et al., 2005). Other recommendations include a gender sensitisation intervention and a programme aimed at ensuring a culturally sensitive and appropriate curriculum (Department of Education, 2008).

Given the findings of studies on the importance of a sense of affinity and, conversely, the negative impact of discrimination in the multicultural classroom, to students' learning experiences and achievement (McCroskey and Richmond, 1992, Obiakor, 2004, Wilson, 2006, Horsford, 2010), this state of lingering racism is extremely concerning and provides insights into the possible reasons for the persisting race related academic achievement gap.

2.7.5.2 Language factors

South Africa's heterogeneity is no better exemplified than in its diversity of languages. The South African Constitution (Republic of South Africa, 1996) recognises no less than eleven official languages, as per Table 2-10.

It is significant 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.

Over the many decades preceding 1994, various pieces of legislation played their respective roles in keeping segregation in education alive. Section 37 of the Constitution of the Union of South Africa provided for the use of Dutch and English as the medium of instruction for White learners. The Bantu Education Act of 1953 facilitated the establishment of two separate educational systems in South Africa- one for Whites and another for non-Whites. In terms of this Act, home language education was compulsory up to Standard 6, with Afrikaans and English being compulsory subjects from day one and being used equally as the languages of instruction from Standard 7 onwards.

Official Language	Home Language Speakers	Home Language Percentages
Afrikaans	5,983,420	13.35%
English	3,673,206	8.2%
isiNdebele	711,825	1.59%
Sesotho sa Leboa	4,208,974	9.39%
Sesotho	3,555,192	7.93%
SiSwati	1,194,433	2.66%
Setswana	3,677,010	8.2%
Xitsonga	1,992,201	4.44%
Tshivenda	1,021,761	2.28%
isiXhosa	7,907,149	17.64%
isiZulu	10,677,315	23.82%
Other	217,291	0.48%
TOTAL	**44,819,777**	**100%**

Table 2-10 South Africa's language landscape (Source: Statistics South Africa (2001); De Wet and Wolhuter (2009))

The reaction of the Black community was strong, not only to the use of Afrikaans as a medium of instruction, but also to the use of home languages. These communities saw the language policies as an attempt to perpetuate segregation (including intra-racial language-based divisions) and to disempower Blacks economically and educationally. This discontent with educational and language policy led to the 1976 uprisings and the subsequent scrapping of Afrikaans and African languages as a compulsory medium of instruction. Although home language instruction still predominated in the early school years, by 1978 more than 96% of Black learners in South Africa were taught through the medium of English from Standard 5 onwards.

De Wet et al. (2009) cite a number of language policy related milestones on the road to South Africa's educational transformation, including the National Forum in 1985 and the Harare Language Workshop of 1990 that reinforced resistance to Afrikaans, emphasised the importance of English and the need to defend the value of African languages in education. More recently, the South African

Schools Act and the National Education Policy, both of 1996, reiterated the right of all learners to education in their language of choice. In 2001, the Department of Education recommitted to the principle of multilingualism, stating in its report entitled “Education in South Africa: Achievements since 1994”: “Speaking the language of other people not only facilitates meaningful communication, but also builds openness and respect as barriers are broken down and new meanings are explored. We are committed to providing an initial grounding in mother-tongue education. We are considering ways to increase second-language learning. Given the historical onus on Black learners to learn English and Afrikaans, it is reciprocally important now that non-African learners acquire at least one African language. Multilingualism must be a more central educational requirement, particularly for learners entering the fields of education, welfare and health.” (Department of Education, 2001:31).

De Wet et al. (2009) suggest that the ideal of multilingualism and African language renaissance has not translated into implementation on the ground for various reasons including the dominance of English as social, political and commercial language of choice, ignorance about the value of home language instruction and the fear that use of African languages will cause divisions. Furthermore, they are of the opinion that the negative legacy of the Bantu Education Act of 1953 diminishes the possibility that Black communities will embrace the government’s drive for Black languages to resume their place in education, especially while Black languages are increasingly sidelined in favour of English in all arenas of South African society, including politics and industry. As a consequence, language use in education has not changed significantly since 1994. Learners are still taught primarily in English or Afrikaans. Multilingualism remains an ideal and English has strengthened its position as de facto language of education (De Wet and Wolhuter, 2009).

Howie et al. consider the impact of multilingual policy on learner performance in their study entitled: “The effect of multilingual policies on performance and progression in reading in South African primary schools” (Howie et al., 2008). The National Department of Education’s language policy is referred to in this study and specifically the policy that South African children should receive instruction at school in their home language until grade 3. The only exposure African language speakers have in the classroom to English or Afrikaans prior to grade 4 is when teachers choose to ‘code switch’ (i.e. switch between the African language that predominates and English or Afrikaans). Although current government language policy advocates the use of home language from grade 1 to 12, the reality on the ground is that most schools switch the language of instruction to either English or Afrikaans at grade 4. As a result, about 80% of the nation’s learners are required to switch to a second language of instruction (English or Afrikaans) in grade 4 as this is the percentage of learners at this level whose home language is not English or Afrikaans. Verhoeven (1990) refers to the linguistic challenges this second language learning environment creates, citing both inter-lingual learning problems as a result of mother tongue interference and intra-lingual issues related to the structure of the second language. Verhoeven cites difficulties with phonemic mapping, orthographic pattern recognition and direction recognition for learners who switch to a second language (Verhoeven, 1990, Howie et al., 2008, De Wet and Wolhuter, 2009).

Howie and her associates sought to investigate the levels of reading proficiency among learners for the language of reading instruction received to grade 3 and the relationship between performance in the test language and the home language of the learner. They found that in both grade 4 and 5 the mean score in reading for South African learners was significantly lower than the international mean scores, with the exception of grade 5 English home language learners who scored above the international average. Moreover, the results indicated that the largest disparity in performance was between English home language speakers and non-English home language speakers in the English language test. Learners whose home language was not English performed significantly worse than English home language learners on the English test (Howie et al., 2008). These results are disturbing since 80% of South African learners are instructed from Grade 4 and beyond in a second language (English or Afrikaans) and are clearly not proficient in their language of instruction.

In view of the foregoing, it would be remiss of any strategy aimed at redressing the educational disparities between the cultural groups in South Africa to ignore the role language has and continues to play in South African education.

2.7.5.3 Cultural learning differences

A scan of the literature shows that cultural learning differences are an international phenomenon (Dunn et al., 1990, Matthews, 1991, Woodrow and Sham, 2001, Xiaojing et al., 2010). The plethora of research conducted on the subject of 'multicultural pedagogy' has been spawned from the belief that different cultures do indeed learn differently and that a 'single size fits all' teaching approach to multicultural classrooms is inappropriate (Milner, 2003, Allen, 2004, Tong et al., 2006, Villegas, 2008, Picower, 2009). Particularly in South Africa, where reports such as the "Report of the Ministerial Committee on Transformation and Social Cohesion and the Elimination of Discrimination in Public Higher Education Institutions" (Department of Education, 2008) show clearly that racial tensions continue to form a disturbing dimension of students' experiences in education, educators ignore cultural learning preferences at their peril.

Le Roux (2000) makes the point that most teachers in South Africa have been trained in a 'monocultural' context and have to date, therefore, been ill-equipped to deal with the real challenges on the ground of a multicultural classroom. He suggests that teacher education should include specific training to equip teachers to teach students of various cultures and optimise their impact as educators in the classroom, but adds a sober caveat in the form of a caution that what is required is a “paradigm shift, a change of heart, an unprejudiced reorientation and an innovative attitude” rather than simply an academic change of teacher training curriculum.

Le Roux (2000) compares the two approaches typically adopted by teachers when confronted with a multicultural classroom. On the one hand, a teacher who is ‘monocultural’ teaches a multicultural class as if it were any other monocultural group of students. Learners who do not share the teacher’s culture (or dominant culture of the classroom) are simply ‘assimilated’ rather than catered for. On the other hand, the multicultural teacher manages the learning experiences of the students proactively with culturally appropriate and sensitive teaching styles that cater for the diversity of learning styles among students, consciously avoiding stereotyping or discriminatory language and striving to remove culture bias from evaluation strategies. Le Roux (2000) cites Lemmer and Squelch (1993) who prescribe three conditions for successful multicultural education- one, teachers should be trained to have appropriate expectations of culturally diverse students; two, the classroom climate should be controlled by the teacher to optimise a sense of well-being (affinity) for each student regardless of culture; and third, the curriculum should reflect the multicultural nature of the students. Le Roux (2000) recommends that universities in particular need to pay attention to the issue of multicultural pedagogy and demonstrate their desire to effect change by ensuring that teacher training programmes are reviewed in line with the need for multicultural pedagogy and through interventions aimed at developing the multicultural skills of existing educators.

Indeed, it is hard to imagine that educators who have grown up in South Africa would not see the value in making an effort to address the various needs of their diverse student base. South African’s speak anecdotally, but wisely, about the ‘fact’ that different races or cultural groups have different learning preferences. For example, Blacks and Whites alike speak in respectful terms of ‘Ubuntu’, which literally means ‘humanity to others’, as characterising Black African culture. In the educational context, this means that to Black Africans, learning is a social process whereby students interact with other students and teachers. Makoe (2006) makes precisely this point in discussing the response of Black students to the distance learning approaches of universities such as UNISA (University of South Africa), noting that most Black students are socialised in environments that are profoundly different to the institutions of higher learning they are expected to adjust to.

2.8 Conclusion

The foregoing has provided an overview of the findings of international studies that consistently demonstrate that culture-based academic performance gaps are a reality wherever multicultural classrooms exist. The plethora of studies in the international literature discussing the potential merits of ‘multicultural pedagogy’ testifies to the attention this challenge is getting worldwide. With globalisation, more cultures are being ‘thrown together’ and multicultural classrooms are becoming the norm rather than the exception. A key component in this trend is the dynamic between student and teacher. Teachers are increasingly being expected to adapt and review their own stereotypes and teaching approaches in response the student diversity that is thrust upon them. Students are relying on educators who are often resistant to change or ill-qualified to deal with the special challenges multicultural classrooms represent. In this context, the literature review has considered the findings of a number of studies on the impact of teacher student congruence in terms of race, home language and gender on student learning. In addition, the relationship between teacher student congruence and the concepts of ‘immediacy’ and ‘affinity’ was discussed with a view to understanding why congruence impacts learning. Similarly, racial identity and the role of teacher and student perceptions in academic performance were explored in the light of the findings of various international studies on the subject.

Finally, the unique South African context was considered. In terms of culture and race based academic achievement gaps, South Africa shares a common challenge with the rest of the world. South African studies find similarly to international studies that different races perform differently in the classroom. In South Africa, Black students continue to perform poorly in the classroom in comparison with other races as they struggle to overcome the social and political demons of the recent past. The foregoing considered the troubled history and current landscape of education in South Africa, including the lingering legacy of Apartheid, language issues and cultural learning differences.

This review of international research and the South African educational landscape provides an appropriate backdrop for the research conducted as part of this study, which explores the extent to which international findings on culture-based academic performance disparities and the impact of teacher student congruence can be duplicated in a South African Information Systems and Technology university classroom, and attempts to explain the unique (sometimes apparently anomalous) results that only make sense in the South African context.

Chapter 3: Research design and methodology

3.1 Introduction

By way of contextualising the discussion that follows on the research design and methodology adopted in this study, this chapter begins by re-articulating the research problem and related research questions. The sections that follow present the theoretical framework for the study and describe the research model, design, methodology and data analysis models in detail.

3.2 Research problem

Information systems and technology skills development stakeholders (including government and the private sector) continue to invest heavily in IS&T related skills development and education in South Africa. The return on investment, however, is poor, as reflected in the fact that the number and quality of graduates continues to decline alarmingly. The government's culture-based equity targets in respect of Black and female entrants into the workplace, high industry demand for specialised IS&T skills and the poor quality of IS&T graduates emerging from South Africa's institutions of higher learning create a compelling case for urgent scrutiny of both the nature of the culture based achievement gap in South African IS&T education and training, and credible, research-based means of addressing this challenge (ISETT SETA, 2010, National Planning Commission, 2011).

In the light of the above, this study investigates the factors that impact and predict culture based differences in IS&T academic performance, with a view to contributing significantly to:

1. identifying ways to close the culture (and particularly 'race') based academic performance gaps in IS&T education and training;
2. improving the returns on training investment that IS&T skills development stakeholders in South Africa are able to realise.

3.3 Research questions

This study 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?"*

Research question 2(RQ2): *"Does matching teacher and student in respect of cultural factors impact student cognitive test performance in information systems and technology education?"*

Sub-question 2.1(SQ2.1): *"Does matching teacher and student in respect of race impact student cognitive test performance in information systems and technology education?"*

Sub-question 2.2(SQ2.2): *"Does matching teacher and student in respect of home language impact student cognitive test performance in information systems and technology education?"*

Sub-question 2.3(SQ2.3): *"Does matching teacher and student in respect of gender impact student cognitive test performance in information systems and technology education?"*

Research question 3(RQ3): *"Do student perceptions of collective self-efficacy (in respect of teacher capability), vary among cultural groupings?"*

Sub-question 3.1(SQ3.1): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among race groupings?"*

Sub-question 3.2(SQ3.2): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among home language groupings?"*

Sub-question 3.3(SQ3.3): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among gender groupings?"*

Sub-question 3.4(SQ3.4): *"How does culture-based variation in student perceptions of collective self-efficacy (in respect of teacher capability) relate to culture-based differences in the impact of teacher student congruence on student cognitive test performance in information systems and technology education?"*

3.4 Theoretical framework

3.4.1 Social Cognitive Theory

3.4.1.1 Background

As per Table 3-1, Social Cognitive Theory (SCT), also known as Observational Learning Theory (OLT) and Social Learning Theory (SLT), has widely been referred to in information systems research related to such topics as the impact of computer self-efficacy on information systems learning, student perceptions of their computer skills versus actual ability, ways to enhance e-learning and computer based training systems and user awareness of security countermeasures and its impact on information systems misuse (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).

Information Systems research articles using Social Learning Theory as a theoretical framework
Marakas, G.M., Yi, M.Y., Johnson, R.D., 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(2), 126 - 163.
Compeau, D., Higgins, C., 1995. Computer self-efficacy: Development of a measure and initial test. MIS Quarterly, 19(2), 189-211.
Alavi, M., Marakas, G.M., Yoo, Y., 2002. A Comparative Study of Distributed Learning Environments on Learning Outcomes. Information Systems Research, 13(4), 404 - 415.
Yi, M.Y., Davis, F.D., 2003. Developing and Validating an Observational Learning Model of Computer Software Training and Skill Acquisition. Information Systems Research, 14(1), 146 - 169.
Santhanam, R., Sasidharan, S., Webster, J., 2008. Using Self-Regulatory Learning to Enhance E-Learning-Based Information Technology Training. Information Systems Research, 19(1), 26 - 47.
Grant, D.M., Malloy, A.D., Murphy, M.C., 2009. A Comparison of Student Perceptions of their Computer Skills to their Actual Abilities. Journal of Information Technology and Education, vol. 8, 141-160.
Arcy, J.D., Hovav, A., Galletta, D., 2009. User Awareness of Security Countermeasures and Its Impact on Information Systems Misuse: A Deterrence Approach. Information Systems Research, 20(1), 79 - 98.

Table 3-1 Information Systems research articles using Social Learning Theory as a 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).

3.4.1.2 Development of the theory

Social Learning Theory (SLT) is firmly grounded in psychology. Although aspects of both ‘social’ and ‘behavioural’ psychology provided a foundational framework for the theory, it was mainly under the umbrella of behaviourism that SLT developed. Behaviourism, introduced by John Watson in 1913, attempts to explain human and animal behaviour in terms observable acts that could be described in terms of stimulus-response sequences. The theory assumes that all behaviour can be explained without reference to internal mental states or consciousness. The learner (of behaviour) is essentially passive and responds to environmental stimuli. At infancy, the learner has a ‘clean state’ (‘tabula rasa’) and future behaviour is shaped via positive or negative reinforcement from the environment. As per Figure 3-1, learning (also referred to as ‘operant conditioning’) is seen as a process of continual interaction between ‘antecedents’, ‘behaviour’ and the ‘consequences’ of that behaviour (Crosbie-Brunett and Lewis, 1993).

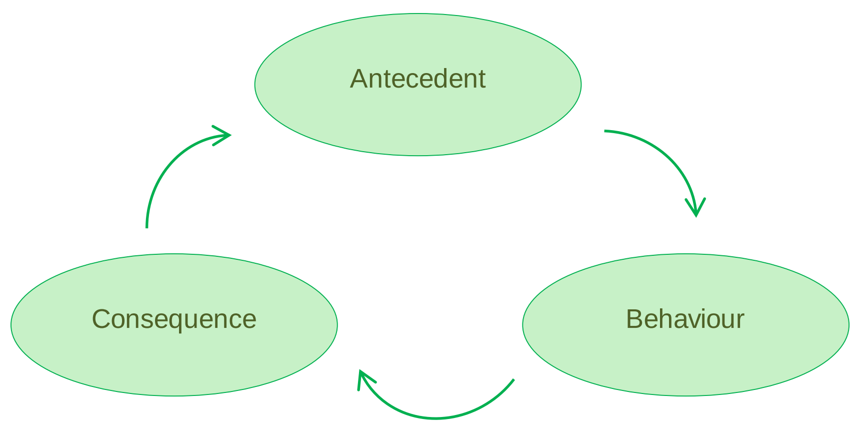


Figure 3-1 Operant conditioning in behaviourism (Source: Adapted from (Crosbie-Brunett and Lewis, 1993))

There has continued to be debate among behaviourists about the relative roles of ‘consequence’ and ‘antecedents’ as primary governors of behaviour. Over the years, different theorists have postulated various ‘mediating variables’, such as ‘habit’ (William James), ‘instinct’ (Sigmund Freud) and ‘cognitions’ (Edward Tolman) (Woodward, 1982).

Social psychology also contributed significantly to the development of SLT. For example, the foundations of SLT’s emphasis on the interaction between personal factors and the environment can be found in William James' (1842-1910) concept of 'social self', and later in Kurt Lewin's (1890-1947) work on behaviour as a function of the person in their environment. Alfred Adler's (1870-1937) work on goal-based motivation, the significance of one's perception of environment in influencing behaviour and his view that thoughts, feelings and behaviours are related to one's social environment still resonate in SLT's 'reciprocal determinism'. Edward Tolman's (1886-1959) promotion in the 1930's of the idea of 'unobservable cognitions' that mediated between stimulus and response also laid the groundwork for the development of significant aspects of SLT. Thus by the late 1930's, many of the foundational concepts that would form the SLT were well articulated in the literature (Crosbie-Brunett and Lewis, 1993).

With Miller and Dollard's publication of "Social Learning and Imitation" in 1941, SLT was officially born. This early version of SLT had as its core principles of learning 'reinforcement', 'punishment', 'extinction' and 'imitation of models' and attempted to explain how both humans and animals observed behaviours. Miller and Dollard suggested that human behaviour was motivated by 'drives' and that one organism's response could serve as another's stimulus. Their expansion of the reciprocal relationship between environment and behaviour provided an early glimpse into the 'reciprocal determinism' of modern versions of SLT. Miller and Dollard's work created a watershed for behaviourist studies in that it represented a shift in emphasis among researchers from development of theoretical models to conducting of empirical studies (Woodward, 1982).

3.4.1.3 Current Social Learning Theory perspective

Tolman's influence on current SLT thinking is seen in the emphasis on cognitive variables as a mediator between stimulus and response. Tolman referred to 'unobservable cognitions' in the space between stimulus and response. Modern SLT theory asserts that 'human cognition' is a mediator, thus providing for individual control over responses to stimuli (Tolman, 1932). Although there are a number of versions of SLT to which researchers currently subscribe, they all share three basic tenets (Woodward, 1982, Thomas, 1990, Crosbie-Brunett and Lewis, 1993) .

- **Tenet 1:** The likelihood that a person will repeat a particular behaviour in a given situation is influenced by response consequences (e.g. 'rewards' or 'punishments').
- **Tenet 2:** People can learn by observing others ('vicarious learning') and by taking note of rewards and punishments experienced by the one being observed ('model').
- **Tenet 3:** Learning by the modeling of observed behaviour is enhanced when the 'observer' identifies with the 'model'. Furthermore, this sense of observer/model identification is

influenced by the extent to which the observer perceives the model to be similar to the observer and the extent to which the observer feels a sense of affinity toward the model.

Predominant SLT theorists and their perspectives

Two of the most influential modern SLT theorists in whose work these three tenets are represented are Julian Rotter and Albert Bandura.

Julian Rotter's focus was on SLT's application to clinical psychology. His 'interactionalist theory' is founded on five main assumptions: one, human behaviour is a function of the interaction of environmental and personal factors; two, human personality is learned and is therefore modifiable via learning; three, personality, although capable of being changed by learning, is relatively stable and immune to whimsical influences; four, motivation is goal-directed (people tend to choose directions that move them closer to anticipated goals); and, fifth, people are capable of deliberately altering their environments and personalities (Rotter, 1954).

Albert Bandura is viewed as the most influential of current researchers in the field of SLT (Crosbie-Brunett and Lewis, 1993). Bandura's version of SLT is heavily based on cognitive concepts and focuses on how cognitions (particularly in respect of peoples' social experiences) influence behaviour, development and learning. Over the years, Bandura has introduced a number of key concepts to SLT, including the notion of modeling (or vicarious learning) as a form of social learning, reciprocal determinism and self-efficacy. Since 1986, Bandura has referred to his theory as Social Cognitive Theory (SCT) (rather than the traditional Social Learning Theory (SLT)), demonstrating a distancing of himself and his theory from the behaviourist approach (Bandura, 1986).

Overview of Bandura's Social Cognitive Theory

Social Cognitive Theory has as its purpose the understanding of the ability to predict individual and group behaviour, as well as the identification of methods in which behaviour can be modified or changed.

Learning theories attempt to explain how people think and what factors determine their behaviour. SCT focuses on the learning that occurs within the social context. It considers that people learn from each other and includes such concepts as observational learning, imitation and modeling. SCT is grounded in the belief that human learning is determined by the following three main independent constructs:

- **Cognitive** factors (also called ‘personal factors’), such as knowledge, expectations and attitudes;
- **Environmental** factors, such as social norms, access in community and influence on others (ability to change own environment);
- **Behavioural** factors, such as skills, practice, self-efficacy.

This three-way relationship between cognitive factors, environmental influences, and behaviour, is illustrated in Figure 3-2.

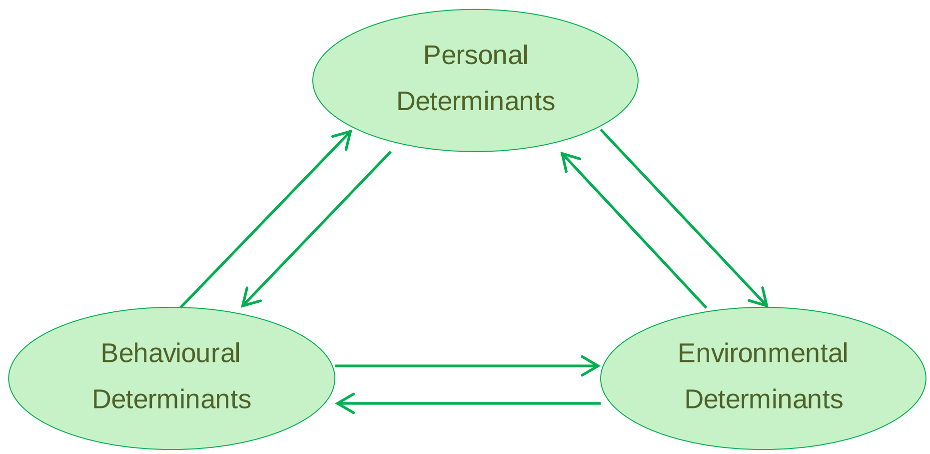


Figure 3-2 Schematisation of triadic reciprocal causation in the causal model of social cognitive theory (Source: Adapted from Bandura (2001))

Showing its ties with behaviourism, SCT asserts that behaviour is mediated by consequences. However, SCT also contends that cognitive processes regulate behaviour antecedently, and that response consequences are used to form expectations of behavioural outcomes, thus giving the individual the ability to predict the outcomes of potential behaviour before having to actually engage in that behaviour. In SCT, most behaviour is learned vicariously.

Cognition plays an important role in SCT, which sees the mind as an active constructor of an individual’s reality through selective encoding of information, anticipating outcomes of potential behaviour before actually engaging in that behaviour and self-imposition of cognitive structures to guide one’s actions. The concept of ‘reciprocity’ is key in SCT, with the reciprocal interplay between environment and one’s own cognitions shaping an individual’s sense of reality. SCT recognises that an individual’s cognitions (such as their ability to memorise, symbolise, pay attention and reason) change over time through natural maturation and experience. It is precisely the understanding of the processes involved in the construction of each person's reality that enables researchers to understand, predict and change human behaviour (Bandura, 1989, Crosbie-Brunett and Lewis, 1993).

3.4.1.4 Key constructs of Bandura's Social Cognition Theory

Figure 3-3 graphically depicts the key constructs from Bandura's Social Cognitive Theory that are relevant to this research. The highlighted components in the figure identify those constructs that are focused on in the study. This section describes these constructs and how they relate to learning.

Reciprocal determinism

Reciprocal determinism is a core concept in describing how learning takes place in SCT. As per Figure 3-2, SCT explains behaviour (and learning) with reference to the interaction between environment, personal factors and behaviour. However, these three determinants of behaviour are not necessarily equally influential. SCT acknowledges that certain sources of influence will be stronger than others and may not occur simultaneously. These interactions, timings and relative strengths of influence are determined by the individual concerned, the specific behaviour and the specific situation in which the interactions take place (Phillips and Orton, 1983, Bandura, 1989, Stone, 1993).

While the model is triadic (comprises three inter-related causation factors), Bandura describes the triad in terms of three bi-directional interactions, viz. the person-behaviour interaction, the environment-personal factors interaction, and the interaction between behaviour and the environment (Bandura, 1977a, 1986, 1989).

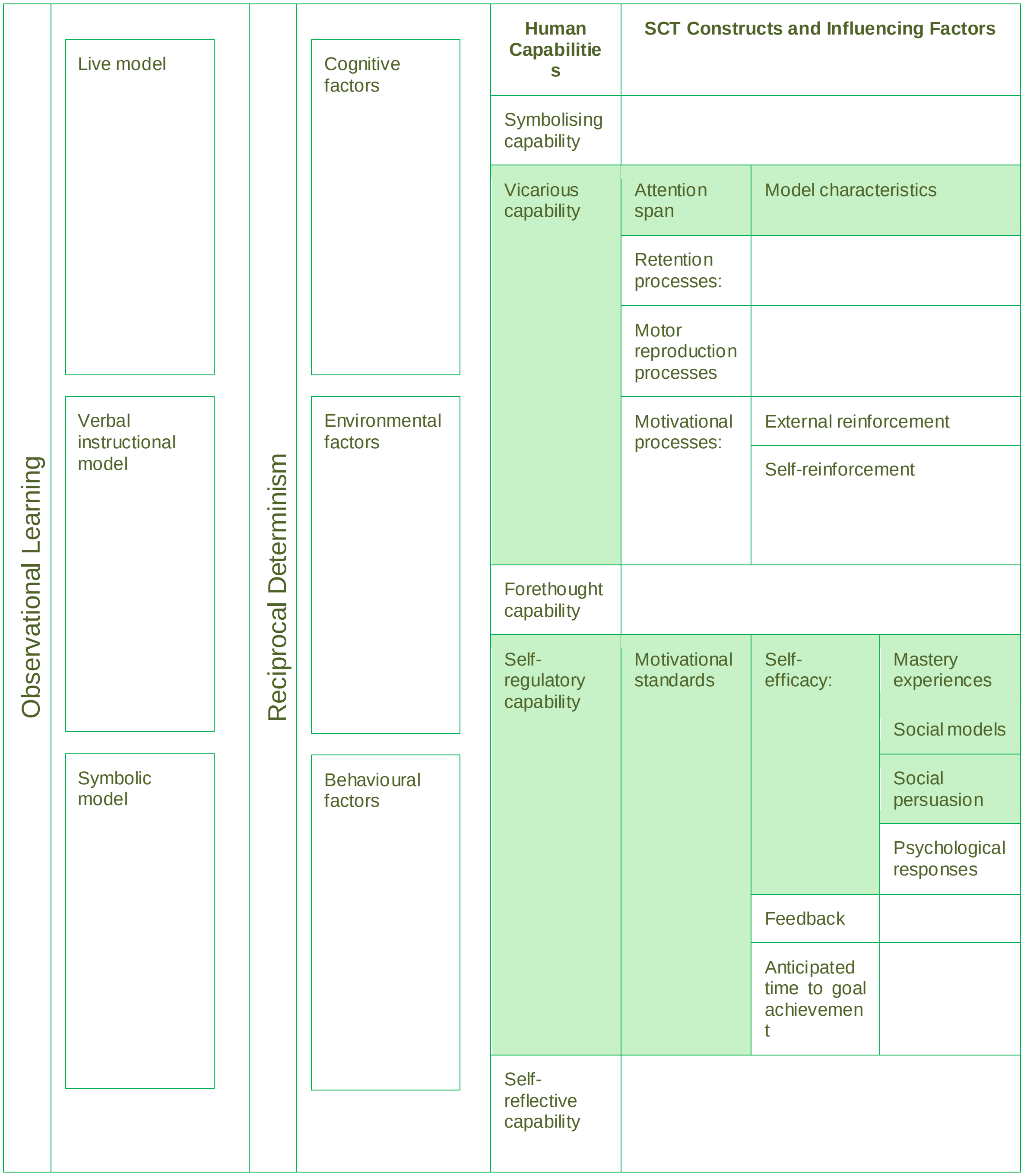


Figure 3-3 Key SCT constructs referred to in the study (Source: (Bandura, 1989))

The person-behaviour interaction involves the bi-directional influences of personal factors (such as thoughts, emotions, and biological properties) and behaviour. A person's knowledge, expectations, attitudes and belief system influence behaviour. However, the interaction is reciprocal in that the behaviours are not without consequence and, in turn, can affect the person's thoughts and emotions. In this respect, SCT allows for variations in personal factors, such as gender, ethnicity and temperament and the way in which these influence how different individuals experience the person-behaviour interaction (Bandura, 2002).

The interaction between environment and personal factors is also bi-directional. A person's knowledge, expectations, attitudes and belief systems are impacted by the environment (social influences, persuasions and structures, for example). In turn, the social environment 'responds' to personal factors such as race, age, gender, language grouping and physical attractiveness.

The third bi-directional interaction occurs between behaviour and the environment. Bandura suggests that people are not passive products of their environment, they are also capable of producing their environment in the sense that they can choose who they associate with, where they live and the activities they engage in. They can even create environments through their behaviour, such as when an aggressive person creates a hostile environment. In turn, environments can determine the behaviour of people within them (Bandura, 1989).

Human capabilities

An important notion in SCT (and of 'reciprocal determinism' specifically) is the idea that human behaviour is neither entirely shaped by the environment nor the individual. Behaviour is shaped by a reciprocal interaction of influences and humans are capable of influencing their behaviour. Thus, humans are characterised by five basic capabilities that provide the cognitive means to determine their own behaviour: symbolising, vicarious, forethought, self-regulatory and self-reflective capability (Bandura, 1989):

- **Symbolising capability:** Bandura suggests that it is through the formation of symbols (such as images or words) that humans give meaning to their experiences and that it is through these symbols that humans are capable of storing information in their memory that can help guide future behaviour. These stored symbols allow humans to model observed behaviour and engage in cognitive problem solving and what Bandura refers to as 'foresightful' action. Bandura asserts that 'foresight' is the ability to think through the consequences (potential 'punishment' or 'reward') associated with any given potential future behaviour without actually having to perform that behaviour. Bandura cites research suggesting a that much of human thought is linguistically based and the correlation between cognitive development and language acquisition to support his contention (Bandura, 1989, 1991).

- **Vicarious capability:** 'Vicarious capability' refers to the ability of humans to learn, not only by direct experience, but by observation of others ('observational learning'). Thus, a human is able to develop an idea of how a behaviour is formed and how that behaviour results in consequences for a 'model' (the one being observed), without necessarily having to perform the behaviour personally. Since humans are capable of 'symbolising', this information can be coed into symbols and stored in memory as a guide to future behaviour. This process allows humans to avoid time-consuming (and potentially dangerous) trial and error and facilitates the quick formation of behaviour patterns (Bandura, 1989, 1991).

Bandura has identified three basic models of observational learning:

1. a live model, which involves an individual demonstrating or acting out a behaviour;
2. a verbal instructional model, which involves descriptions and explanations;
3. a symbolic model, which involves real or fictional characters displaying behaviours in books, films, television programs, or other electronic media (Bandura, 1989).

Thus, Bandura's 'observational learning' is not limited to imitation of demonstrated behaviour or tasks. As per model 2 above, observational learning (and related constructs and influencing factors) can also involve 'verbal instruction', or a combination of any of the three learning models described above (Bandura, 1989). In this study, for example, IS&T teaching methods included a combination of demonstration and verbal instruction by a teacher ('model').

According to Bandura, observational learning is governed by four processes: attention span, retention processes, motor reproduction processes and motivational processes (Bandura, 1989).

- **Attention span:** 'Attention span' refers to an individual's ability to observe actions and behaviours in the environment in a selective fashion. Moreover, 'attention span' allows the observer to regulate the type and amount of observation that is experienced. Thus, an individual might be more attentive to certain activities based on the complexity or relevance of the actions in terms of the observer's frame of reference. Similarly, an observer is more likely to be attentive to models with whom the observer feels affinity or who are similar to the observer in some way. Moreover, characteristics such as attractiveness, trustworthiness and perceived competence have been shown to enhance a model's effectiveness (Bandura, 1977a, 1989).

- **Retention processes:** Retention is clearly an important concept for observational learning, as observed behaviours can only be modeled if they are retained in memory. The cognitive tools of cognitive organisation and motor rehearsal are only made possible by the human capability to symbolise and store these symbols in memory.
- **Motor reproduction processes:** Key to observational learning is the ability to replicate the behaviour that the model has just demonstrated and which has been coded symbolically in the observer's memory. This means that the observer has to be able to replicate the action, which could be a problem with a learner who is not ready developmentally to replicate the action. Motor reproduction processes include the concepts of physical capabilities, self-observation of reproduction, and accuracy of feedback.
- **Motivational processes:** The final necessary ingredient for modeling (observational learning) to occur is motivation. Learners must want to demonstrate what they have learned. Motivational processes include external and self-reinforcement and reflect the theory that a modeled behaviour is more likely to be adopted by an observer when the behaviour has a valued outcome.

- **Forethought capability:** SCT posits that human behaviour is purposive and regulated by 'forethought' (i.e. the ability to weigh probable consequences of actions, establish goals, and plan courses of action). The ability to symbolise allows humans to cognitively consider the potential outcome of performing behaviours before actually performing them. Previous experiences and observations of outcomes experienced by models who engaged in similar behaviour create expectations of behavioural outcomes and provide the mechanism for foresightful behaviour (Bandura, 1989).
- **Self-Regulatory capability:** Self-regulatory capability refers to the ability of individuals to control their own thoughts, feelings, motivations and actions, rather than be 'dictated to' by the environment. Self-regulation, therefore, governs an individual's behaviour and the self-imposed consequences of that behaviour, and is the result of the interplay between external and self-produced sources of influence. 'Motivational standards' and 'social and moral standards' are two such sources of influence in self-regulation (Tamir and Mauss, 2011).

Motivational standards involve ‘goal setting’ and ‘working at attaining goals that have been set’ (referred to by Bandura as ‘discrepancy production’ and ‘discrepancy reduction’ respectively (Bandura, 1989)). According to Bandura, people continually set goals for themselves and compare their personal accomplishments at any point in time to those goals, and thus people tend to be ‘motivated’ to change their behaviour with a view to attaining these goals (standards). Such motivation can be ‘external’ (as in the case of monetary reward) or ‘internal’ (as in the case of a personal sense of accomplishment or pride).

Bandura identifies three factors that determine the degree of motivation a person feels (Bandura, 1989):

1. **Self-efficacy:** Self-efficacy refers to a person’s sense of capability to perform a particular task or engage in specific behaviour. A person who has a high sense of self-efficacy in respect of a particular behaviour or goal is more likely to succeed in performing that behaviour or achieving that goal.
2. **Feedback:** Feedback is essential as it allows an individual to re-appraise progress toward the attainment of a goal and adjust behaviour, if required.
3. **Anticipated time to goal achievement:** Simply put, proximal goals are more effective as motivators of behaviour than are distal goals.

Social and moral standards are another key influencer of self-regulation and relate to Bandura’s concept of the ‘exercise of moral agency’ which is seen to mediate the relationship between thought and action (Bandura, 1989). Behaviour is regulated on the basis of ‘self-reactions’, whereby an individual will avoid certain behaviours because the consequence is ‘self-reprimand’, and engage in other behaviours because they result in being rewarded by ‘self-approval’. The moral standards that dictate the self-reactions are formed from a variety of influences, including instruction, feedback from other people, modeling and structured institutions (such as religion, education and political agencies). An important concept in modeling as an influencer of standards of behaviour is that people do not passively absorb every standard of behaviour they are exposed to. The extent to which an observer internalises standards is strongly dependent on factors such as similarity of model to observer, the value of the behaviour and the extent to which the observer has control over the behaviour (Bandura, 1989, 1991).

- **Self-reflective capability:** Self-reflective capability refers to the ability of an individual to 'meditate' on, or analyse, one's own characteristics and thought processes and make adjustments where necessary.

  One important concept related to self-reflective capability, and which has become a central focus point in Bandura's research because of its key role as a determinant of self-regulation, is 'self-efficacy'. Given the importance of this construct for this study, it is discussed in detail in the following section.

3.4.1.5 Self-efficacy

According to Bandura, a person's attitudes, abilities, and cognitive skills comprise what is known as the self-system. This system plays a major role in how we perceive situations and how we behave in response to different situations. Self-efficacy plays is an essential part of this self-system and is described by Bandura as "the belief in one's capabilities to organise and execute the courses of action required to manage prospective situations" (Bandura, 1995). Thus, self-efficacy may be described as a person's belief in their ability to succeed in a given situation or in respect of a particular task or behaviour (Bandura, 1994, Ausburn et al., 2009, Tamir and Mauss, 2011).

According to Bandura, "a strong sense of efficacy enhances human accomplishment and personal well-being in many ways" (Bandura, 1994). People with a strong sense of self-efficacy tend to view difficult tasks as challenges rather than as threats to be avoided and tend to engross themselves with a high degree of interest in the accomplishment of the tasks they feel capable of achieving. They tend also to set challenging goals and are committed to achieving these goals. People with high self-efficacy levels do not easily give up when confronted with disappointment or apparent failure. Such people tend to 'back themselves' and have a high level of self-assurance that they have personal control over the success or failure of the task at hand (Bandura, 1994, Busch, 1995).

On the other hand, people who have a low sense of self-efficacy (i.e. people who doubt their own capabilities), tend to shy away from challenging tasks and give up easily when confronted with difficulties. Such people tend to dwell on their inadequacies and are quick to lose faith in their capabilities (Bandura, 1994, Reid, 2010).

According to Bandura, there are four major sources of self-efficacy:

1. **Mastery Experiences:** Bandura explains that the experience of mastering a task in itself cultivates a sense of self-efficacy. The more a person succeeds at any given task, the stronger

their sense of capability will be when confronted with the same or a similar task in future. Conversely, if a person regularly fails at a task, they will likely develop a weakened sense of self-efficacy and are more likely to doubt their own capabilities when confronted with a similar challenge in future (Koul and Rubba, 1999, Kurbanoglu, 2003).

2. **Social Models:** According to Bandura: “Seeing people similar to oneself succeed by sustained effort raises observers' beliefs that they too possess the capabilities to master comparable activities required to succeed” (Bandura, 1994). The importance of observer-model similarity is a recurring theme in Bandura’s SCT. Bandura drives this point home by noting as follows: “The impact of modeling on perceived self-efficacy is strongly influenced by perceived similarity to the models. The greater the assumed similarity the more persuasive are the models' successes and failures. If people see the models as very different from themselves their perceived self-efficacy is not much influenced by the models' behaviour and the results it produces. Modeling influences do more than provide a social standard against which to judge one's own capabilities. People seek proficient models that possess the competencies to which they aspire. Through their behaviour and expressed ways of thinking, competent models transmit knowledge and teach observers effective skills and strategies for managing environmental demands. Acquisition of better means raises perceived self-efficacy” (Bandura, 1994, Koul and Rubba, 1999, Kurbanoglu, 2003).
3. **Social Persuasion:** Bandura also asserted that people could be persuaded to belief that they have the skills and capabilities to succeed, or conversely, persuaded that they do not have the capabilities to succeed. As Bandura puts it, “people who have been persuaded that they lack capabilities tend to avoid challenging activities that cultivate potentialities and give up quickly in the face of difficulties. By constricting activities and undermining motivation, disbelief in one's capabilities creates its own behavioural validation” (Bandura, 1994, Koul and Rubba, 1999, Kurbanoglu, 2003).
4. **Psychological Responses:** Bandura expresses the thought that psychological factors such as mood, emotional states and stress levels can also influence an individual’s sense of self-efficacy (Bandura, 1994, Koul and Rubba, 1999, Kurbanoglu, 2003).

Teachers and self-efficacy

When discussing the factors (‘agencies’) that influence the development of self-efficacy over an individual’s life-span, Bandura notes the impact of social structures, such as schools, and of models that operate within these structures, such as teachers. Acknowledging the importance of an individual’s experiences at school in the development of a positive (or negative) sense of self-efficacy, Bandura points out that 'during the crucial formative period of children's lives, the school functions as the primary setting for the cultivation and social validation of cognitive competencies" (Bandura, 1994). Moreover, Bandura states that 'many social factors, apart from the formal instruction, such as peer modeling of cognitive skills, social comparison with the performances of other students' contribute to the development of learners' sense of intellectual efficacy (Ashton and Webb, 1986, Bandura, 1994, Koul and Rubba, 1999, Tamir and Mauss, 2011).

One very important influence in the development of a learner's sense of self-efficacy is the teacher. Bandura focuses on the role of teacher as agent in self-efficacy development as follows: "The task of creating learning environments conducive to development of cognitive skills rests heavily on the talents and self-efficacy of teachers. Those who are have a high sense of efficacy about their teaching capabilities can motivate their students and enhance their cognitive development. Teachers who have a low sense of instructional efficacy favor a custodial orientation that relies heavily on negative sanctions to get students to study" (Bandura, 1994, King et al., 2001, Tschannen-Moran and Hoy, 2001, Angle and Moseley, 2009, Moseley and Taylor, 2011)

Collective self-efficacy

'Collective self-efficacy' is a term Bandura uses to refer to a group's 'shared belief in its conjoint capabilities to attain their goals and accomplish desired tasks' (Bandura, 1986, 1994, 2000). According to Bandura, perceptions of collective efficacy may be a predictor of group performance, and it is expected that a community's collective efficacy will influence the group's dialogue, goal setting, collective effort and especially their persistence when barriers arise.

The concept of a sense of 'collective efficacy' (i.e. a group rather than an individual having a sense of the capability of the group as a whole) is alluded to by Bandura in describing the impact of the social context in which the teachers and learners operate: "Teachers operate collectively within an interactive social system rather than as isolates. The belief systems of staffs create school cultures that can have vitalising or demoralising effects on how well schools function as a social system. Schools in which the staff collectively judge themselves as powerless to get students to achieve academic success convey a group sense of academic futility that can pervade the entire life of the school. Schools in which staff members collectively judge themselves capable of promoting academic success imbue their schools with a positive atmosphere for development that promotes academic attainments regardless of whether they serve predominantly advantaged or disadvantaged students" (Bandura, 1994). This principle would apply by extension for the broader social milieu both teachers and learners are a part of. If the pervasive social environment were to condition a certain race, for example, to believe they were less capable than other races, it would create a sense of weakened self-efficacy, not only for individuals of that race, but also for the collective (i.e. all people who belong to that race, including teachers and learners) (Bandura, 1995, Oettingen, 1995, Tschannen-Moran and Barr, 2004).

3.4.2 Phillips' 5 level framework for ROI in training analysis

This study's focus is on identifying the factors that influence learning at level 2 of Phillips' ROI in training framework, with a view to maximising the ROI achived on IS&T related training and education programmes (Phillips, 1997, Phillips and Stone, 2002). According to Phillips et al. (Phillips and Stone, 2002), improving the results attained at a lower level (such as level 2, 'learning') in his ROI framework inevitably positively affects higher levels via a 'chain of impact', thus improving the total ROI achieved (Phillips and Stone, 2002). Participants' improvement/gain scores on the level 2 training objectives identified for each of the three courses involved in this study (viz. database skills, network skills and spreadsheet skills respectively) are presented on a graphical template that illustrates their context in terms of the other 4 levels of Phillips' model (see Figure 5-1 to Figure 5-3). Figure 3-4 illustrates how the data from this study that focusses on level 2 (learning) gains could provide the basis for further analysis of ROI at higher levels in Phillips' framework. Thus, while the findings of this study aim directly at identifying factors that can improve the effectiveness of the learning that takes place in the university IS&T classroom, the framework used (viz. Phillips' ROI in training framework) allows for extended application to training programmes in the workplace where training impact can appropriately be measured at levels 3, 4 and 5 (Phillips, 1997, Phillips and Stone, 2002).

In the example presented in Figure 3-4, the level 2 data (learning that has taken place, as reflected in the improvement/gain scores of the participants in terms of the objective "Database Skills"), is highlighted graphically to indicate the focus of this study. For illustrative purposes, fictional data is inserted for levels 1, 3, 4 and 5 to demonstrate how this study could be extended in a corporate setting, for example, to include an analysis of the impact of Course DB101 at all 5 levels of measurement.

For example, if this was a training initiative aimed at improving the service standards of contact centre support agents for a firm of database developers, the following objectives might have been identified at each measurement level of Phillips' framework:

- Level 1 (Reaction): The objective would simply be 'a satisfactory learning experience' and would be based on learner feedback on the quality of the programme, including teacher quality, environment, courseware, venue quality and other factors that would typically be reported on via ‘happy sheets’ or programme feedback forms. Often, this level of measurement is either not included in the ROI analysis or a decision is made to consider level one’s objective to have been achieved if the average learner feedback score meets a predetermined criterion, such as an 80% learner satisfaction score using a Likert scale (Kirkpatrick, 1998, Phillips and Stone, 2002, Meyer et al., 2003).

- Level 2 (Learning): The objectives identified at level 2 relate to the skills, attitudes and behaviours that are expected to be learned by the participants. In this case, the training relates to database skills and the impact of the programme at this level is measured by the improvement scores of participants on cognitive testing related to the course. The performance improvement scores are obtained by subtracting the mean post-test scores (‘post-training performance’) from the mean pre-test scores (‘baseline performance’) to obtain what the graphic refers to as ‘performance improvement’. In view of the fact that this study seeks to identify the factors that maximise the effectiveness of training and skills transfer at level 2 (and, via the chain of impact, the overall ROI realized), results are grouped in terms of various factors (independent variables), such as teacher student match or mismatch on race, home language or gender, and the improvement scores obtained at level 2 for each of these factors compared. Thus, in the example presented in Figure 3-4, one would conclude that maximum ROI is achieved for Course DB101 when teacher and student are matched in terms of race (improvement score of 13% at level 2) and home language (improvement score of 10% at level 2), as opposed to teacher student mismatch in terms of race (improvement score of 6%) and home language (improvement score of 2%).
- Level 3 (Application): The example in Figure 3-4 illustrates the type of level 3 objective that may be identified. For example, management may identify the need for the training to result in improved ‘numbers of cases resolved on a daily basis’ per support agent/student. Thus, the objective might be stated as ‘Number of cases resolved on a daily basis’. This measures the application of skills learnt on Course DB101 in terms of the extent to which students/agents are able to apply what they have learnt at level 2 on the course to their job, as measured in this instance by an increase in cases resolved each day compared with pre-training performance (‘baseline performance’).
- Level 4 (Business impact): Objectives at level 4 are either ‘tangible’ or ‘intangible’. In the example in Figure 3-4, an intangible business impact measure may be ‘improved (internal) customer satisfaction ratings’ (the database developers making use of the support agents would be considered internal clients in this case). A tangible impact measure might be ‘monthly database development team revenue from completed projects’, assuming that the

training of support agents to be more effective is considered to have contributed to the ability of the database development team to complete more projects on time and therefore increase their revenue.

- Level 5 (ROI%): This final ROI% analysis is only possible if tangible benefits of training were identified at level 4. Furthermore, at least one of the tangible benefits would need to be expressed in financial terms. For example, in Figure 3-4, ‘monthly database development team revenue from completed projects’ was identified at level 4. At the point at which ROI analysis is undertaken, the formula for the ROI% would be:

$$\text{ROI\%} = \frac{\text{Total financial benefit of training to date - Total cost of training}}{\text{Total cost of training}} \text{ X } 100$$

Thus, in the example in Figure 3-4, we assume that 6 months have elapsed since Course A was completed, and that the training cost totaled R10,000. Monthly revenue in the database development team has increased from an average of R50,000 per month prior to training, to an average of R60,000 per month. Over 6 months, that means that the financial benefit to the company of the training has been R60,000 (R10,000 for each of 6 months since the training was conducted). Using the above formula, therefore, the ROI% is 500% ((R60,000-R10,000)/R10,000, multiplied by 100). This means that for every R1,00 spent on training, R5,00 was realised as financial benefit to the organisation as a result of the training.

The example in Figure 3-4 illustrates Phillips’ ‘chain of impact’. A satisfactory learning experience (level 1) is followed by effective learning and skills transfer occurring at level 2, as exemplified by the increased post-performance scores compared with the baseline performance scores. In turn, the learning that takes place at level 2 allows participants to perform more effectively in terms of the objectives related to ‘application’ in the workplace, as measured at level 3. Application of skills learned results in ‘business impact’ at level 4, viz. improved ‘customer satisfaction’ and increased revenues for the database development team, allowing one to calculate the ROI realized from this training intervention.

The focus of this study is on identifying factors that improve performance at level 2 (learning), on the assumption that, via the chain of impact illustrated above, this will ultimately result in higher overall ROI, whether in the university IS&T classroom or a corporate training venue.

Level	Objectives	Independent Variables	Baseline Performance	Post-Training Performance	Performance Improvement
1. Reaction	Satisfactory learning environment/experience				
2. Learning	Course DB101 (Database Skills)	Teacher Student Match (Race)	52%	65%	13%
		Teacher Student Mismatch (Race)	49%	55%	6%
		Teacher Student Match (Home Language)	51%	61%	10%
		Teacher Student Mismatch (Home Language)	51%	53%	2%
		Teacher Student Match (Gender	53%	57%	4%
		Teacher Student Mismatch (Gender)	54%	58%	4%
3. Application	Number of cases resolved on a daily basis		5	8	3
4. Impact	Monthly revenue from completed projects		R50,000	R60,000	R10,000
	Customer satisfaction rating		50%	80%	30%
5. ROI%					500%

Figure 3-4 Sample ROI analysis on Phillips' 5 level framework (Source: Adapted from Phillips (Phillips, 1997, Phillips and Stone, 2002))

3.4.3 Research model

Figure 3-5 contextualises the research questions in terms of the theoretical frameworks referred to in the study.

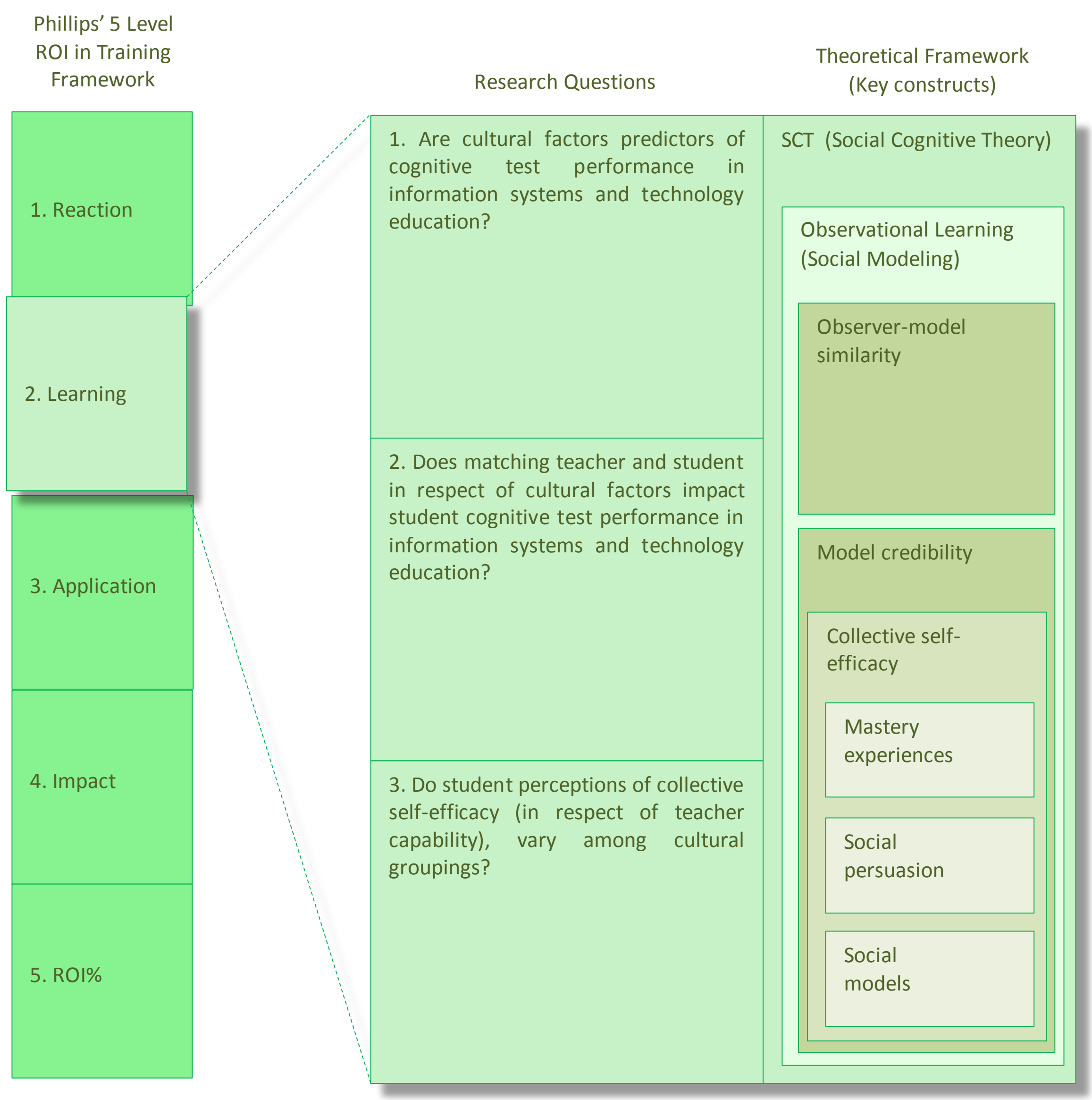


Figure 3-5 Theoretical context for study

As per Figure 3-5, the study focuses on level 2 of Phillips' ROI framework, viz. improvement in terms of 'learning' based performance objectives. 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 3-6 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 3-6, the research model for this study posits that observer-model similarity as a construct affects observational learning, with model credibility as a moderator which is, in turn, affected by collective self-efficacy. Thus, on one hand, when model and observer are similar, and the model has credibility in the eyes of the observer, which in turn is dependent upon the collective sense of self-efficacy the observer's reference group has of itself, learning is enhanced. On the other hand, if due to a weakened sense of collective self-efficacy the model does not have credibility in the eyes of the observer, learning will not be as effective, despite the similarity of the model and the observer.

Collective self-efficacy is influenced by three factors that are relevant to this study, viz. social models, social persuasion and mastery experiences. The impact of these three factors on collective self-efficacy is moderated by cultural factors, such as the race, home language and gender of the observer.

Associated with the construct of 'collective self-efficacy' are three independent measured variables, viz. student perceptions of the efficacy of teachers of their own race, their own home language and their own gender respectively (as shown in Figure 3-6). Observer-model similarity links to the dichotomous independent variables of teacher 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 3-6 links to the measurable variables 'student race', 'student home language' and 'student gender'.

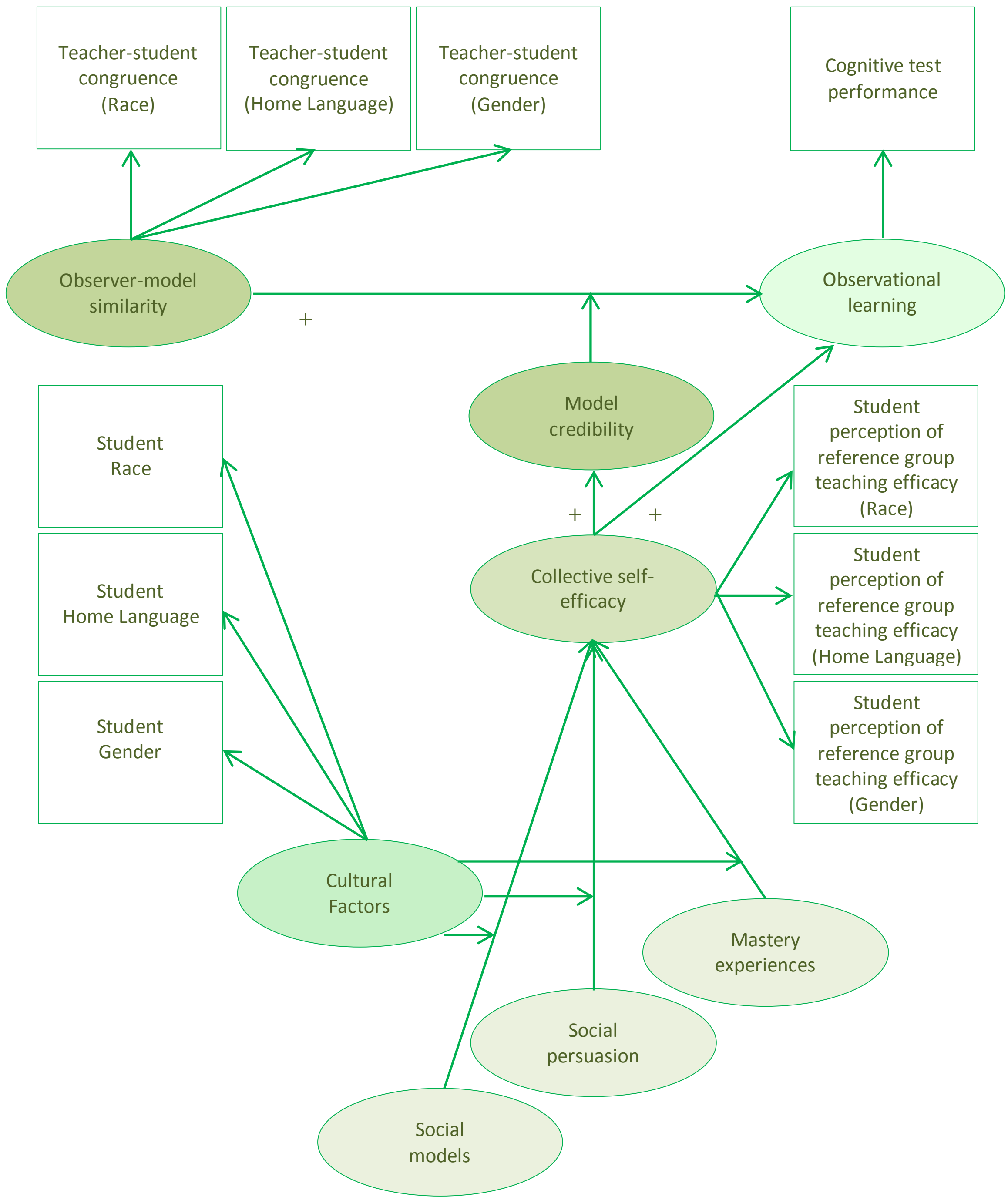


Figure 3-6 Research model

3.5 Research design

The study involved three cohorts of IS&T students drawn from two tertiary institutions in South Africa- one public and one private. The term ‘cohort’ as used in this study refers to ‘membership of a group as defined by some factor other than a time-based one, and not in the sense of a chronological study of the treatment of the same group of people over a period of time (Dodge, 2003). While the use of multiple cohorts allowed for the refinement of variables and methodologies in response to each cohort’s data and results, all three cohorts relate to precisely the same study and research questions. Moreover, while cohorts two and three differ in terms of sample, the research methods and models applied to these two cohorts are identical and so they are often considered together in the sections and chapters that follow (Table 3-2).

Table 3-2 presents a summary of the major differences between the three cohorts.

	Cohort one	Cohort two	Cohort three
Institution	1	1	2
Institution type	Public tertiary	Public Tertiary	Private Tertiary
Students (Participants in match/mismatch study)	509	4825	1278
Teachers (Participants in match/mismatch study)	3	20	56
Student respondents to S-CTSE survey	609	737	636
Teacher respondents to T-CTSE survey	-	15	37
Different Modules/ Courses	3	48	118
Test scores (Unique student test scores in dataset)	1479	12013	6358

Measures and instruments		
Match/mismatch effect		
Dependent variable	Student test scores • Raw test score (post-test) • Improvement score (post-test score minus pre-test score)	• 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	Teacher student match mismatch (Race, Home Language, Gender)	
Data source/instrument	Pre and post tests	Student records (class marks)
Collective teaching self-efficacy (CTSE)		
Dependent variable	• Student CTSE	• 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 • Match → Student test score effect (CTSE as a moderating variable)[2]

Independent variable	• Demographics	• Student CTSE • Teacher CTSE • CTSE sub-factors: -Subject Expertise -Classroom Management -Instructional Strategies -Student Engagement
Data source/instrument	Perception Questionnaire	• S-CTSE survey • T-CTSE survey
Statistical methods and models	• Multiple regression • Point-Biserial correlation	• Generalized Estimating Equations (GEE) • Confirmatory factor analysis • Structural equation modelling • Comparisons of means: Paired sample T-Tests, single-sample T-Tests • Multiple regression and Robust Regression: M-type and S-type • Non-parametric repeated measures ANOVA (Friedman K-way ANOVA) • Moderation analysis using variable interaction

Table 3-2 Cohort comparison

3.5.1 Cohort one

3.5.1.1 Research sample

The research comprised two components:

1. An investigation of cognitive test performance;
2. An investigation of student perceptions of collective self-efficacy.

[2] The symbol → is used to express 'prediction' here and elsewhere in the text. Thus, *Match* → *Student test score* means '*Match* predicts *Student test score*'.

3.5.1.1.a Cognitive testing sample

In addressing the research objectives related to cognitive testing performance in a multicultural setting as described in the foregoing, 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 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.

The demographics of the lecturers and students are summarised in Table 3-3:

		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				

Table 3-3 Demographics of cohort one (cognitive testing)

The demographics in respect of race, home language and gender match (M) and mismatch (MM) are presented in Table 3-4:

	Course A		Course B		Course C	
	Match	Mismatch	Match	Mismatch	Match	Mismatch
Gender	204	292	279	195	212	297
Race	348	148	129	345	355	154
Home Language	0	496	6	468	375	134

Table 3-4 Match/mismatch totals for cohort one (cognitive testing)

Notes:

- Because of the small numbers in some categories of home language and race, categories were combined as follows:
  - Race:
    - Black, Indian and Other.
  - Home Language:
    - English, African languages and Other.
- The above groupings do not affect the match/mismatch variables.

3.5.1.1.b Perceptions of collective self-efficacy sample

The component of the study related to investigating student perceptions of collective self-efficacy related to the same group of students from which the cognitive testing component derived its sample, viz. students in three different first year Information Systems and Technology courses at a public university in KwaZulu Natal, South Africa. As with the cognitive testing sample, a census of the 1,157 first year Information Systems and Technology students was attempted, with a total of 609 students completing the perception questionnaire.

For the purposes of analysis, data for race and home language were grouped. Races were grouped into Black, Asian (synonymous in this context with ‘Indian’) and Other. The new home language categories were English, African Languages and Other. Table 3-5 describes the demographic profile of this sample:

		Ungrouped		Grouped	
	Categories	**N**	**%**	**N**	**%**
Gender	Male	274	45	274	45
	Female	335	55	335	55
Race	Black	246	40	246	40
	Asian	308	51	308	51
	White	13	2		
	Coloured	11	2	55	9
	Other	31	5		
Home Language	English	356	59	356	59
	Zulu	209	34		
	Xhosa	10	2		
	Swazi	6	1		
	Ndebele	1	.2		
	South Sotho	1	.2	249	39
	North Sotho	2	.3		
	Tsonga	5	.8		
	Tswana	3	.5		
	Venda	2	.3		
	Afrikaans	1	.2		
	Other	12	2	14	2
	Unspecified	1	.2		

Table 3-5 Demographics of cohort one (Perception)

Table 3-6 below provides a cross tabulation of races and home languages represented in the sample for cohort one:

		Home Language												
		English	Afrikaans	Zulu	Xhosa	Swazi	Ndebele	South Sotho	North Sotho	Tsonga	Tswana	Venda	Other	Total
Race	Black	7	0	206	10	5	1	1	2	2	3	1	8	246
	White	8	0	1	0	0	0	0	0	0	0	1	3	13
	Asian	303	1	1	0	1	0	0	0	1	0	0	1	308
	Coloured	11	0	0	0	0	0	0	0	0	0	0	0	11
	Other	28	0	1	0	0	0	0	0	2	0	0	0	31
Total		356	1	209	10	6	1	1	2	5	3	2	12	609

Table 3-6 Race and home language cross tabulation for cohort one (Perception)

3.5.1.2 Data collection methods and tools

The research objectives outlined in the foregoing comprise two categories:

1. Objectives related to examining cognitive test performance;
2. Objectives related to investigating student perceptions of collective self-efficacy (in respect of teaching capability).

3.5.1.2.a Examining cognitive test performance

3.5.1.2.a.1 Measures of cognitive test performance

A number of international studies that investigate the impact of teacher student congruence on learning use a single post training cognitive test score at the end of a study period as the dependent variable (Jussim et al., 1996, Oates, 2003, Zhang, 2006). Other studies use an ‘improvement score’ as the dependent variable (Sheehan and Marcus, 1977, Stroter, 2008). It is the opinion of the author that the use of a single post test score only as the dependent variable in a study of this nature is inappropriate as it does not take into account entry point disparities in education. Much of the research in this field reports race based performance gaps and suggests that socio-economic factors and historical educational disadvantage account for this (Oates, 2003, Obiakor, 2004, Stroter, 2008, Horsford, 2010). It is therefore possible that certain groupings of students may enter the educational context for these studies with a pre-existing disadvantage that will be reflected in lower test scores, but may not reflect the real impact of learning in the 'new learning environment'. Thus, a Black student who enters university from a school environment that is inferior to that of his White counterparts may score lower marks than his White classmates, reflecting the legacy of his disadvantaged schooling, but now that the 'playing field is leveled', may find his 'improvement score' matching that of the White students.

This is best explained by a hypothetical example. Black, previously disadvantaged students may score on average 20% lower in cognitive tests at the end of their first year at university than White, 'privileged' classmates. A researcher would draw certain conclusions on the impact of various factors (such as teacher student race match) on the performance of these students. For example, if Black students consistently obtained lower test scores than their White counterparts, despite being taught by Black teachers (with whom they are racially congruent), a researcher might conclude that teacher student race match is not a predictor of cognitive test performance. However, this could be misconceived. If, for example, a comparison of a pre-test score conducted at the beginning of the year was made with a post-test score at the end of the year, it may be found that Black students who were taught by Black teachers improved by a greater margin than their White counterparts. If such previously disadvantaged students were to improve in their cognitive test performance to a greater extent than their 'privileged' classmates, for example, it would demonstrate that such previously disadvantaged students were equally capable students at least, despite lower overall test scores and would suggest that any race based performance gaps were indeed the result of a disadvantaged educational environment rather than inherent learning deficiencies. Such insights would not be possible by using a single post test score as a dependent variable. A researcher would draw a very different set of conclusions about the impact of teacher student racial congruence under these circumstances. It is the opinion of the author that this use of an 'improvement score' rather a single post test score as the dependent variable in studies of this nature provides a more accurate view of the impact of factors such as teacher student congruence.

In order to compare the results of this study with many of those conducted internationally using a single test score as the independent variable, two analyses of the data are performed: one using a single post test score as dependent variable and another using 'improvement score'. The results obtained by using each of the approaches are compared.

3.5.1.2.a.2 Overview of cognitive test performance research approach

In respect of the research objectives related to examining cognitive test performance, a pre- and post-training assessment test instrument was developed to assess the students' cognitive learning in respect of each of the three courses' subject matter (see *Appendix A: Pre- and Post Assessment Test*). To ensure consistent assessment, the same instrument was used as both pre- and post-assessment tool. The assessment test 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). Although the assessment instrument contains questions relating to six subjects ('word processing', 'spreadsheets', 'databases', 'using a computer and managing files', 'I.T. concepts' and 'information and communication (networks)', only the results for 'spreadsheets', 'databases' and 'information and communication (networks)' were included in the study. This was due to the fact that there were no specific lectures held in respect of the excluded subjects ('word processing', 'using a computer and managing files' and 'I.T. concepts') during the semester in which the study was conducted, thus precluding any analysis of the impact of teacher student congruence factors in learning outcomes. In the case of the included subjects, 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'. This approach is consistent with Phillips' (2002) ROI analysis model which uses improvement score as a measure of what Phillips terms the 'second level of measurement' (viz. Learning). Phillips' model refers to a 'baseline level' of performance in terms of any objectives identified at level 2 of his framework, and a 'post training performance level', which are compared to produce a 'performance improvement score'. In this study, the pre-test score corresponds to Phillips' 'baseline score' at level 2, while the post test score represents the 'post training performance' level of each student (Phillips, 1997, Phillips and Stone, 2002).

3.5.1.2.b Investigating student perceptions of collective self-efficacy

The objectives related to student perceptions of collective self-efficacy (in respect of teaching ability) for cohort one were investigated by means of a survey conducted with the same group of students that participated in the pre and post assessment components of the research (see *Appendix B: Perception Questionnaire*). This instrument was designed to measure students' perceptions of the efficacy of teachers within their own reference groups (in this case, reference groups in respect of race, home language and gender). This is taken to be a measure of what Bandura terms 'collective self-efficacy', which refers to a group's 'shared belief in its conjoint capabilities to attain their goals and accomplish desired tasks', (in this case, IS&T related teaching capability) (Bandura, 1986, 1994, 2000). Bandura's guidelines on the development of instruments to measure collective self-efficacy informed the creation of the instruments used in this study, as described in Table 3-7.

Bandura's guidelines for the development of inctruments for measuring collective self-efficacy (Bandura, 1994, 1995, 2000)		Justification for 'Perception/ Collective Self-Efficacy' Instrument (See *Appendix B: Perception Questionnaire*)	
Measurement guideline	**Measurement options**	**Choice**	**Justification**
1. Bandura refers to two possible approaches to the measurement and evaluation of collective self-efficacy:	a. The aggregation of appraisals by members of a reference group of their their personal capabilities in terms of the functions they peform in the group;		Since the efficacy of the teacher (not the student) was being measured, option b was selected to inform the development of the 'perception/ collective self-efficacy' instrument used in this study.
	b. Aggregate appraisals by members of the capabilities of the group as a whole	✓	
2. Measurement of collective self-efficacy should occur in terms of one of three dimensions:	a. Perceived efficacy to take action as a group.		The dimension referred to in option b (viz. 'perceived capability of other community members') was selected for the 'perception/ self-efficacy' instrument used in this study as it was the students' perception of the efficacy of individual teachers within the reference group that was being measured.
	b. Perceived capability of other community members.	✓	
	c. Perceived efficacy to solve problems as a group.		
3. Perceptions of self-efficacy may vary with the tasks at hand and with other contextual factors. Questions about perceived self-efficacy should be precise and refer to specific circumstances.		✓	The questions selected for this instrument referred specifically to 'teaching capability'.

Table 3-7 Instrumentation justification based on Bandura's guidelines (Source: (Bandura, 1994, 1995, 2000)

The perception survey asked the following questions of each student:

1. Which of the following is true about your teacher's gender?
    a. I learn better from a teacher who is of the same gender as me.
    b. I learn better from a teacher who is not of the same gender as me.
    c. The teacher's gender makes no difference to how I learn.
2. Which of the following is true about your teacher's race?
    a. I learn better from a teacher who is of the same race as me.
    b. I learn better from a teacher who is not of the same race as me.
    c. The teacher's race makes no difference to how I learn.
3. Which of the following is true about your teacher's home language?
    a. I learn better from a teacher whose home language is the same as mine.
    b. I learn better from a teacher whose home language is not the same as mine.
    c. The teacher's home language makes no difference to how I learn.
4. Which of the following is true about your teacher speaking your home language while teaching you?
    a. I learn better when my teacher speaks my home language while teaching me.
    b. I learn better when my teacher does not speak my home language while teaching me.
    c. The teacher using my home language while teaching makes no difference to how I learn.

Questions 3 and 4 both relate to home language as a reference group for collective self-efficacy, but differ in focus. Whereas question 3 focuses on the home language of the teacher, whether spoken as a medium of instruction or not, question 4 focuses on the actual language used during teaching.

For each question, and for each of the demographic variable categories (gender, race, home language and language of instruction), a Chi-square goodness-of-fit test was applied to investigate the frequency of response. Table 3-8 shows how response frequencies in respect of specific questions were interepreted in relation to a measurement of collective self-efficacy.

Reference group	Question	Response option	Interpretation of response frequencies as a function of an estimation of collective self-efficacy (in respect of teaching ability): Higher than expected response frequency	Lower than expected response frequency
Gender	1. Which of the following is true about your teacher's gender?	a. I learn better from a teacher who is of the same gender as me.	High collective self-efficacy	Low collective self-efficacy
		b. I learn better from a teacher who is not of the same gender as me.	Low collective self-efficacy	High collective self-efficacy
		c. The teacher's gender makes no difference to how I learn.	Passive (no impact on collective self-efficacy rating)	Passive (no impact on collective self-efficacy rating)
Race	2. Which of the following is true about your teacher's race?	a. I learn better from a teacher who is of the same race as me.	High collective self-efficacy	Low collective self-efficacy
		b. I learn better from a teacher who is not of the same race as me.	Low collective self-efficacy	High collective self-efficacy
		c. The teacher's race makes no difference to how I learn.	Passive (no impact on collective self-efficacy rating)	Passive (no impact on collective self-efficacy rating)
Home Language	3. Which of the following is true about your teacher's home language?	a. I learn better from a teacher whose home language is the same as mine.	High collective self-efficacy	Low collective self-efficacy
		b. I learn better from a teacher whose home language is not	Low collective self-efficacy	High collective self-efficacy

Reference group	Question		Response option		Interpretation of response frequencies as a function of an estimation of collective self-efficacy (in respect of teaching ability): Higher than expected response frequency	Lower than expected response frequency
				the same as mine.		
			c.	The teacher's home language makes no difference to how I learn.	Passive (no impact on collective self-efficacy rating)	Passive (no impact on collective self-efficacy rating)
	4.	Which of the following is true about your teacher speaking your home language while teaching you?	a.	I learn better when my teacher speaks my home language while teaching me.	High collective self-efficacy	Low collective self-efficacy
			b.	I learn better when my teacher does not speak my home language while teaching me.	Low collective self-efficacy	High collective self-efficacy
			c.	The teacher using my home language while teaching makes no difference to how I learn.	Passive (no impact on collective self-efficacy rating)	Passive (no impact on collective self-efficacy rating)

Table 3-8 Interpretation model for 'perception questionnaire' response frequencies

3.5.1.3 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 and 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 primarily uses a multiple regression model for cohort one to identify the extent to which the various independent variables (such as race, home language and gender match or mismatch) contribute to the variance of the dependent variables (improvement and post test scores).

By way of comparison, however, a secondary analysis of some of the data is conducted using a lesser known correlation model (Point-Biserial Correlation) designed for situations where either the independent variable or dependent variable is dichotomous while the other variable is non-dichotomous. In the case of the match/mismatch components of this study, the independent variable is indeed dichotomous (either match or mismatch) and therefore ideally suited to this model.

3.5.1.3.a 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. 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.

3.5.1.3.b Point-Biserial correlation

Point-Biserial Correlation is a special version of the Pearson product-moment correlation. This correlation model is designed to meet the needs of data involving either of the independent or dependent variables being dichotomous and the other variable being non-dichotomous. In the case of this study, the dichotomous variable is the independent variable, teacher student match/mismatch (in terms of race, home language or gender). The dependent variable is non-dichotomous, both in the case where a single post test score is used as the dependent variable and where an improvement (gain) score is used.

The Point-Biserial Correlation coefficient is calculated using the following formula:

$$r_{pb} = \frac{M_p - M_q}{S_t} \sqrt{pq}$$

Notes on Point-Biserial Correlation Formula:

- M_p is the mean for the non-dichotomous values in connection with the variable coded 1;
- M_q is the mean for the non-dichotomous values for the same variable coded 0;
- S_t is the standard deviation for all non-dichotomous entries;
- p and q are the proportion of the dichotomous variable coded 1 and 0 respectively.

It should be noted that even if the coefficient of determination indicates a relationship between variables, the correlation may not be significant. An interpretive index such as the coefficient of determination is not meaningful by itself. It has to be statistically significant. In order to determine if the correlation is significant, the null hypothesis must be rejected. To begin, the null hypothesis always states that r_{pb} equals zero. Any evaluation of a correlation begins with the disprovable statement that there is no correlation between the two variables. Although rarely stated explicitly, the research hypothesis is always formulated with the null hypothesis in mind. If the null hypothesis is rejected, the alternative or research hypothesis can be accepted, namely, r_{pb} is greater or less than zero. Research hypotheses involving the point-biserial correlation will either be positive or negative. In order to reject the null hypothesis, a one-tailed t-test for independent means is applied to the correlation coefficient, as per the following formula:

$$t = \frac{r_{pb}\sqrt{n-2}}{\sqrt{1-r_{pb}}}$$

Notes on the t-test:

- n is the number of cases;
- n-2 is the degrees of freedom;
- r_{pb} is the point-biserial correlation coefficient.

A one-tailed t-test is used instead of a two-tailed t-test because correlations are almost always, though not necessarily, directional. That is, a given research or alternative hypothesis will usually state some variable is positively or negatively related to another variable as opposed to simply just being related.

If the value of t obtained is less than the critical value for a one-tailed t-test for independent means associated with the degrees of freedom (n-2) then the null hypothesis cannot be rejected. If the value of t is greater than the critical value associated with the relevant degrees of freedom, then the null hypothesis can be rejected and the research hypothesis supported.

3.5.2 Cohorts two and three

For cohorts two and three, a number of refinements were made to the research design and methodology employed for cohort one (see Table 3-2 above that compares the three cohorts). In particular, these involved a larger and more varied sample, as well as refined data collection methods and tools (including refinement of the student collective teaching self-efficacy (S-CTSE) research instrument, inclusion of a teacher collective teaching self-efficacy (T-CTSE) survey and the use of higher order statistical analysis methods). These refinements are discussed in detail in the sections that follow.

3.5.2.1 Research sample

In the descriptives and in all analyses that follow for cohorts two and three, cohort two is synonymous with Institution 1 and cohort three is synonymous with Institution 2. It should be noted that the sample for cohort one (discussed in the foregoing sections) was from Institution 1. Cohort two expands on the study conducted with cohort one by selecting a larger and more varied sample than that used for cohort one from Institution 1 (see Table 3-2). Additionally, whereas cohort one focused entirely on student collective teaching self-efficacy perceptions (S-CTSE), cohorts two and three included a teacher's collective teaching self-efficacy (T-CTSE) survey in addition to the S-CTSE survey.

Table 3-9 and Table 3-10 provide the student and teacher demographic descriptives for cohorts two and three. Specific descriptives are provided per analysis where necessary in the sections that follow.

	Cohort two (Institution 1)				Cohort three (Institution 2)			
	N	%	M	SD	N	%	M	SD
Total Students	4825	100.00			1278	100.00		
Age	4825	100.00	19.71	2.77	1278	100.00	20.60	5.21
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					81	6.34		
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		
-Xhosa	158	3.27			30	2.35		
-Swazi	53	1.10			26	2.03		
-Ndebele	14	0.29			13	1.02		
-Southern Sotho	27	0.56			40	3.13		
-Northern Sotho	12	0.25			202	15.81		
-Tsonga	12	0.25			24	1.88		
-Tswana	9	0.19			198	15.49		
-Venda	11	0.23			40	3.13		
-Other	129	2.67			62	4.85		
Gender								
Male	2396	49.66			671	52.50		
Female	2429	50.34			607	47.50		

Table 3-9 Student demographics for cohorts two and three

	Cohort two (Institution 1)				Cohort three (Institution 2)			
	N	%	M	SD	N	%	M	SD
Total Teachers	20	100.00			56	100.00		
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		
-Xhosa	1	5.00			0	0.00		
-Swazi	0	0.00			0	0.00		
-Ndebele	0	0.00			2	3.57		
-Southern Sotho	0	0.00			0	0.00		
-Northern Sotho	0	0.00			2	3.57		
-Tsonga	0	0.00			0	0.00		
-Tswana	0	0.00			0	0.00		
-Venda	0	0.00			0	0.00		
-Other	1	5.00			7	12.50		
Gender								
Male	14	70.00			30	53.57		
Female	6	30.00			26	46.43		

Table 3-10 Teacher demographics for cohorts two and three

3.5.2.2 Data collection methods and tools

In line with the approach adopted above in describing the data collection methods and tools related to cohort one, the component of the study related to cohorts two and three is considered below under two main sections entitled *Examining cognitive test performance* (relating primarily to Research Question 1 and Research Question 2) and *Investigating student and teacher perceptions of collective self-efficacy* (relating to Research Question 3).

3.5.2.2.a Examining cognitive test performance

The following describes refinements for cohorts two and three of the cognitive test performance components of the study, specifically with regard to the measures and data collection procedures employed.

3.5.2.2.a.1 Measures of cognitive test performance

Student test score

As explained in the foregoing, for cohort one the measures of student academic performance were students' single post-test scores and improvement scores (post-test score – pre-test score) during a semester. For cohorts two and three, 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 teacher combinations per student. As shown in Table 3-2, three measures in respect of student test score were variously used in the analyses to standardize the data and to control for varying class difficulty levels (student scores were spread across a variety of modules and teachers), viz. raw scores, raw scores converted to simple deviations of student score from class mean, and raw scores converted to z-scores (deviation of student score from class mean, divided by the standard deviation).

Demographic match/mismatch

The analysis fundamentally requires comparisons of student academic performance between and across different comparisons of student-teacher demographics. A match in a given demographic is where the student and teacher share the same demographic (e.g. a Black student and Black teacher would be a match, an Indian student and Black teacher would be a mismatch). There are various ways to assess match/mismatch. On a broad basis, one can simply record match/mismatch without recognition of which combination it stems from, creating binary match/mismatch data. This can also be constructed into complex multiple factor combinations such as match/mismatch across race, language and gender simultaneously. In addition, recognition of the exact combinations is possible, whereby, for instance, English student-Afrikaans teacher can be compared to Afrikaans teacher-English student and so forth. Various approaches are attempted and analysed below for cohorts two and three.

3.5.2.2.a.2 Overview of cognitive test performance research approach

While cohort one made use of a pre and post-assessment test per subject/class, cohorts two and three drew on institutional records of each student's assessment results for each module for which the student had received teacher led instruction during the academic years 2011/2012. This approach allowed for a vastly larger dataset of relevant student test scores and thus a broader analysis (see Table 3-2 which describes the increased size and variety of data included in the sample set for cohorts two and three in comparison with cohort one).

3.5.2.2.b Investigating student and teacher perceptions of collective self-efficacy

The following describes refinements to the student collective teaching self-efficacy (S-CTSE) instrument used for cohorts two and three, as well as the addition of a teacher collective teaching self-efficacy (T-CTSE) instrument.

Refined research instruments

The results from cohort one's collective self-efficacy survey suggested that collective self-efficacy may account for match/mismatch data for some demographic groups (*4.2.3.2.c Summary of findings for cohort one*). For cohorts two and three, the collective self-efficacy instrument was refined with a view to allowing more robust and nuanced testing of the potentially moderating effect of the collective teacher self-efficacy variable on the match mismatch effect.

Furthermore, to test for the potentially confounding influence of teacher perceptions of collective teaching self-efficacy, a teacher collective teaching self-efficacy instrument was developed. This is based on the premise that teacher student interactions that influence academic performance do not necessarily relate only to the perceptions and attitudes of students. Although student perceptions and their impact on academic performance are the focus of this study, the fact that the literature abounds with studies that show a significant relationship between teacher attitudes and perceptions and the academic performance of their students cannot be ignored entirely in a study of this nature (Jussim et al., 1996, Oates, 2003, Obiakor, 2004).

Thus two survey instruments were developed for use with cohorts two and three- a student collective teaching self-efficacy questionnaire (S-CTSE) and a teacher collective teaching self-efficacy questionnaire (T-CTSE) (see Appendices D and E). The S-CTSE questionnaire was used to identify students' perceptions of the collective teaching efficacy of reference groups they identified with (viz. race, home language and gender). This instrument was a refinement of that used with cohort one (see Appendix B) with the introduction of six point Likert scale items and sub-scales to allow for factor analysis. The T-CTSE allowed for the analysis of teacher perceptions of the collective teaching efficacy of reference groups they identified with (viz. race, home language and gender) with a view to identifying possible moderating effects of this construct on the teacher student match/mismatch data.

In addition to those referred to in Table 3-7, four guidelines emerge from the literature in respect of the development of self-efficacy research instruments, viz. the questionnaire should be multidimensional, should emphasise the use of the 'I' pronoun, should use verbs such as 'can' and 'be able to' and each item should contain 'barrier expressions' where possible (Skaalvik, et al. (2007), Goddard et al. (2000), Tschannen-Moran et al. (2001), Bandura (1997)).

The S-CTSE and T-CTSE instruments used with cohorts two and three were developed according to the aforementioned guidelines as follows:

- *The questionnaire should be multidimensional:* The S-CTSE (student collective teaching self-efficacy) and T-CTSE (teacher collective teaching self-efficacy) instruments include four dimensions, viz. subject expertise (SEX), instructional strategies (IS), classroom management (CM) and student engagement (SEN). This allows for a four dimensional factor analysis of factors that contribute to collective teaching self-efficacy scores (see Table 3-11 Data source/instrument and question number mapping to variables
- *The questionnaire should emphasise the use of the 'I' pronoun:* Skaalvik et al. (2007) point out that this guideline ensures 'expression of subjective perception of the participant' and explain their use of the 'I' pronoun as follows: "...the object in each statement was I because the aim was to assess each teacher's subjective belief about his or her own capability" (Skaalvik, et al., 2007). In line with this guideline, all items in the S-CTSE and T-CTSE begin with "I believe…", "I have confidence in…", "I am confident that…" or similar expressions (see Appendices D and E).
- *The questionnaire should use verbs such as 'can' and 'be able to':* Skaalvik et al. (2007) justify the use of verbs like 'can' and 'be able to', as follows: " …the items contained verbs like can or be able to so that the items clearly asked for mastery expectations because of personal competence" (Skaalvik, et al., 2007). The S-CTSE and T-CTSE items align with this guideline wherever possible. For example, item 4.1 is worded as follows: "I have confidence in the ability of teachers that are of the same race as me to teach computer related subjects effectively" (see Appendices D and E).

- *Each item should contain 'barrier expressions' where possible:* Bandura (1997) notes that if "there are no obstacles to surmount, the activity is easy to perform, and everyone has uniformly high perceived self-efficacy for it" (Bandura, 1997, p. 42). The S-CTSE and T-CTSE items therefore include barrier expressions where appropriate. For example, item 4.30 includes the 'barrier expression' "the most difficult students: "I believe that teachers that are of the same race as me are effective at getting through to the most difficult students" (see Appendices D and E).

It should be noted that in the literature reviewed on collective teacher self-efficacy as it applies in education, reference is typically made to school or university 'faculties' as the reference group that defines the 'collective' (Bandura, 1995, Oettingen, 1995, Tschannen-Moran and Barr, 2004). The theoretical design principles for faculty based collective teacher self-efficacy instruments found in the literature have in this study been adapted for use with culture-based reference groups (race, home language and gender). Similarly, while many studies in the literature focus on the teachers' own perceptions of collective teacher self-efficacy (Bandura, 1995, Oettingen, 1995, Tschannen-Moran and Barr, 2004), this study, in addition to researching the effect of teachers' own perceptions, also explores the effect of student perceptions of the teaching efficacy of teacher reference groups (viz. race, home language and gender groupings). Furthermore, there is no evidence in the literature that collective self-efficacy has previously been explored as a potential moderating variable for the match → academic performance effect.

Variable	Subscales/Factors	Data Source/Instrument and Question Number Key: S-CTSE: Student Collective Teacher Self-Efficacy Questionnaire (see Appendix D) T-CTSE: Teacher Collective Teacher Self-Efficacy Questionnaire (see Appendix E)
Student ID		S-CTSE
Teacher Student Match (Race)		S-CTSE 2, T-CTSE 2
Teacher Student Match (Home Language)		S-CTSE 3, T-CTSE 3
Teacher Student Match (Gender)		S-CTSE 1, T-CTSE 1
Student Race		S-CTSE 2
Student Home Language		S-CTSE 3
Student Gender		S-CTSE 1
Student CTSE (Race)		S-CTSE 4.1, 4.2, 4.3, 4.10, 4.11, 4.12, 4.19, 4.20, 4.21, 4.28, 4.29, 4.30
	Student CTSE (Race) Subject Expertise (SEX)	S-CTSE 4.1, 4.2, 4.3
	Student CTSE (Race) Instructional Strategies (IS)	S-CTSE 4.10, 4.11, 4.12
	Student CTSE (Race) Classroom Management (CM)	S-CTSE 4.19, 4.20, 4.21
	Student CTSE (Race) Student Engagement (SEN)	S-CTSE 4.28, 4.29, 4.30
Student CTSE (Home Language)		S-CTSE 4.4, 4.5, 4.6, 4.13, 4.14, 4.15, 4.22, 4.23, 4.24, 4.31, 4.32, 4.33
	Student CTSE (Home Language) Subject Expertise (SEX)	S-CTSE 4.4, 4.5, 4.6
	Student CTSE (Home Language) Instructional Strategies (IS)	S-CTSE 4.13, 4.14, 4.15
	Student CTSE (Home Language) Classroom Management (CM)	S-CTSE 4.22, 4.23, 4.24
	Student CTSE (Home Language) Student Engagement (SEN)	S-CTSE 4.31, 4.32, 4.33
Student CTSE (Gender)		S-CTSE 4.7, 4.8, 4.9, 4.16, 4.17, 4.18, 4.25, 4.26, 4.27, 4.34, 4.35, 4.36
	Student CTSE (Gender) Subject Expertise (SEX)	S-CTSE 4.7, 4.8, 4.9
	Student CTSE (Gender) Instructional Strategies (IS)	S-CTSE 4.16, 4.17, 4.18
	Student CTSE (Gender) Classroom Management (CM)	S-CTSE 4.25, 4.26, 4.27
	Student CTSE (Gender) Student Engagement (SEN)	S-CTSE 4.34, 4.35, 4.36
Teacher ID		T-CTSE

Variable	Subscales/Factors	Data Source/Instrument and Question Number Key: S-CTSE: Student Collective Teacher Self-Efficacy Questionnaire (see Appendix D) T-CTSE: Teacher Collective Teacher Self-Efficacy Questionnaire (see Appendix E)
Teacher Race		T-CTSE 2
Teacher Home Language		T-CTSE 3
Teacher Gender		T-CTSE 1
Teacher CTSE (Race)		T-CTSE 4.1, 4.2, 4.3, 4.10, 4.11, 4.12, 4.19, 4.20, 4.21, 4.28, 4.29, 4.30
	Teacher CTSE (Race) Subject Expertise (SEX)	T-CTSE 4.1, 4.2, 4.3
	Teacher CTSE (Race) Instructional Strategies (IS)	T-CTSE 4.10, 4.11, 4.12
	Teacher CTSE (Race) Classroom Management (CM)	T-CTSE 4.19, 4.20, 4.21
	Teacher CTSE (Race) Student Engagement (SEN)	T-CTSE 4.28, 4.29, 4.30
Teacher CTSE (Home Language)		T-CTSE 4.4, 4.5, 4.6, 4.13, 4.14, 4.15, 4.22, 4.23, 4.24, 4.31, 4.32, 4.33
	Teacher CTSE (Home Language) Subject Expertise (SEX)	T-CTSE 4.4, 4.5, 4.6
	Teacher CTSE (Home Language) Instructional Strategies (IS)	T-CTSE 4.13, 4.14, 4.15
	Teacher CTSE (Home Language) Classroom Management (CM)	T-CTSE 4.22, 4.23, 4.24
	Teacher CTSE (Home Language) Student Engagement (SEN)	T-CTSE 4.31, 4.32, 4.33
Teacher CTSE (Gender)		T-CTSE 4.7, 4.8, 4.9, 4.16, 4.17, 4.18, 4.25, 4.26, 4.27, 4.34, 4.35, 4.36
	Teacher CTSE (Gender) Subject Expertise (SEX)	T-CTSE 4.7, 4.8, 4.9
	Teacher CTSE (Gender) Instructional Strategies (SEN)	T-CTSE 4.16, 4.17, 4.18
	Teacher CTSE (Gender) Classroom Management (CM)	T-CTSE 4.25, 4.26, 4.27
	Teacher CTSE (Gender) Student Engagement (SEN)	T-CTSE 4.34, 4.35, 4.36

Table 3-11 Data source/instrument and question number mapping to variables

3.5.2.3 Data analysis models

While analysis of the data for cohort one relied mainly on linear regression and biserial correlation models, cohorts two and three attempted to employ higher order statistical analysis methods such as Generalized Estimating Equations (GEE), Structural Equation Modeling (SEM), General Linear Modeling (GLM), repeated measures and nonparametric analysis in an attempt to confirm the results and refine the quality of data analysis from cohort one. (*Table 3-2 Cohort comparison* provides a summary comparison of the statistical analysis methods and models employed by the various cohorts.)

For each of the analyses conducted on cohorts two and three, a two phase approach is adopted. The first phase employs GEE to identify possible significant relationships between the respective variables for both the match mismatch → student test score and the collective teaching self-efficacy components of the study. The second phase follows up the GEE analyses to further explore the data and the results obtained from cohort one and from the GEE analyses conducted on cohort two and three and to provide a more nuanced data analysis than that possible using a method such as GEE. The following sections describe these analysis methods in more detail.

Match mismatch analysis

Given the highly correlated nature of the datasets for cohorts two and three (due to multiple repeated measures (test scores and S-CTSE survey responses) per student and per teacher (T-CTSE survey responses)), GEE was selected for the first phase of analysis. 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 within a student are probably correlated, as is usually the case with repeated measures).

The analyses of the teacher student match mismatch effect on student test scores (Table 4-36 to Table 4-44) apply a Generalized Estimating Equations (GEE) model to the datasets representing cohorts two and three (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.

To further explore and confirm some of the results achieved in the GEE analyses, a variety of higher order statistical models are applied to the cohort two and three datasets, including correlations, comparisons of means (paired sample T-Tests and single-sample T-Tests), multiple regression and robust regression (M-type and S-type) and non-parametric repeated measures ANOVA (Friedman K-way ANOVA) (Friedman, M., 1937, 1940).

Collective teaching self-efficacy (CTSE) analysis

For the CTSE analyses, a subset of the total dataset for cohorts two and three were extracted on the basis of those students and teachers who completed the collective teaching self-efficacy surveys from each institution.

For the phase one (GEE), two separate analyses are conducted- one with the total collective teaching self-efficacy (CTSE) score as independent variable and the student's z-score as the dependent variable (see Figure 3-7) and the other with the CTSE score acting as a moderating variable to the match → z-score effect (see Figure 3-8).

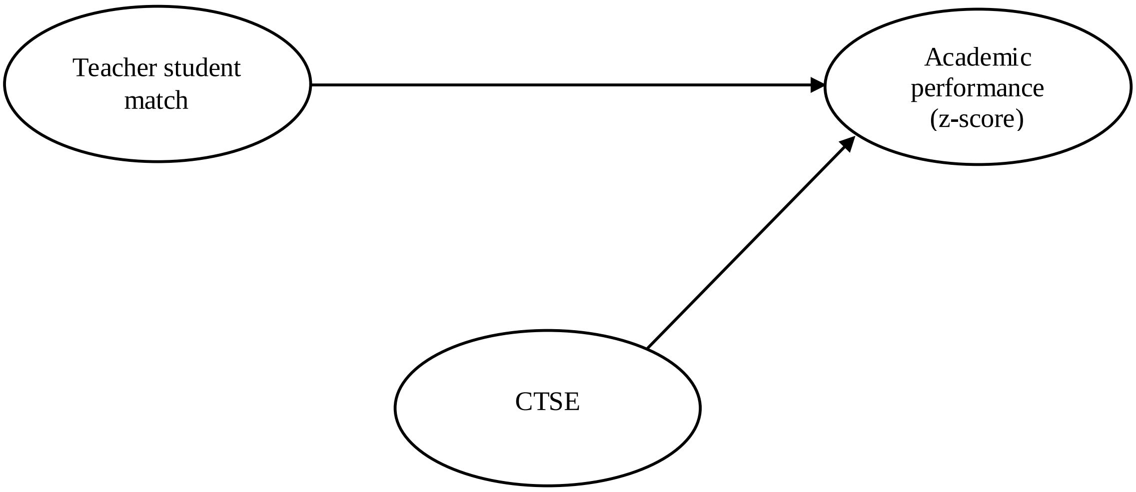


Figure 3-7 CTSE as a direct predictor of test score

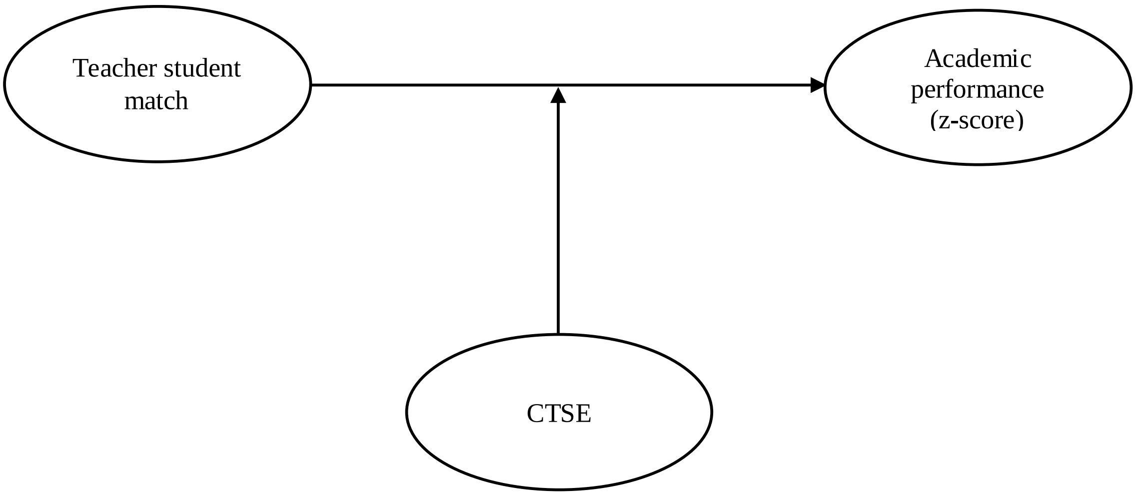


Figure 3-8 CTSE as a moderating variable

The GEE model employed to describe the interaction (moderating) effect of collective teaching self-efficacy on the match → student score effect is as follows (Zeger et al., 1988).

$$\log \mathbf{E}(y_{it}|\mathbf{b}_i) = \mathbf{x}'_{it}\,\beta + \mathbf{z}'_{it}\,\mathbf{b}$$

Thus:

$$\mathbf{E}(y_{it}|\mathbf{b}_i) = e^{\mathbf{x}'_{it}\,\beta + \mathbf{z}'_{it}\,\mathbf{b}}$$

where:

Y_{it} = response values, x_{it} are fixed factor variables, and z_{it} are the covariates (usually the numerically continuous variables);

B = fixed effect betas;

β = random effects.

Written differently:

$$\text{Log Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + b_1 z_1 + b_2 z_2 + \ldots + c_1 x_1 z_1 + \ldots$$

Phase two of the CTSE part of the study applied a variety of higher order statistical models (including comparisons of means (paired sample T-Tests and single-sample T-Tests), multiple regression and robust regression (M-type and S-type) and non-parametric repeated measures ANOVA (Friedman K-way ANOVA)) to provide a more nuanced analysis than that provided by the GEE models (see *4.2.3.3.b Phase 2: Further analysis of the collective teaching self-efficacy effect using higher order statistical methods*).

3.6 Conclusion

This chapter presented Bandura's Social Cognitive Theory as the theoretical framework for the study and provided an overview of the research model, design, methodologies and analysis models employed for each of the three cohorts.

With reference to cohort one, the use of multiple regression using pre-test as a covariate has been justified in the investigation of the extent to which the various independent variables (such as race, home language and gender match or mismatch) contribute to the variance of the dependent variables (improvement and post test scores) in the cognitive testing components of this study. It has also been explained that, by way of comparison, a secondary analysis of the teacher student match/mismatch data is conducted using a lesser known correlation model (Point-Biserial Correlation) designed for situations where either the independent variable or dependent variable is dichotomous while the other variable is non-dichotomous.

Cohorts two and three increased sample sizes and variety within those samples, refined survey instruments and attempted to employ higher order statistical analysis methods, such as structural equation modeling, general linear modeling, repeated measures and nonparametric analysis, in an attempt to confirm the results and provide more nuanced data analyses than those of cohort one.

The following chapter presents the research results and provides an analysis and discussion of the key findings in the light of Bandura's Social Cognitive Theory (Bandura, 1989).

Chapter 4: Results and data analysis

4.1 Introduction

In line with the study's research questions, the results and data analysis are presented within three main sub-headings, reflecting the research focus areas as follows:

1. Race, home language and gender as predictors of cognitive test performance.
2. Teacher student congruence as a predictor of cognitive test performance:
    - Improvement (gain) score as dependent variable;
    - Single post-test score as dependent variable.
3. Student perceptions of collective self-efficacy.

4.2 Results and data analysis

4.2.1 Race, home language and gender as predictors of cognitive test performance

4.2.1.1 Overview

The first of the research questions (and related sub-questions) this study sought to investigate was:

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?"*

This section analyses the data collected in respect of this research question (and the related sub-questions).

4.2.1.2 Results

4.2.1.2.a Cohort one

Separate analyses were conducted for each of the three IS&T classes (Databases, Networks and Spreadsheets) to determine the extent to which the culture related independent variables predicted cognitive test performance.

The data sample for cohort one 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 4-1 presents a summary of race, home language and gender performance for all courses:

		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

Table 4-1 Summary of cognitive test data by race, home language and gender

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.

	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

Table 4-2 Course A: Sample statistics (student gender)

Notes:

- The above scores were not significantly different for the different genders.

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 4-3 Course A: Sample statistics (student race)

	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

Table 4-4 Course A: Sample statistics (student race)- grouped to exclude minor race groups

Notes:

- Post-test and improvement scores were not significantly different.

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 4-5 Course A: Sample statistics (student home language)

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

Table 4-6 Course A: Sample statistics (student home language)- grouped to exclude minor race groups

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.

Course B (Networks):

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

	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

Table 4-7 Course B: Sample statistics (student gender)

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.

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 4-8 Course B: Sample statistics (student race)

	Student Race	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

Table 4-9 Course B: Sample statistics (student race)- grouped to exclude minor race groups

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.

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 4-10 Course B: Sample statistics (student home language)

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

Table 4-11 Course B: Sample statistics (student home language)- grouped to exclude minor race groups

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.

	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

Table 4-12 Course C: Sample statistics (student gender)

Notes:

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

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 4-13 Course C: Sample statistics (student race)

	Student Race	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

Table 4-14 Course C: Sample statistics (student race)- grouped to exclude minor race groups

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.

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 4-15 Course C: Sample statistics (student home language)

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

Table 4-16 Course C: Sample statistics (student home language)- grouped to exclude minor race groups

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.

4.2.1.2.b Cohorts two and three

Table 4-17 below presents the statistically significant results obtained for cohorts two and three in respect of student age, gender, race and home language.

	Institution 1		Institution 2	
	B	**SE**	**B**	**SE**
Intercept	4.68*	2.73	-3.45	2.89
Age	-0.29**	0.11	0.09	0.07
Male	0.05	0.45	-2.97***	0.77
Black	-1.97	1.63	5.93**	2.43
White	4.15***	1.21	9.27***	2.50
English	3.23**	1.63	0.13	1.46

*Notes: *** = p < .01, *** = p < .05, * = p < .10. The benchmark category for race is Indian and Coloured students. The benchmark for languages is non-English home languages.*

Table 4-17: Regressions of student demographics on deviation from class average

4.2.1.3 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 (Sheehan and Marcus, 1977, Dunn et al., 1990, Calder and Ashbaugh, 2005, Stroter, 2008, Wiggan, 2008, Stockly, 2009). The following highlights some of the salient aspects of these findings related to race, home language and gender cognitive test performance:

Cohort one

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 (Table 4-1). Blacks scored an average of 47.66% on pre-tests, while their Indian counterparts scored 56.31% (i.e. Blacks scored on average 8.65% lower on pre-testing than Indian students). The scores for post-tests are similar: Blacks 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 (Table 4-1).
    - 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 Blacks 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 (Table 4-8, Table 4-13). For Course B (Networks), Indians scored an average of 15.14% more than Blacks on the pre-test and 14.66% on the post-test. For Course C (Spreadsheets), Indians scored on average 6.21% more than Blacks 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-testing, 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 (Table 4-1). All the results showing home language disparities in pre and post-test performance for Course A, B and C were statistically significant (Table 4-6, Table 4-11, Table 4-16).
- There were significant 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 (Table 4-7, Table 4-12). 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%) (Table 4-1).

Improvement (gain) scores:

- 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) (Table 4-1).
- Black students improved by an average of 12.15% while Indian students improved by 11.81% (an insignificant difference of 0.34%) (Table 4-1).
- 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%) (Table 4-1).

- Males out-performed females by 0.58% on average across all courses (Table 4-1).

Cohorts two and three

Table 4-17 above shows the results of regressing student demographics on deviations from class means. In support of the results from cohort one, Table 4-17 suggests that there is some evidence for demographic effects. In the dataset for cohort two, age is significantly negatively related to scores. Moreover, White and English speaking students perform better on average than Indian/Coloured students. In cohort two, Indian and Coloured students underperform other races and men under perform women.

4.2.2 Teacher student congruence as a predictor of cognitive test performance

4.2.2.1 Overview

The second of the research questions (and related sub-questions) this study sought to investigate was:

Research question 2(RQ2): *"Does matching teacher and student in respect of cultural factors impact student cognitive test performance in information systems and technology education?"*

> Sub-question 2.1(SQ2.1): *"Does matching teacher and student in respect of race impact student cognitive test performance in information systems and technology education?"*
>
> Sub-question 2.2(SQ2.2): *"Does matching teacher and student in respect of home language impact student cognitive test performance in information systems and technology education?"*
>
> Sub-question 2.3(SQ2.3): *"Does matching teacher and student in respect of gender impact student cognitive test performance in information systems and technology education?"*

This section analyses the data collected in respect of this research question (and related sub-questions).

4.2.2.2 Cohort one

4.2.2.2.a Results

Separate analyses were conducted for each of the three IS&T classes (Databases, Networks and Spreadsheets) to determine the extent to which teacher student congruence in respect of race, home language and gender predicted cognitive test performance. Moreover, two separate analyses were conducted using a *single post-test score* and the *improvement (gain) score* respectively as the dependent variable.

The results obtained by using a multiple regression model were compared with those obtained by using point-biserial correlation.

4.2.2.2.a.1 Improvement (gain) score as dependent variable

Table 4-18 describes the student teacher match/mismatch data for cohort one:

Variable	Course	N	Mean	SD	Min	Max
Improvement Score	**A (Databases)**	496	17.96	21.69	-30	90
Pre Test Score		496	51.67	17.86	0	100
Post Test Score		496	69.64	18.41	20	100
Gender M/MM		496	0.41	0.49	0	1
Race M/MM		496	0.70	0.46	0	1
Language M/MM		-	-	- -	- -	-
Improvement Score	**B (Networks)**	474	6.20	19.09	-30	80
Pre Test Score		474	63	19.99	0	100
Post Test Score		474	69.20	18.91	0	90
Gender M/MM		474	0.59	0.49	0	1
Race M/MM		474	0.27	0.44	0	1
Language M/MM		474	0.01	0.011	0	1
Improvement Score	**C (Spreadsheets)**	509	11.38	18.38	-30	60
Pre Test Score		509	47.29	16.20	10	90
Post Test Score		509	58.66	15.16	10	90
Gender M/MM		509	0.42	0.49	0	1
Race M/MM		509	0.70	0.46	0	1
Language M/MM		509	0.74	0.044	0	1

Table 4-18 Cohort one student teacher match/mismatch data descriptives

Table 4-19 describes the average improvement scores for each of the three courses by match and mismatch:

		Course A (Databases)		Course B (Networks)		Course C (Spreadsheets)	
Variable	**Match/Mismatch**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Gender	Match	18.14	22.29	5.73	19.21	11.56	18.83
	Mismatch	17.84	21.29	6.87	18.94	11.25	18.09
Race	Match	18.07	21.14	6.74	20.85	11.30	18.66
	Mismatch	17.70	23.01	6.00	18.42	11.56	17.79
Home Language	Match	-	-	5.00	16.43	11.25	18.48
	Mismatch	17.96	21.69	6.22	19.14	11.72	18.17

Table 4-19 Cohort one average improvement scores by match and mismatch

Notes:

- An independent samples t-test on means for each of these match/mismatch pairs showed that there were no significant differences between the mean of match and the mean of mismatch for any pair.
- Models to measure the effect of the match/mismatch variables on the improvement score:
  - For these models, multiple regression was applied. The dependent variable is improvement score and the independent variables are pre-test score (as a covariate) and the match/ mismatch variable.

The results are summarised by course as follows:

Course A:

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

	Gender	Race	Home Language
β Pre-test score(p)	-.585(<.0005)	-.588(<.0005)	N/A
β m/mm(p)	.048(ns)	.064(ns)	N/A
R^2	.340	.342	N/A
F	127.262	128.265	N/A
df	2, 493	2, 493	N/A
p	<.0005	<.0005	N/A

Table 4-20 Course A analysis model: predicting improvement score from gender/race/home language match/mismatch, controlling for pre-test score

Gender

Improvement scores were regressed on gender match/mismatch and controlled for pre-test score. These predictors accounted for 34% of the variance in improvement score (R^2 = .34), which was highly significant at the p<.0005 level. Pre-test (β = -.585, p<.0005) was the only significant predictor.

As the pre-test score increased, there was a decrease in the improvement score. Gender match/mismatch was not a good predictor of improvement score for Course A.

Race

Improvement scores were regressed on race match/mismatch and controlled for pre-test score. These predictors accounted for 34.2% of the variance in improvement score (R^2=.342), which was highly significant at the p<.0005 level. Pre-test (β = -.588, p<.0005) was the only significant predictor.

As the pre-test score increased, there was a decrease in the improvement score. Race match/mismatch was not a good predictor of improvement score for Course A.

Home Language

No analysis was possible as there was no home language match in the case of Course A.

Course B:

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

	Gender	Race	Home Language
β Pre-test score(p)	-.541(<.0005)	-.596(<.0005)	-.533(<.0005)
β m/mm(p)	- .082(0.035)	-.186(<.0005)	.004(ns)
R^2	.290	.314	.284
F	96.338	107.868	93.241
df	2, 471	2, 471	2, 471
p	<.0005	<.0005	<.0005

Table 4-21 Course B analysis model: predicting improvement score from gender/race/language match/mismatch, controlling for pre-test score

Gender

Improvement scores were regressed on gender match/mismatch and controlled for pre-test score. These predictors accounted for 29% of the variance in improvement score (R^2 = .290), which was highly significant at the p<.0005 level. Pre-test (β = -.541, p<.0005) was the most influential predictor, followed by race match/mismatch (β = -.082, p = .035).

As the pre-test score increased, there was a decrease in the improvement score. Gender match/mismatch was a significant predictor of improvement score. Gender mismatch scored significantly higher on improvement score than gender match for Course B.

Race

Improvement scores were regressed on race match/mismatch and controlled for pre-test score. These predictors accounted for 31.4% of the variance in improvement score (R^2=.314), which was highly significant at the p<.0005 level. Pre-test (β = -.596, p<.0005) was the most significant predictor, followed by race match/mismatch (β = -.186, p = <.0005).

As the pre-test score increased, there was a decrease in the improvement score. Race mismatch scored significantly higher on improvement score than race match for Course B. (Although the raw improvement scores appear to contradict this conclusion (6.74% for match and 6.00% for mismatch), the analysis model applies multiple regression with pre-test score as a covariate and correctly presents race mismatch as the predictor of highest performance in this case. See *4.2.2.2.c Summary of findings for cohort one* for a detailed explanation.)

Home Language

Improvement scores were regressed on home language match/mismatch and controlled for pre-test score. These predictors accounted for 28.4% of the variance in improvement score (R^2=.284), which was highly significant at the p<.0005 level. Pre-test (β = -.533, p<.0005) was the only significant predictor.

As the pre-test score increased, there was a decrease in the improvement score. Home language match/mismatch was not a good predictor of improvement score for Course B.

Course C:

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

	Gender	Race	Home Language
$\beta_{\text{Pre-test score}}(p)$	-.627(<.0005)	-.636(<.0005)	-.640(<.0005)
$\beta_{\text{m/mm}}(p)$	.058(ns)	.091(.009)	.101(.004)
R^2	.391	.395	.397
F	162.136	165.401	166.635
df	2, 506	2, 506	2, 506
p	<.0005	<.0005	<.0005

Table 4-22 Course C analysis model: predicting improvement score from gender/race/language match/mismatch, controlling for pre-test score

Gender

Improvement scores were regressed on gender match/mismatch and controlled for pre-test score. These predictors accounted for 39.1% of the variance in improvement score (R^2 = .391), which was highly significant at the p<.0005 level. Pre-test (β = -.627, p<.0005) was the only influential predictor.

As the pre-test score increased, there was a decrease in the improvement score. Gender match/mismatch was not a good predictor of improvement score for Course C.

Race

Improvement scores were regressed on race match/mismatch and controlled for pre-test score. These predictors accounted for 39.5% of the variance in improvement score (R^2=.395), which was highly significant at the p<.0005 level. Pre-test (β = -.636, p<.0005) was the most significant predictor, followed by race match/mismatch (β = .091, p = .009).

As the pre-test score increased, there was a decrease in the improvement score. Race match scored significantly higher on improvement score than race mismatch for Course C. (Although the raw improvement scores appear to contradict this conclusion (11.30% for match and 11.56% for mismatch), the analysis model applies multiple regression with pre-test score as a covariate and correctly presents race match as the predictor of highest performance in this case. See *4.2.2.2.c Summary of findings for cohort one* for a detailed explanation.)

Home Language

Improvement scores were regressed on home language match/mismatch and controlled for pre-test score. These predictors accounted for 39.7% of the variance in improvement score (R^2=.397), which was highly significant at the p<.0005 level. Pre-test (β = -.640, p<.0005) was the most significant predictor, followed by race match/mismatch (β = .101, p = .004).

As the pre-test score increased, there was a decrease in the improvement score. Home language match scored significantly higher on improvement score than home language mismatch for Course C. (Although the raw improvement scores appeared to contradict this conclusion (11.25% for match and 11.72% for mismatch), the analysis model applied multiple regression with pre-test score as a covariate and correctly presented home language match as the predictor of highest performance in this case. See *4.2.2.2.c Summary of findings for cohort one* for a detailed explanation.)

Further analyses

Ranking of match/mismatch variables

Race match/mismatch appeared to be the most important predictor of improvement score as it was shown to be a significant predictor in two of the three courses. Gender match/mismatch was significant in one of the three courses. Language was significant in one out of the two that it could be tested.

Impact of combinations of match/mismatch variables

Multiple regression analysis was performed to ascertain whether combinations of the match/mismatch variables would have a bigger impact on the improvement score than the individual variables. It was found that, for all courses, a race and gender match as opposed to a race match only did not impact significantly on the improvement score. Similarly, for all courses, a language and gender match as opposed to a language match only did not impact significantly on the improvement score. No similar analysis was possible for a combination of race and language as they were not independent of each other.

4.2.2.2.a.2 Single post-test score as dependent variable

Table 4-23 describes the average post-test scores for each of the three courses by match and mismatch:

		Course A (Databases)		Course B (Networks)		Course C (Spreadsheets)	
Variable	**Match/Mismatch**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Gender	Match	71.32	18.85	67.10	19.58	60.38	16.58
	Mismatch	68.46	18.03	72.21	17.52	57.44	13.96
Race	Match	70.86	17.83	58.60	21.68	60.23	14.77
	Mismatch	66.76	19.46	73.16	16.09	55.06	15.48
Home Language	Match	-	-	71.67	14.72	60.24	14.76
	Mismatch	69.64	18.41	69.17	18.97	54.25	15.43

Table 4-23 Average post-test scores by match and mismatch

An independent samples t-test was applied to each of these match/mismatch pairs to test whether there are significant differences between the mean post-test scores of matched students and the mean post-test scores of mismatched students for any pair. The results are summarised as follows:

- **Course A (Databases):** Students with a race match (Indians) performed significantly ($p=.028$) better in the post-test (70.86) than the mismatched students (Blacks, Whites and others: 66.76).
- **Course B (Networks):** Students with a gender mismatch (males) performed significantly ($p=.004$) better in the post-test (72.21) than those with a match (females: 67.10). The race mismatched students (non-Blacks) also performed better (73.16) than the race matched students (Blacks: 58.60; $p < .0005$).
- **Course C (Spreadsheets):** Gender matched (male) performed significantly ($p = .036$) better in the post-test (60.38) than the mismatched students (female: 57.44). The race matched students (Indian) performed better (60.23) than race mismatched (non-Indian: 55.06). Language matched students (English) performed better (60.24) than language mismatched students (African languages: 54.25, $p<.0005$).

Models to measure the effect of the match/mismatch variables on the post-test score

For these models, linear regression was applied. The dependent variable was post-test score and the independent variable was the match/mismatch variable.

The results are summarised by course below:

Course A:

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

	Gender	Race	Home Language
$\beta_{m/mm}(p)$	.077(ns)	.102(.023)	N/A
R^2	.006	.010	N/A
F	2.920	5.208	N/A
df	1,494	1,494	N/A
p	.088	.023	N/A

Table 4-24 Course A analysis model: predicting post-test score from gender/race/home language match/mismatch

Gender

Gender match/mismatch was not a significant predictor of post-test scores for Course A.

Race

Post-test scores were regressed on race match/mismatch. The predictor accounted for 1% of the variance in post-test score (R^2=.010), which was significant at the p=.023 level. Race match/mismatch (β = .102, p=.023) was a significant predictor.

Race match was associated with a higher post-test score than race mismatch.

Home Language

No analysis was possible as there was no home language match.

Course B:

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

	Gender	Race	Home Language
$\beta_{m/mm}(p)$	- .133(0.004)	-.343(<.0005)	.0015(ns)
R^2	.018	.118	.000
F	8.511	62.922	.103
df	1,472	1,472	1,472
p	.004	<.0005	.748

Table 4-25 Course B analysis model: predicting post-test score from gender/race/language match/mismatch

Gender

Post-test scores were regressed on gender match/mismatch. The predictor accounted for 1.8% of the variance in post-test score (R^2 = .018), which was significant at the p=.004 level. Gender match/mismatch (β = -.133, p=.004) was a significant predictor.

Gender mismatch scored significantly higher on post-test score than gender match.

Race

Post-test scores were regressed on race match/mismatch. The predictor accounted for 11.8% of the variance in post-test score (R^2=.118), which was significant at the p<.0005 level. Race match/mismatch (β = -.343, p<.0005) was a significant predictor.

Race mismatch scored significantly higher on post-test score than race match for Course B.

Home Language

Post-test scores were regressed on Home Language match. The predictor accounted for 0% of the variance in post-test score (R^2=.000), which was not significant.

Course C:

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

	Gender	Race	Home Language
$\beta_{m/mm}(p)$	.096(.031)	.157(<.0005)	.174(<.0005)
R^2	.009	.025	.030
F	4.677	12.739	15.851
df	1,507	1,507	1,507
p	.031	<.0005	<.0005

Table 4-26 Course C analysis model: predicting post-test score from gender/race/home language match/mismatch

Gender

Post-test scores were regressed on gender match/mismatch. The predictor accounted for 0.9% of the variance in post-test score (R^2 = .009), which was significant at the p=.031 level. Gender match/mismatch was a significant (.031) predictor of post-test score for the Spreadsheets course.

Gender match scored significantly higher on post-test score than gender mismatch.

Race

Post-test scores were regressed on race match/mismatch. The predictor accounted for 2.5% of the variance in post-test score (R^2=.025), which was highly significant at the p<.0005 level. Race match/mismatch was a significant predictor with race match scoring significantly higher on post-test score than race mismatch for the Spreadsheets course.

Home language

Post-test scores were regressed on home language match/mismatch. The predictor accounted for 3% of the variance in post-test score (R^2=.030), which was highly significant at the p<.0005 level. Home language match/mismatch was a significant predictor with home language match scoring significantly higher on post-test score than home language mismatch.

Further analyses

Ranking of match/mismatch variables

Race match/mismatch was a significant predictor for Course A (Databases). Gender and race match/mismatch were significant predictors for Course B (Networks). All three independent variables (race, home language and gender) were significant predictors for Course C (Spreadsheets).

It is interesting to see that higher post-test scores were achieved in Course B (Networks) when there was a gender and race mismatch. On the other hand, matches in gender, race and home language led to higher post-test scores in Course C (Spreadsheets). Race match was the important variable for Course A (Databases).

Impact of combinations of match/mismatch variables

Analysis (multiple regression) was performed to ascertain whether combinations of the match/mismatch variables had a bigger impact on the post-test score than the individual variables. It was found that, for all courses, a race and gender match as opposed to a race match only did not impact significantly on the post-test score. Similarly, for all courses, a home language and gender match as opposed to a home language match only did not impact significantly on the post-test score. No similar analysis was possible for a combination of race and home language as they were not independent of each other.

Examining the effect of match/mismatches for the different demographic sub-groups

Table 4-27 compares race match/mismatch results by gender:

	Course A (Databases)		**Course B (Networks)**		**Course C (Spreadsheets)**	
Gender	**m**	**f**	**m**	**f**	**m**	**f**
$\beta_{\text{Race m/mm}}$	.137	.077	-.375	-.327	.151	.167
p	ns	ns	<0.005	<.0005	.028	.004

Table 4-27 Cohort one race match/mismatch- by gender

Notes:

- There were no significant differences between males and females for Course A (Databases).
- For Course B (Networks), both males and females who did not have a race match performed better than those who did.

- For Course C (Spreadsheets), both males and females who had a race match performed better than those who did not.

Table 4-28 compares home language match/mismatch results by gender:

	Course B		Course C	
Gender	m	f	m	f
β Home Language m/mm	.008	.015	.144	.201
p	ns	ns	.037	<.0005

Table 4-28 Cohort one home language match/mismatch- by gender.

Notes:

- There was no difference between males and females for Course B (Networks).
- For Course C (Spreadsheets), the males and females who had a home language match performed better than those who do not.
- Because of the nature of the data, other combinations of variables were not possible.

4.2.2.2.b An alternative analysis model: point-biserial correlation

As a comparative model and to provide correlation analysis as an alternative to the multiple regression applied in the foregoing, the data related to teacher student congruence is analysed below using the point-biserial correlation model.

For all the analyses below the null hypothesis is:

H_0: No correlation between the independent variable and the dependent variable.

The independent variable is the match/mismatch variable, coded mismatch = 0 and match = 1.

The dependent variables are the post-test score and improvement score.

Table 4-29 presents the results for Course A (Databases) using point-biserial correlation as an analysis model:

	Gender		Race	
	Post Test Score	Improvement Score	Post Test Score	Improvement Score

r	**0.076574**	**0.006688**	**0.102179**	**0.009729**
n	**496**	**496**	**496**	**496**
t	1.771113	0.149152	2.396804	0.217306
t (critical)	1.964778	1.964778	1.964778	1.964778
			sig r>0	
Coefficient of determination			0.010441	
			Weak	

Table 4-29 Cohort one (Databases): Point-biserial correlation

Notes:

- The post-test score was significantly positively correlated with race match (i.e. those with a race match tended to have a higher post-test score).
- The correlation was weak: only 1% of the variation in the post-test score could be explained by race match.

Table 4-30 presents the results for Course B (Networks) using point-biserial correlation as an analysis model:

	Gender		Race		Home Language	
	Post Test Score	**Improvement Score**	**Post Test Score**	**Improvement Score**	**Post Test Score**	**Improvement Score**
r	**-0.13295**	**-0.02931**	**-0.34261**	**0.017351**	**0.014782**	**-0.008476292**
n	**474**	**474**	**474**	**474**	**474**	**474**
t	-2.71364	-0.62765	-6.42381	0.380265	0.323541	-0.183376653
t (critical)	1.965003	1.965003	1.965003	1.965003	1.965003	1.965002595
	sig r<0		sig r<0			
Coefficient of determination	0.017676		0.117379			
	Weak		Weak			

Table 4-30 Cohort one (Networks): Point-biserial correlation

Notes:

- The post-test score was significantly negatively correlated with both gender and race match (i.e. those with a race or gender match tended to have a lower post-test score).
- The correlations were weak: only 1.8% of the variation in the post-test score could be explained by gender mismatch and 11.7% by race mismatch.

Table 4-31 presents the results for Course C (Spreadsheets) using point-biserial correlation as an analysis model:

	Gender		Race		Home Language	
	Post Test Score	Improvement Score	Post Test Score	Improvement Score	Post Test Score	Improvement Score
r	**0.095508**	**0.008331**	**0.156406**	**-0.00656**	**0.173948**	**-**
n	**509**	**509**	**509**	**509**	**509**	**509**
t	2.261204	0.188369	3.834343	-0.14723	4.30942	-0.24830311
t (critical)	1.964654	1.964654	1.964654	1.964654	1.964654	1.964653936
	sig r>0		sig r>0		sig r>0	
Coefficient of determination	0.009122		0.024463		0.030258	
	Weak		Weak		Weak	

Table 4-31 Cohort one (Spreadsheets): Point-biserial correlation

Notes:

- The post-test score was significantly positively correlated with gender, race and home language match (i.e. those with a gender/race/home language match tended to have a higher post-test score).
- The correlations were weak: only .9% of the variation in the post-test score could be explained by gender match, 2% by race match and 3% by home language match.

4.2.2.2.c Summary of findings for cohort one

Evidence from cohort one of teacher student match/mismatch (in terms of race, home language and gender) as a predictor of cognitive test performance was inconclusive.

The analysis of correlation using the point-biserial correlation model revealed no significant correlations between improvement scores and the teacher student congruence variables. A variety of weak correlations between post-test scores and the match/mismatch variables were evident, some positive (for example, Course C-race, home language and gender) and some negative (such as Course B in respect of gender and race).

The multiple regression analysis provided the most significant results and is discussed below in terms of the two dependent variables used in the analysis, viz. *Single post-test score as dependent variable* and *Improvement (gain) score as dependent variable*.

Single post-test score as dependent variable

Race match was shown to be a statistically significant predictor of cognitive test performance in two of the three courses in the study (viz. Course A (Databases) and Course C (Spreadsheets)). Students whose race matched that of the lecturer scored significantly higher post-test scores than mismatched students in Course A and C. However, the race mismatched students in Course B scored significantly higher marks than the matched students.

Teacher student gender match accounted for significantly higher post-test scores for Course C, whereas gender mismatched students scored higher in Course B. Although gender matched students in Course A had higher mean scores than the gender mismatched students, the result was not statistically significant.

Home language match/mismatch data was available for Course B and C only. Only Course C's results were statistically significant and showed home language match students out-performing mismatched students. Home language match students scored higher mean scores than the mismatched students in Course B, but the results were not statistically significant.

Improvement (gain) score as dependent variable

The results for the analysis conducted using the single post-test score and the analysis conducted for improvement score were very similar. In all but one case (race match/mismatch for Course A), the statistically significant results were identical for both these models and suggested that teacher student match/mismatch (in terms of gender, home language and race) is a significant predictor of improvement scores. However, the results are inconsistent.

For example, students who were gender matched with their lecturer for Course C scored significantly higher improvement scores (11.56%) than their mismatched counterparts (11.25%).

However, it was the gender mismatched students who improved more for Course B (6.87% compared with 5.73% for the matched students). Although gender matched students improved by 18.14% versus 17.84% for the mismatched students for Course A, the result was not statistically significant.

There were three other significant results for the data related to improvement score. These relate to race match/mismatch for Course B and Course C, as well as home language match/mismatch for Course C. The results appear at first glance to be contradictory and inconsistent with the mean scores achieved and are worthy of further discussion and explanation.

A note on the multiple regression based analysis

Table 4-32 highlights the three sets of results in question (scores in bold and underlined):

		Gender		Race		Home Language	
		Match	**Mismatch**	**Match**	**Mismatch**	**Match**	**Mismatch**
Course A	**(Databases)**	18.14	17.84	18.07	17.7	-	17.96
Course B	**(Networks)**	5.73	6.87	**<u>6.74</u>**	**<u>6.00</u>**	5	6.22
Course C	**(Spreadsheets)**	11.56	11.25	**<u>11.30</u>**	**<u>11.56</u>**	**<u>11.25</u>**	**<u>11.72</u>**

Table 4-32 Cohort one average improvement scores by match and mismatch (anomalies)

Interestingly, in all three cases highlighted in Table 4-32 (scores in bold and underlined), it is not the match/mismatch variable with the highest improvement score that is statistically the significant predictor of improvement score. When multiple regression is applied, the following results are obtained:

- In the case of race match/mismatch for Course B, it is the mismatch variable that scores significantly higher than the race match variable, despite the raw mean score for match being higher than that of mismatch.
- For race match/mismatch for Course C, although race mismatch appears to have the higher mean score, it is the match variable that scores significantly higher than the mismatch variable.
- Similarly, for Course C, despite home language mismatch having a higher raw mean score than match, it is the home language match variable that is statistically the higher scoring variable.

Although this appears at first glance to be anomalous, it is correct in view of the use of pre-test score as a covariate in the multiple regression model that is applied. In short, the higher the pre-test score, the less chance a student has of improvement, as per the following formulae:

- Potential Improvement = 100 – Pre-Test score;
- % of Potential Improvement = Improvement score/Potential Improvement X 100.

This value, then, identifies the percentage of the possible improvement the student has in fact attained. Table 4-33, Table 4-34 and Table 4-35 demonstrate how this 'percentage of potential improvement score' explains the three apparently 'anomalous' results highlighted in Table 4-32:

Race Match/Mismatch	Improvement Score	Pre Test Score	Post Test Score	Potential improvement	% of Potential Improvement

Mismatch	6.00	67.16	73.16	32.84	**<u>18.27</u>**
Match	6.74	51.86	58.60	48.14	14.00

Table 4-33 Cohort one (Course B- Networks): Potential improvement score by race match/mismatch

Race Match/Mismatch	Improvement Score	Pre Test Score	Post Test Score	Potential improvement	% of Pot. Improvement
Mismatch	11.56	43.50	55.06	56.50	20.46
Match	11.30	48.93	60.23	51.07	**<u>22.13</u>**

Table 4-34 Cohort one (Course C- Spreadsheets): Potential improvement score by race match/mismatch

Home Language Match/Mismatch	Improvement Score	Pre Test Score	Post Test Score	Potential Improvement	% of Pot. Improvement
Mismatch	11.72	42.53	54.25	57.47	20.40
Match	11.25	48.99	60.24	51.01	**<u>22.05</u>**

Table 4-35 Cohort one (Course C- Spreadsheets): Potential improvement score by home language match/mismatch

The bold, underlined '% of Potential Improvement' scores show that looking only at absolute improvement scores on their own can be misleading when using a multiple regression model that utilises pre-test score as a covariate. If the pre-test scores were the same for all students, then one could look at the improvement scores as is. However, these students all start out from a different (pre-test) level and thus one needs to look more closely at the results as per the foregoing.

4.2.2.3 Cohorts two and three

4.2.2.3.a Phase 1: GEE analysis

The following analyses (Table 4-36 to Table 4-44) present the results of applying a Generalized Estimating Equations (GEE) model to the datasets representing cohorts two and three (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.

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***
Mismatch(Race)	0[b]	.	.	.	.	.	.
(Scale)	.980						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchRace
a. Institution_ID = Institution 1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-36 Teacher 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)	-.057	.0194	-.095	-.019	8.687	1	.003
Match(Race)	.112	.0286	.056	.168	15.368	1	.000***
Mismatch(Race)	0[b]	.	.	.	.	.	.
(Scale)	.979						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchRace
a. Institution_ID = Institution 2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-37 Teacher student match effect on student test scores (Institution 2, 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***
Mismatch(Race)	0[a]	.	.	.	.	.	.
(Scale)	.980						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchRace
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-38 Teacher student match effect on student test scores (combined institutions, race 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***
Mismatch(Home Language)	0[b]	.	.	.	.	.	.
(Scale)	.963						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchHomeLanguage
a. Institution_ID = Institution 1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-39 Teacher 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)	-.018	.0159	-.050	.013	1.347	1	.246
Match(Home Language)	.075	.0362	.004	.146	4.334	1	.037*
Mismatch(Home Language)	0[b]	.	.	.	.	.	.
(Scale)	.981						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchHomeLanguage
a. Institution_ID = Institution 2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-40 Teacher student match effect on student test scores (Institution 2, 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***
Mismatch(Home Language)	0[a]	.	.	.	.	.	.
(Scale)	.971						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchHomeLanguage
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-41 Teacher student match effect on student test scores (combined institutions, home language 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]
Mismatch(Gender)	0[b]	.	.	.	.	.	.
(Scale)	.983						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchGender
a. Institution_ID = Institution 1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-42 Teacher 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)	.029	.0226	-.016	.073	1.586	1	.208
Match(Gender)	-.052	.0292	-.109	.005	3.206	1	.073[ns]
Mismatch(Gender)	0[b]	.	.	.	.	.	.
(Scale)	.981						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchGender
a. Institution_ID = Institution 2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-43 Teacher student match effect on student test scores (Institution 2, gender match)

Parameter Estimates

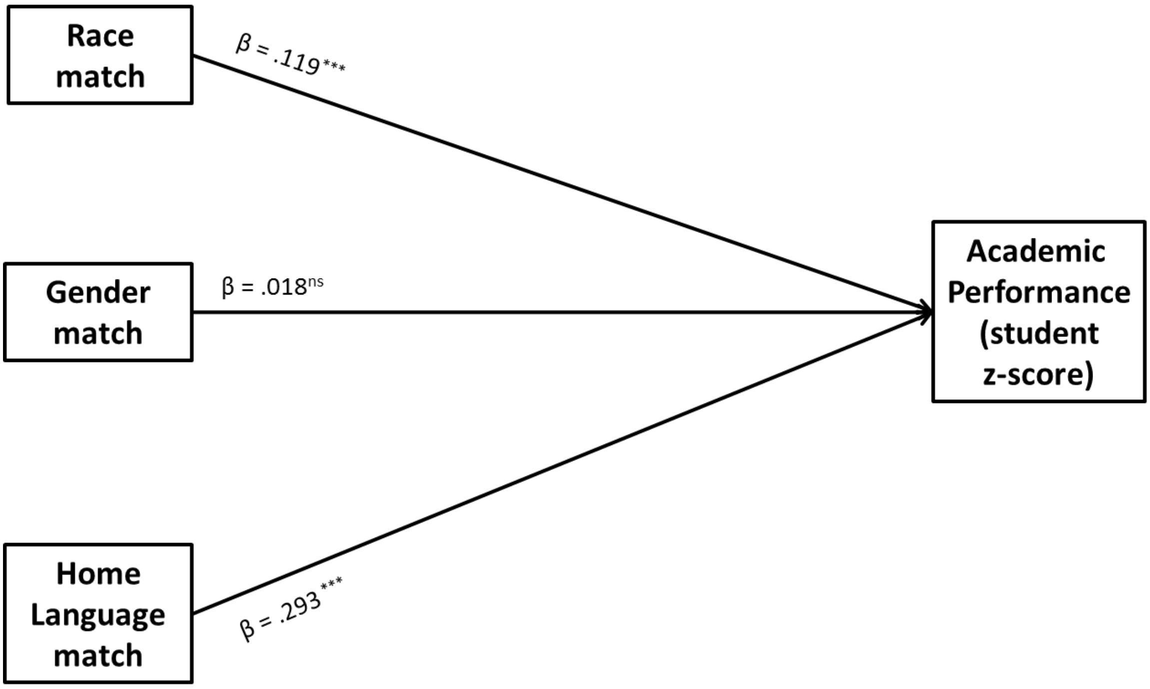
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.003	.0130	-.023	.028	.050	1	.823
Match(Gender)	-.006	.0172	-.040	.028	.131	1	.718[ns]
Mismatch(Gender)	0[a]	.	.	.	.	.	.
(Scale)	.983						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchGender
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-44 Teacher student match effect on student test scores (combined institutions, gender match)

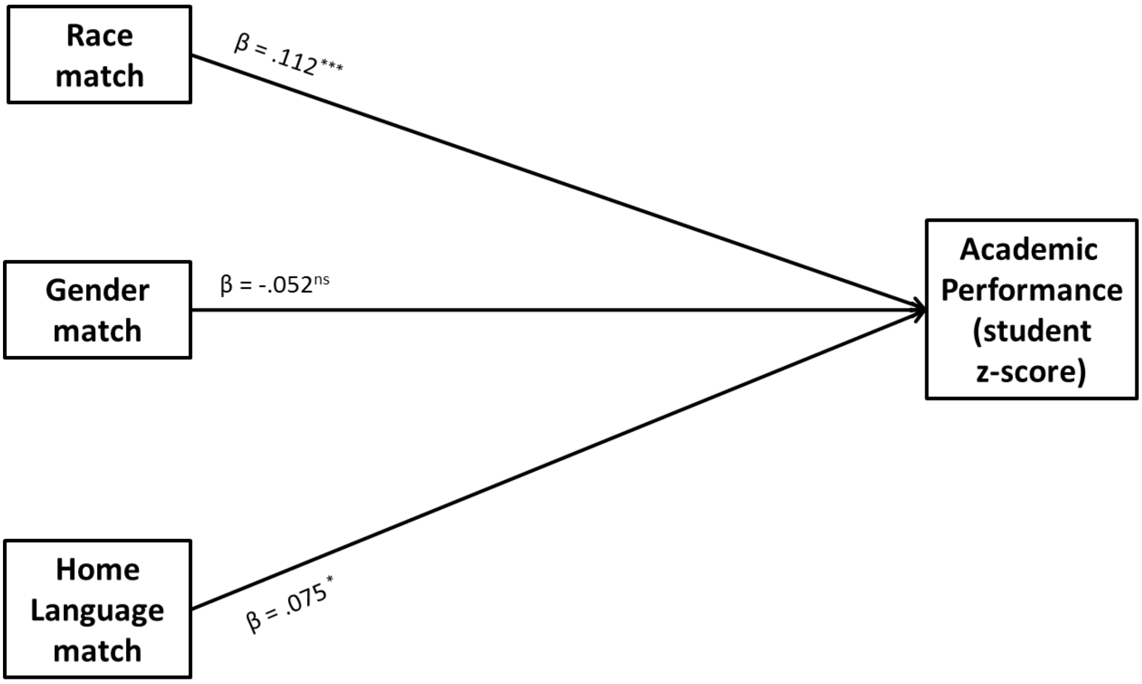
Clearly, Table 4-36 to Table 4-44 shows significant match/mismatch effects for both cohorts one and two in respect of race and home language. The results for gender are not significant (in line with the results achieved with cohort one- see *4.2.2.2.c Summary of findings for cohort one*).

Figure 4-1 to Figure 4-3 shows the match effects from Table 4-36 to Table 4-44 in the form of path diagrams.



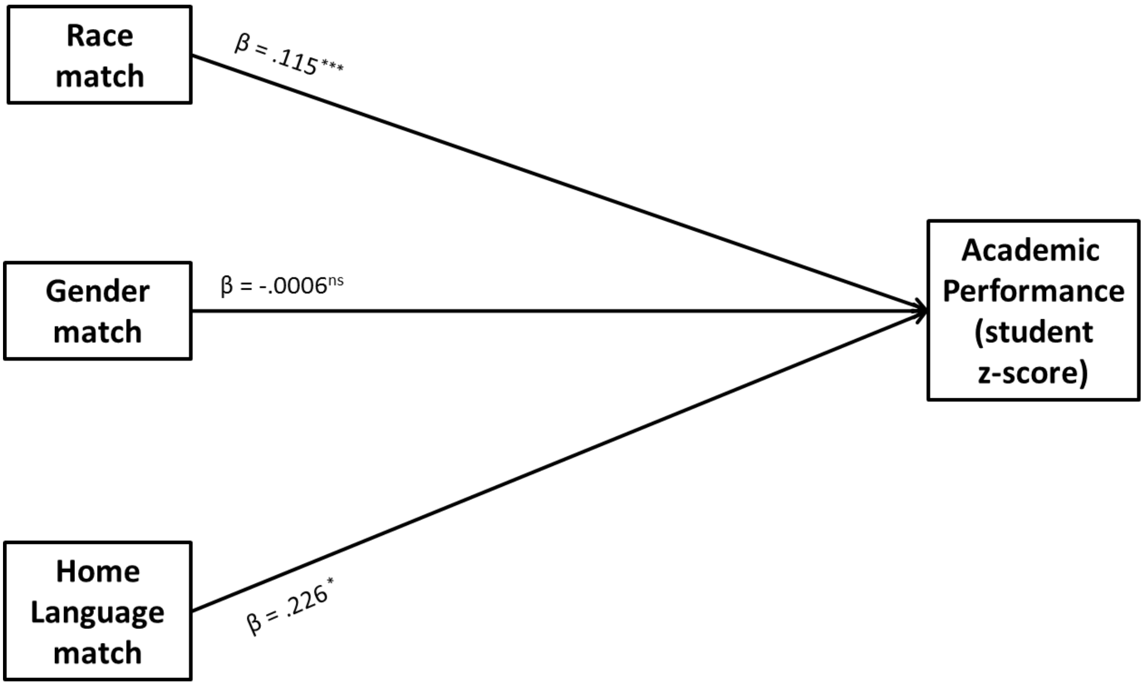
Notes:
-Institution 1
-All paths are standardised betas.
*** = p < .001, ** = p < .01, * = p <.05, ns = not significant (p > .05)

Figure 4-1 Teacher student match effects on student test scores (Institution 1)



Notes:
-Institution 2
-All paths are standardised betas.
*** = p < .001, ** = p < .01, * = p <.05, ns = not significant (p > .05)

Figure 4-2 Teacher student match effects on student test scores (Institution 2)



Notes:
-Combined Institutions
-All paths are standardised betas.
*** = $p < .001$, ** = $p < .01$, * = $p <.05$, ns = not significant ($p > .05$)

Figure 4-3 Teacher student match effects on student test scores (combined institutions)

Table 4-45 to Table 4-47 below present 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. This effect is most prominent when the datasets of the two institutions are combined (Table 4-47), which shows clearly that high levels of match index occupy positions one, two and three in the test score ranking, while the highest levels of mismatch occupy the lowest test score rankings. This 'index of match' phenomenon will be explored further in *4.2.2.3.b Phase 2: Further analysis of match mismatch effects using higher order statistical methods*.

Case Summaries[a]

Student Test Score (z-Score)

Race	Home Language	Gender	N	Rank	Median	Mean	Std. Deviation	Variance	Std. Error of Mean
Mismatch	Mismatch	Mismatch	2644	21	-.049195	-.108112	.9974781	.995	.0193987
		Match	2982	24	-.050760	-.122996	.9709398	.943	.0177803
		Total	5626	22	-.049195	-.116001	.9834413	.967	.0131114
	Match	Mismatch	830	9	.203253	.137609	.9807470	.962	.0340422
		Match	849	1	.316372	.238565	.9122887	.832	.0313097
		Total	1679	3	.232485	.188658	.9478125	.898	.0231311
	Total	Mismatch	3474	18	-.046797	-.049405	.9988783	.998	.0169472
		Match	3831	16	-.046797	-.042870	.9698344	.941	.0156690
		Total	7305	17	-.046797	-.045977	.9836915	.968	.0115093
Match	Mismatch	Mismatch	723	19	-.046797	-.103792	1.0175043	1.035	.0378414
		Match	727	27	-.046797	-.158552	.9741450	.949	.0361290
		Total	1450	26	-.046797	-.131247	.9960336	.992	.0261571
	Match	Mismatch	1427	7	.174420	.138039	.9876228	.975	.0261444
		Match	1787	4	.200551	.187802	.9879565	.976	.0233709
		Total	3214	6	.177347	.165707	.9879642	.976	.0174268
	Total	Mismatch	2150	12	.058325	.056716	1.0040588	1.008	.0216541
		Match	2514	10	.103129	.087643	.9962475	.993	.0198694
		Total	4664	11	.058325	.073386	.9998674	1.000	.0146407
Total	Mismatch	Mismatch	3367	20	-.046797	-.107184	1.0016614	1.003	.0172623
		Match	3709	25	-.046797	-.129966	.9715399	.944	.0159526
		Total	7076	23	-.046797	-.119125	.9859833	.972	.0117213
	Match	Mismatch	2257	8	.193467	.137881	.9848823	.970	.0207309
		Match	2636	2	.262587	.204151	.9643529	.930	.0187829
		Total	4893	5	.203253	.173583	.9743368	.949	.0139290
	Total	Mismatch	5624	15	-.028374	-.008836	1.0021007	1.004	.0133625
		Match	6345	13	-.017312	.008842	.9823832	.965	.0123329
		Total	11969	14	-.028374	.000535	.9916946	.983	.0090646

a. Institution_ID = Institution 1

Table 4-45 Ranked index of match effect (Institution 1)

Case Summaries[a]

Student Test Score (z-Score)

Race	Home Language	Gender	N	Rank	Median	Mean	Std. Deviation	Variance	Std. Error of Mean
Mismatch	Mismatch	Mismatch	1198	23	.099549	-.054825	1.0040304	1.008	.0290080
		Match	1219	20	.081766	-.045182	.9725043	.946	.0278541
		Total	2417	21	.083115	-.049962	.9880632	.976	.0200977
	Match	Mismatch	351	19	.203414	-.041601	1.0116923	1.024	.0540001
		Match	497	27	.130725	-.102720	1.0196097	1.040	.0457357
		Total	848	26	.158614	-.077422	1.0161880	1.033	.0348960
	Total	Mismatch	1549	22	.100989	-.051829	1.0054593	1.011	.0255469
		Match	1716	25	.087636	-.061847	.9864249	.973	.0238125
		Total	3265	24	.100989	-.057094	.9953605	.991	.0174196
Match	Mismatch	Mismatch	824	6	.204634	.082056	1.0119628	1.024	.0352534
		Match	1778	16	.129973	-.022160	.9626693	.927	.0228303
		Total	2602	10	.165990	.010843	.9795539	.960	.0192032
	Match	Mismatch	206	1	.540473	.418469	.8988761	.808	.0626277
		Match	288	3	.364116	.193579	1.0093721	1.019	.0594778
		Total	494	2	.454503	.287359	.9702620	.941	.0436542
	Total	Mismatch	1030	4	.290937	.149339	.9990739	.998	.0311300
		Match	2066	11	.167287	.007914	.9719414	.945	.0213833
		Total	3096	8	.204098	.054964	.9831514	.967	.0176693
Total	Mismatch	Mismatch	2022	13	.137400	.000956	1.0092653	1.019	.0224448
		Match	2997	18	.109119	-.031524	.9665859	.934	.0176562
		Total	5019	15	.120763	-.018439	.9840321	.968	.0138899
	Match	Mismatch	557	5	.318621	.128551	.9958049	.992	.0421936
		Match	785	12	.205464	.005986	1.0252280	1.051	.0365920
		Total	1342	7	.253173	.056857	1.0145459	1.029	.0276946
	Total	Mismatch	2579	9	.189175	.028514	1.0075507	1.015	.0198400
		Match	3782	17	.132007	-.023738	.9790262	.958	.0159197
		Total	6361	14	.160497	-.002553	.9909436	.982	.0124247

a. Institution_ID = Institution 2

Table 4-46 Ranked index of match effect (Institution 2)

Case Summaries[a]

Student Test Score (z-Score)

Race	Home Language	Gender	N	Rank	Median	Mean	Std. Deviation	Variance	Std. Error of Mean
Mismatch	Mismatch	Mismatch	3842	25	-.046797	-.091496	.9996999	.999	.0161284
		Match	4201	27	-.046797	-.100417	.9719202	.945	.0149953
		Total	8043	26	-.046797	-.096156	.9852365	.971	.0109858
	Match	Mismatch	1181	10	.203253	.084347	.9930013	.986	.0288951
		Match	1346	7	.215565	.112548	.9670875	.935	.0263599
		Total	2527	8	.203717	.099368	.9791904	.959	.0194789
	Total	Mismatch	5023	20	.005564	-.050152	1.0008128	1.002	.0141212
		Match	5547	18	0.000000	-.048740	.9749474	.951	.0130904
		Total	10570	19	.002777	-.049411	.9872769	.975	.0096029
Match	Mismatch	Mismatch	1547	16	.090212	-.004801	1.0184607	1.037	.0258940
		Match	2505	21	.051682	-.061743	.9678015	.937	.0193367
		Total	4052	17	.061389	-.040003	.9877120	.976	.0155166
	Match	Mismatch	1633	3	.277146	.173415	.9810429	.962	.0242770
		Match	2075	1	.262587	.188604	.9907121	.982	.0217490
		Total	3708	2	.264102	.181914	.9863616	.973	.0161982
	Total	Mismatch	3180	9	.156670	.086717	1.0032268	1.006	.0177904
		Match	4580	12	.126917	.051678	.9860489	.972	.0145702
		Total	7760	11	.129435	.066037	.9932094	.986	.0112748
Total	Mismatch	Mismatch	5389	22	-.028374	-.066609	1.0057917	1.012	.0137011
		Match	6706	24	-.028374	-.085971	.9704919	.942	.0118511
		Total	12095	23	-.028374	-.077344	.9863818	.973	.0089690
	Match	Mismatch	2814	6	.227288	.136034	.9868831	.974	.0186039
		Match	3421	4	.229330	.158679	.9820461	.964	.0167902
		Total	6235	5	.229010	.148459	.9842176	.969	.0124644
	Total	Mismatch	8203	13	.058325	.002907	1.0039057	1.008	.0110843
		Match	10127	15	.058325	-.003325	.9812091	.963	.0097504
		Total	18330	14	.058325	-.000536	.9914081	.983	.0073227

a. Institution_ID = Combined

Table 4-47 Ranked index of match effect (Combined institutions)

The foregoing analyses for cohorts two and three suggest that race and home language teacher student match are significant predictors of test scores. Furthermore, the analyses in Table 4-45 to Table 4-47 suggest that at least for certain factors there is evidence for an 'index of match' effect on student test scores (i.e. the higher the level of match, the stronger the match effect on test scores.

To further explore and confirm some of the results achieved in the foregoing analyses, the following section applies a variety of higher order statistical models to the cohort two and three datasets, including correlations, comparisons of means (paired sample T-Tests and single-sample T-Tests), multiple regression and robust regression (M-type and S-type) and non-parametric repeated measures ANOVA (Friedman K-way ANOVA).

4.2.2.3.b Phase 2: Further analysis of match mismatch effects using higher order statistical methods

The analyses that follow are quite complex, with several complicating factors including repeated measures and subjects (the majority of students are measured over multiple classes and teachers), and multiple ways of operationalizing the main variables.

By virtue of the fundamental differences between cross-sectional and repeated measures data, the analysis proceeds in two separate parts, as follows:

Part 1: Single score students. This involves analysis of those students for whom there are no feasible repeated measures data. This data is therefore cross-sectional and relies on one-off comparisons of groups between those who match the demographics of their teacher and those who do not. The limitations of such data are lack of within-student comparisons of different teachers, i.e. those for which there is or is not demographic match.

Part 2: Repeated measures data. In this case, several scores exist for the same student across classes and therefore teachers, allowing for controls of student ability and comparisons of what happens to student scores as their teachers change.

The following sections accordingly start with single measure scores.

4.2.2.3.b.1 Part 1: Analysis of single score students

Analyses for students with one class score only is somewhat deficient in that within-student performance cannot be benchmarked (i.e. the student's innate ability). However, it is useful to proceed with the analysis as it may indicate initial trends and guide the second phase of research into the repeated measures scores.

This section on single scores only shows the analysis for the deviation from class average dependent variable, since these results are substantially similar to the actual raw percentages (given that one is merely subtracting a constant). The advantage of the deviation from class average is that it provides means that can be tested against zero (i.e. against no difference from class average).

4.2.2.3.b.1.1 Descriptive statistics

Table 4-48 below shows descriptive statistics for various combinations of demographic match/mismatch for deviations from class average across groups, including a 95% confidence interval that tests the hypothesis that the deviation from class average is zero.

Institution	Match in			N	M	SD	95% CI
	Race	Gender	Language				
1	Match	Match	Match	212	2.37**	12.92	.62 to 4.12
1	Match	Match	Mismatch	217	-6.11	17.38	-8.44 to -3.79
1	Match	Mismatch	Match	109	.67	16.24	-2.41 to 3.75
1	Match	Mismatch	Mismatch	244	-4.10	16.16	-6.13 to -2.06
1	Mismatch	Match	Match	36	3.24**	9.47	.04 to 6.44
1	Mismatch	Match	Mismatch	565	-.24	15.11	-1.49 to 1.01
1	Mismatch	Mismatch	Match	40	-.42	14.80	-5.15 to 4.31
1	Mismatch	Mismatch	Mismatch	539	2.87	15.18	1.59 to 4.15
2	Match	Match	Match	283	-.36	14.46	-2.05 to 1.34
2	Match	Match	Mismatch	103	1.71	15.60	-1.34 to 4.76
2	Match	Mismatch	Match	110	1.75	16.59	-1.39 to 4.88
2	Match	Mismatch	Mismatch	80	3.81**	13.74	.75 to 6.87
2	Mismatch	Match	Match	125	-.91	21.60	-4.73 to 2.92
2	Mismatch	Match	Mismatch	133	-2.37	18.16	-5.48 to 0.75
2	Mismatch	Mismatch	Match	35	-2.81	21.36	-10.15 to 4.52
2	Mismatch	Mismatch	Mismatch	233	-1.51	17.88	-3.81 to 0.8

Notes. ** = $p < .05$

Table 4-48: Mean deviations from class average for single-score students

Table 4-48 suggests that as whole groups – that is, without analysis by specific demographic – match/mismatch produces few effects. Perfect demographic match does have a statistically significant albeit not very large positive effect in the Institution 1 sample, in that students perform on average 2.37% better than their class average ($p < .05$). Interestingly, this improvement is amplified when only race mismatches ($M = 3.24$, $p < .05$). In the Institution 2 data, few significant differences were evident, with the exception of a racial match and mismatch in gender and language ($M = 3.81$, $p < .05$).

However, further disaggregation by specific race group suggests differences by teacher. Specifically, the race of the teacher appears to have an effect. In Table 4-49 scores (deviations from class average) for single-score students with White or Indian teachers are displayed. Clear differences can be observed in the data for Institution 1. Notably, matches in race and language generally produced the highest average outperformance of class averages, although interestingly a gender mismatch outperforms a gender match (M = 5.32 vs. 4.42 respectively, for both p < .01). A mismatch in all demographics leads to underperformance of class average by -3.15% on average (p < .01). Once again, a match on language alone seems to mitigate other mismatch effects (M = -.42, ns), and a mismatch on race alone is not a significant deviation from average although a small sample may cause this (M = 2.91, ns, N = 35).

Institution	**Match in**			**N**	**M**	**SD**	**Min**	**Max**
	Race	**Gender**	**Language**					
1	Match	Match	Match	168	4.42^{***}	11.43	2.13	6.72
1	Match	Mismatch	Match	61	5.32^{***}	14.72	.31	10.33
1	Mismatch	Match	Match	35	2.91	9.39	-1.42	7.24
1	Mismatch	Match	Mismatch	191	-2.99^{***}	11.70	-5.20	-.79
1	Mismatch	Mismatch	Match	40	-.42	14.80	-6.76	5.92
1	Mismatch	Mismatch	Mismatch	158	-3.15^{***}	8.99	-5.01	-1.28
2	Match	Match	Match	41	8.99^{***}	11.02	4.34	13.64
2	Match	Match	Mismatch	10	-.40	14.16	-14.95	14.15
2	Match	Mismatch	Match	46	9.52^{***}	13.83	4.03	15.01
2	Match	Mismatch	Mismatch	11	7.36^{***}	7.35	.33	14.38
2	Mismatch	Match	Match	120	-0.82	21.81	-6.03	4.39
2	Mismatch	Match	Mismatch	87	-1.16	18.55	-6.40	4.07
2	Mismatch	Mismatch	Match	37	-3.08	21.67	-12.77	6.61
2	Mismatch	Mismatch	Mismatch	227	-1.53	17.82	-4.60	1.54

Notes. $^{**} = p < .05$.

Table 4-49: Deviation from class average, single-score students, non-Black teachers

For the Institution 2 data for White, Coloured and Indian teachers the deviations from class score are, again, quite different although with uneven cell sizes. As can be seen in Table 4-49, like the previous sample a match in both race and language is generally positive (and statistically significantly higher than class average) especially when there is also a *mismatch* in gender. Interestingly, the only condition for which racial match is not significantly positive is when there is a language mismatch, although this is based on a small sub-sample. Racial mismatch is, conversely, somewhat negative especially when accompanied by a gender mismatch, although these deviations are not statistically significant from zero.

Similarly, in Table 4-50 the results for black teachers indicate that in the Institution 1 sample specifically a match tends to produce worse results (significantly lower than class average scores), while a mismatch presents better results.

Institution	Match in			N	M	SD	95% CI
	Race	Gender	Language				
1	Match	Match	Match	44	-5.47**	15.23	-10.1 to -0.84
1	Match	Match	Mismatch	217	-6.11**	17.38	-8.44 to -3.79
1	Match	Mismatch	Match	48	-5.24**	16.31	-9.98 to -.51
1	Match	Mismatch	Mismatch	244	-4.10**	16.16	-6.13 to -2.06
1	Mismatch	Match	Match	1	14.81	-	-
1	Mismatch	Match	Mismatch	374	1.17	16.42	-.50 to 2.83
1	Mismatch	Mismatch	Mismatch	381	5.37**	16.48	3.71 to 7.03
2	Match	Match	Match	255	-1.27	14.44	-3.05 to 0.51
2	Match	Match	Mismatch	82	.56	16.03	-2.96 to 4.08
2	Match	Mismatch	Match	97	.57	15.34	-2.53 to 3.66
2	Match	Mismatch	Mismatch	37	-1.99	16.45	-7.47 to 3.50
2	Mismatch	Match	Match	6	-3.78	15.85	-20.42 to 12.85
2	Mismatch	Match	Mismatch	45	-4.58	17.57	-9.86 to 0.7

2	Mismatch	Mismatch	Match	1	11.33	-	-
2	Mismatch	Mismatch	Mismatch	3	.19	19.93	-49.33 to 49.71

Notes. ** = $p < .05$.

Table 4-50: Deviations from class average, single-score students & Black teachers

However, these results may speak more to student innate ability than to match/mismatch specifically.

Questions remain about exact race, gender and language combinations may be associated with above more generalised differences. Table 4-51 and Table 4-52 below display the fine sub-group differences between groups for the Institution 1 and Institution 2 students respectively.

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	Teachers	Students	Teachers	Students	Teachers					
Black	Black	Female	Female	African	African	44	-5.47	15.23	-10.1 to -0.84	Sig
Black	Black	Female	Female	English	African	10	-4.94	18.52	-18.19 to 8.31	
Black	Black	Female	Female	Zulu	African	207	-6.17	17.37	-8.55 to -3.79	Sig
Black	Black	Male	Female	African	African	48	-5.24	16.31	-9.98 to -0.51	Sig
Black	Black	Male	Female	English	African	8	5.95	14.94	-6.54 to 18.43	
Black	Black	Male	Female	Zulu	African	236	-4.44	16.12	-6.5 to -2.37	Sig
Black	Indian	Female	Female	African	English	27	-4.83	19.53	-12.56 to 2.89	
Black	Indian	Female	Female	English	English	8	5.53	8.37	-1.46 to 12.53	
Black	Indian	Female	Female	Zulu	English	143	-2.80	10.02	-4.46 to -1.15	Sig
Black	Indian	Female	Male	English	English	1	-1.50	-		
Black	Indian	Male	Female	African	English	12	0.61	8.24	-4.63 to 5.84	
Black	Indian	Male	Female	English	English	3	3.82	9.16	-18.93 to 26.57	
Black	Indian	Male	Female	Zulu	English	109	-3.12	8.95	-4.82 to -1.42	Sig

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	Teachers	Students	Teachers	Students	Teachers					
Black	Indian	Male	Male	African	English	2	-4.00	2.12	-23.06 to 15.06	
Black	Indian	Male	Male	Zulu	English	2	0.97	6.32	-55.8 to 57.74	
Black	White	Female	Female	Zulu	English	4	7.68	9.43	-7.32 to 22.69	
Black	White	Female	Male	African	English	1	-3.63	-		
Black	White	Female	Male	Zulu	English	9	-5.19	9.28	-12.32 to 1.94	
Black	White	Male	Female	African	English	4	-0.07	4.43	-7.13 to 6.99	
Black	White	Male	Female	Zulu	English	22	-5.39	10.07	-9.85 to -0.92	Sig
Black	White	Male	Male	African	English	1	-3.63	-		
Black	White	Male	Male	Zulu	English	9	-5.44	8.68	-12.11 to 1.23	
Coloured	Black	Female	Female	English	African	13	-10.39	15.58	-19.81 to -0.98	Sig
Coloured	Black	Male	Female	English	African	4	3.87	17.21	-23.51 to 31.26	
Coloured	Indian	Female	Female	African	English	1	6.31	-		
Coloured	Indian	Female	Female	English	English	3	-4.60	10.48	-30.64 to 21.43	

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	**Teachers**	**Students**	**Teachers**	**Students**	**Teachers**					
Coloured	Indian	Male	Female	Afrikaans	English	1	4.31	-		
Coloured	Indian	Male	Female	English	English	5	2.81	9.40	-8.85 to 14.48	
Indian	Black	Female	Female	African	African	1	14.81	-		
Indian	Black	Female	Female	English	African	342	1.20	16.46	-0.55 to 2.95	
Indian	Black	Male	Female	English	African	343	5.32	16.78	3.54 to 7.1	Sig
Indian	Coloured	Female	Male	English	English	1	-66.13	-		
Indian	Indian	Female	Female	English	English	164	4.37	11.44	2.61 to 6.14	Sig
Indian	Indian	Female	Male	English	English	2	10.50	0.00		
Indian	Indian	Male	Female	English	English	59	5.14	14.94	1.25 to 9.04	Sig
Indian	Indian	Male	Male	English	English	4	6.57	12.75	-13.72 to 26.86	
Indian	White	Female	Female	English	English	3	3.43	5.20	-9.48 to 16.34	
Indian	White	Female	Male	English	English	8	2.77	10.84	-6.29 to 11.83	
Indian	White	Male	Female	English	English	11	-4.02	7.16	-8.83 to 0.79	

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	**Teachers**	**Students**	**Teachers**	**Students**	**Teachers**					
Indian	White	Male	Male	English	English	4	-1.83	14.14	-24.32 to 20.67	
White	Black	Female	Female	Afrikaans	African	1	14.81	-		
White	Black	Female	Female	English	African	17	8.46	12.51	2.03 to 14.9	Sig
White	Black	Male	Female	Afrikaans	African	2	2.31	26.52	-235.93 to 240.55	
White	Black	Male	Female	English	African	31	6.14	13.35	1.24 to 11.03	Sig
White	Indian	Female	Female	African	English	1	-1.42	-		
White	Indian	Female	Female	Afrikaans	English	1	-17.42	-		
White	Indian	Female	Female	English	English	15	5.07	9.09	0.04 to 10.1	Sig
White	Indian	Female	Male	English	English	1	-3.07	-		
White	Indian	Male	Female	English	English	10	5.04	13.87	-4.88 to 14.96	
White	Indian	Male	Male	English	English	1	-3.07	-		

Table 4-51: Descriptive statistics for difference from class average across Institution 1 student / teacher demographics

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	**Teachers**	**Students**	**Teachers**	**Students**	**Teachers**					
Black	Black	Female	Female	African	African	1	5.02	-		
Black	Black	Female	Male	African	African	97	0.57	15.34	-2.53 to 3.66	
Black	Black	Female	Male	English	African	31	-1.94	17.97	-8.53 to 4.65	
Black	Black	Female	Male	Zulu	African	6	-2.23	3.17	-5.56 to 1.09	
Black	Black	Male	Male	African	African	254	-1.30	14.46	-3.09 to 0.49	
Black	Black	Male	Male	English	African	57	-0.04	17.71	-4.74 to 4.66	
Black	Black	Male	Male	Zulu	African	25	1.92	11.51	-2.83 to 6.68	
Black	Indian	Female	Female	African	English	6	-6.01	19.65	-26.63 to 14.61	
Black	Indian	Female	Female	English	English	98	-0.96	20.45	-5.06 to 3.14	
Black	Indian	Female	Female	Zulu	English	10	-4.20	24.50	-21.73 to 13.32	
Black	Indian	Male	Female	African	English	2	-9.72	24.88	-233.24 to 213.79	
Black	Indian	Male	Female	English	English	31	-2.76	20.81	-10.39 to 4.87	
Black	Indian	Male	Female	Zulu	English	2	-24.41	42.62	-407.31 to 358.5	

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	**Teachers**	**Students**	**Teachers**	**Students**	**Teachers**					
Black	Indian	Male	Male	African	English	1	-5.32	-		
Black	Indian	Male	Male	English	English	4	-23.91	28.08	-68.59 to 20.78	
Black	White	Female	Female	African	Afrikaans	1	-31.59	-		
Black	White	Female	Female	African	English	1	-22.64	-		
Black	White	Female	Female	English	Afrikaans	2	2.49	4.36	-36.72 to 41.69	
Black	White	Female	Female	Zulu	Afrikaans	2	-20.51	39.48	-375.2 to 334.17	
Black	White	Female	Male	African	Afrikaans	179	-2.38	18.43	-5.1 to 0.34	
Black	White	Female	Male	African	English	2	-3.75	5.66	-54.57 to 47.08	
Black	White	Female	Male	Afrikaans	Afrikaans	2	14.13	12.18	-95.26 to 123.52	
Black	White	Female	Male	English	Afrikaans	10	4.49	10.44	-2.97 to 11.96	
Black	White	Female	Male	Zulu	Afrikaans	24	3.26	14.38	-2.81 to 9.33	
Black	White	Male	Male	African	Afrikaans	50	-0.61	18.33	-5.82 to 4.6	
Black	White	Male	Male	English	Afrikaans	5	8.44	8.71	-2.37 to 19.25	

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	**Teachers**	**Students**	**Teachers**	**Students**	**Teachers**					
Black	White	Male	Male	English	English	1	-42.31	-		
Black	White	Male	Male	Zulu	Afrikaans	8	6.44	8.07	-0.3 to 13.19	
Coloured	Black	Female	Male	English	African	1	-6.32	-		
Coloured	Black	Male	Male	African	African	2	6.86	6.33	-49.97 to 63.69	
Coloured	Black	Male	Male	English	African	10	-5.33	15.87	-16.69 to 6.03	
Coloured	Indian	Female	Female	English	English	7	-0.18	31.86	-29.64 to 29.28	
Coloured	White	Female	Male	Afrikaans	Afrikaans	1	-32.26	-		
Coloured	White	Female	Male	English	Afrikaans	3	5.91	13.46	-27.53 to 39.35	
Coloured	White	Male	Male	Afrikaans	Afrikaans	1	-7.73	-		
Coloured	White	Male	Male	English	Afrikaans	1	9.02	-		
Indian	Black	Male	Male	English	African	16	-4.46	19.19	-14.69 to 5.76	
Indian	Indian	Female	Female	English	English	28	7.99	11.94	3.36 to 12.62	Sig
Indian	Indian	Male	Female	English	English	12	10.96	23.83	-4.18 to 26.1	

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	**Teachers**	**Students**	**Teachers**	**Students**	**Teachers**					
Indian	White	Female	Male	English	Afrikaans	3	0.44	9.73	-23.73 to 24.6	
Indian	White	Male	Female	English	Afrikaans	1	5.40	-		
White	Black	Female	Male	African	African	1	11.33	-		
White	Black	Female	Male	Afrikaans	African	1	22.57	-		
White	Black	Female	Male	English	African	1	-15.67	-		
White	Black	Male	Male	African	African	4	-9.11	17.09	-36.31 to 18.09	
White	Black	Male	Male	Afrikaans	African	10	-7.89	17.63	-20.5 to 4.73	
White	Black	Male	Male	English	African	8	-1.26	19.44	-17.52 to 14.99	
White	Indian	Female	Female	English	English	9	15.81	12.25	6.39 to 25.23	Sig
White	Indian	Male	Female	Afrikaans	English	1	6.73	-		
White	Indian	Male	Female	English	English	3	-8.09	33.50	-91.3 to 75.12	
White	White	Female	Female	Afrikaans	English	1	-0.06	-		
White	White	Female	Female	English	Afrikaans	1	-19.59	-		

Race		Gender		Language		N	M	SD	95% CI	Sig at 5%?
Students	**Teachers**	**Students**	**Teachers**	**Students**	**Teachers**					
White	White	Female	Male	African	Afrikaans	1	9.42	-		
White	White	Female	Male	Afrikaans	Afrikaans	33	9.11	8.52	6.08 to 12.13	Sig
White	White	Female	Male	Afrikaans	English	1	0.32	-		
White	White	Female	Male	English	Afrikaans	8	8.52	8.08	1.77 to 15.28	Sig
White	White	Female	Male	English	English	1	5.88	-		
White	White	Male	Male	Afrikaans	Afrikaans	13	11.13	8.74	5.85 to 16.41	Sig
White	White	Male	Male	English	Afrikaans	6	0.83	16.49	-16.48 to 18.14	
Black	Black	Female	Female	African	African	1	5.02	-		

Table 4-52 Descriptive Statistics for difference from class average across Institution 2 student / teacher demographics

4.2.2.3.b.1.2 A general match index regression approach

The inferred impact of match versus mismatch is analysed by constructing an index of match versus mismatch. (For example, the index is three if the student matches the teacher on all of the three demographics, two if they match on any two.)

Since with three demographics the index can only take four values, the index is analysed both as a variable and as a dummy variable (with the index = 0 if there is no match) to ensure relative robustness.

Initial regression analyses indicated no serious collinearity or residual heteroskedasticity issues, but there are highly influential datapoints. To address this, and since in this initial regression analysis there were outliers in both the independent and dependent space, S-type robust regression was implemented through the SAS PROC ROBUSTREG programme (Rousseeuw &Yohai, 1984). A robust regression approach was generally taken in further analyses as outliers persisted throughout.

The initial regression results for both Institution 1 and 2 indicated no apparent effects for the match index as a predictor of academic ability. However, deeper analysis suggested strong differences based on race of the teacher, and, once again, when disaggregated, specific differences between Black teachers and other race groups persisted. Isolated analysis based on Black teachers continued to show no real effects for demographic match. However, there were strong effects for non-Black teachers as explained next.

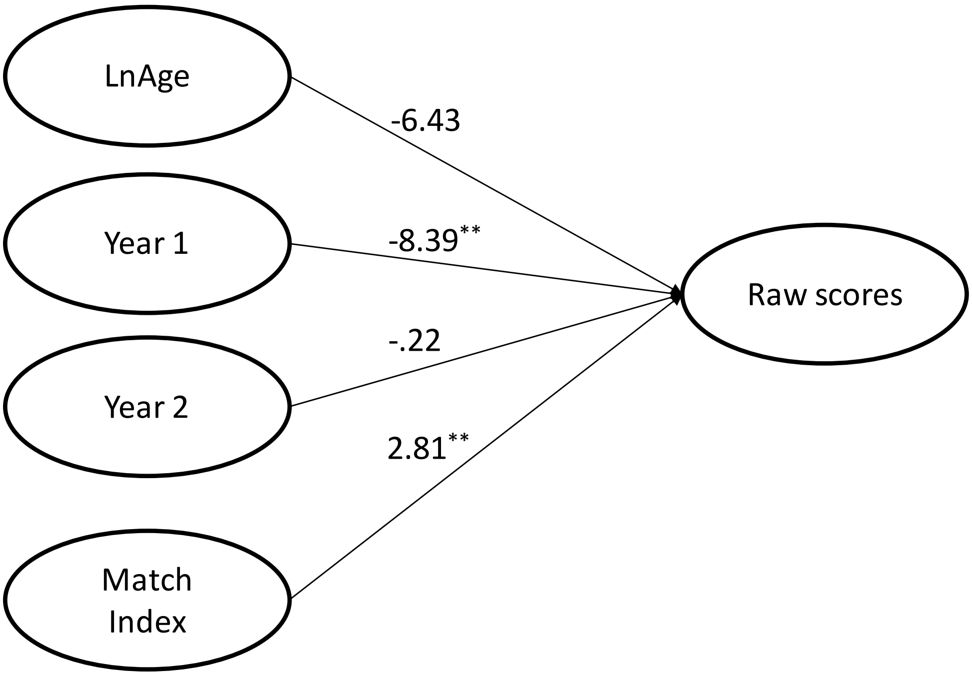
For non-Black teachers, Table 4-53 shows the regression results for the Institution 1 single-score cohort for teachers other than the Black teacher cohort. The models did not have very high R^2, but the match index did have highly significant effects. In the case of the index on its own the unstandardized index slope was $B = 2.81$ and 2.83 ($p< .01$) for raw scores and deviations from class average respectively, suggesting the average gain per extra demographic match (and therefore also average loss from mismatch) in all three demographic areas may run to about 8.5%. Using dummies for match suggested a non-significant gain from match in only one area ($B = .72$, ns) but larger and statistically significant gains of approximately 7.5% ($p <.01$) if there is match in more than one demographic.

	Raw scores				Difference from Class Ave.			
	Match index		Match dummies		Match index		Match dummies	
	B	95% CI	B	95% CI	B	95% CI	B	95% CI
Intercept	82.91***	52.68 to 113.14	83.81***	53.66 to 113.97	19.31	-11.08 to 49.70	19.36	-10.92 to 49.64
LogAge	-6.43	-15.85 to 2.98	-6.40	-15.79 to 2.99	-6.92	-16.36 to 2.53	-6.56	-15.97 to 2.85
Year 1	-8.39***	-13.79 to -2.98	-8.72***	-14.13 to -3.32	-1.92	-7.42 to 3.57	-2.25	-7.73 to 3.24
Year 2	-0.22	-6.33 to 5.90	-0.83	-6.96 to 5.31	-1.74	-7.95 to 4.47	-2.38	-8.59 to 3.84
MatchIndex	2.81***	2.06 to 3.57			2.83***	2.06 to 3.59		
Match Dummies								
• *1 Match*			.92	-1.21 to 3.05			.72	-1.43 to 2.87
• *2 Match*			7.51***	4.78 to 10.24			7.33***	4.58 to 10.09
• *3 Match*			7.50***	5.14 to 9.86			7.53***	5.15 to 9.91

Notes. N = 359. *** = $p < .01$, *** = $p < .05$, * = $p < .10$.

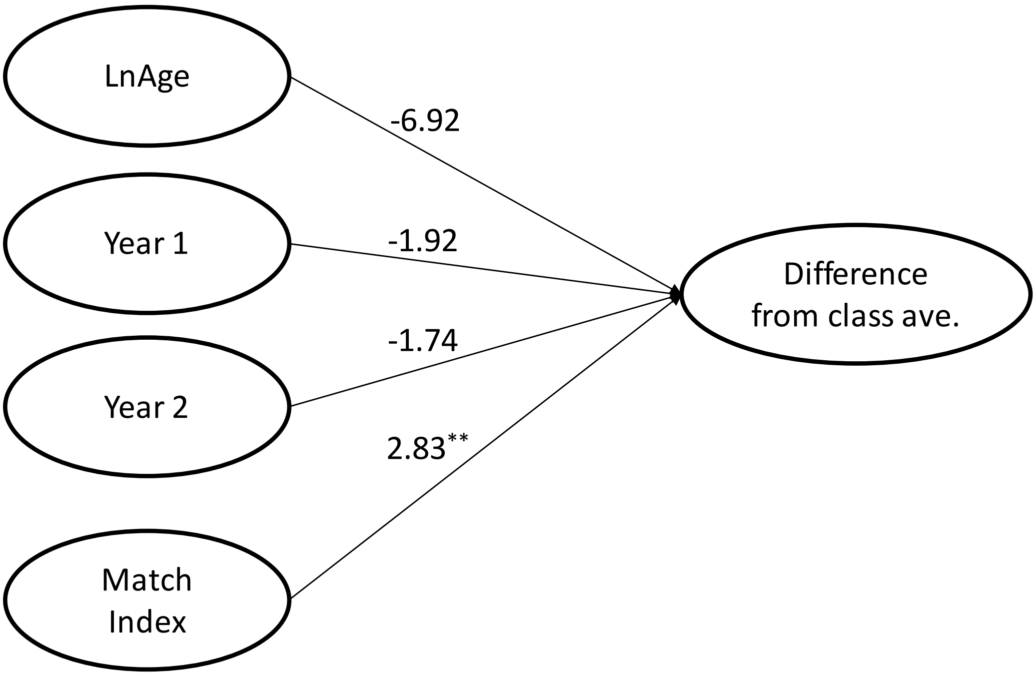
Table 4-53: Regression analyses of match/mismatch as an index for non-black teachers in the Institution 1 data

Figure 4-4 and Figure 4-5 respectively display these regression results.



*N = 359. *** = p < .01, ** = p < .05, * = p < .10.*

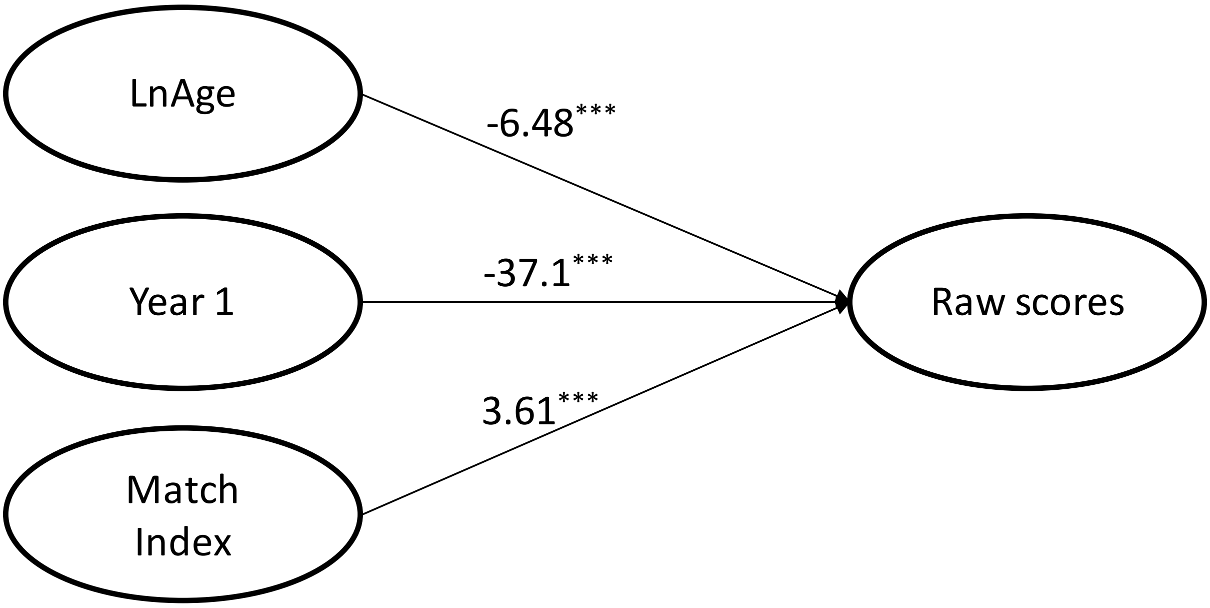
Figure 4-4: Match index effect on Institution 1 raw scores (non-Black teachers)



*N = 359. *** = p < .01, ** = p < .05, * = p < .10.*

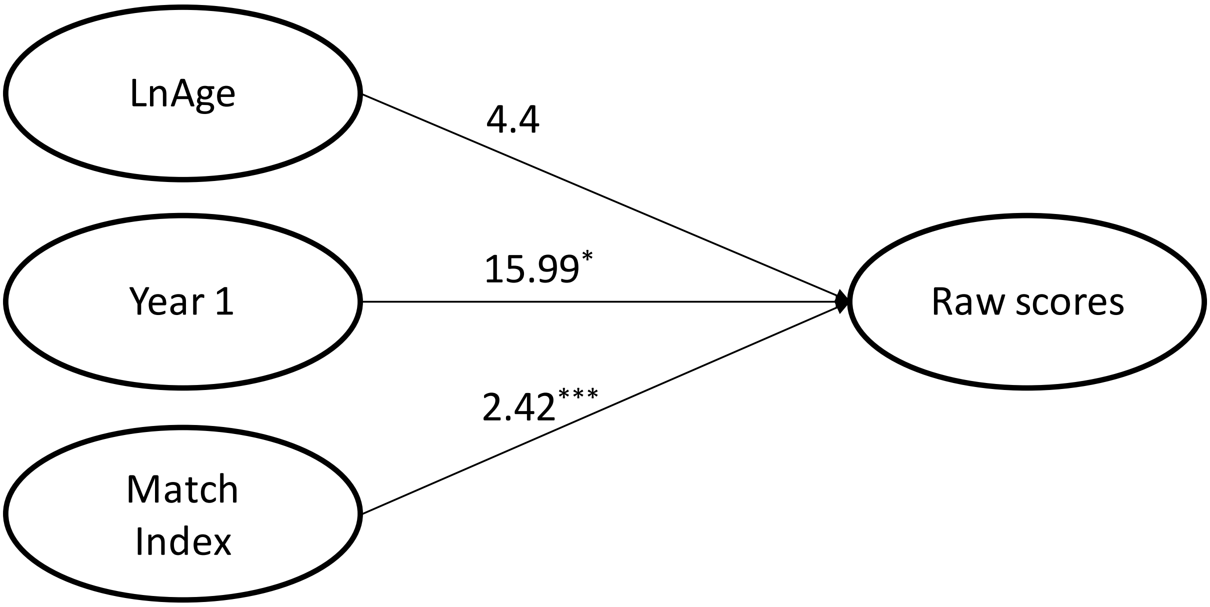
Figure 4-5: Match index effect on Institution 1 difference from average (non-Black teachers)

Similarly, Table 4-54 shows the regression results for the Institution 2 sample for non-Black teachers, in which similar albeit stronger results are found. Here the incremental value of the match index does have highly significant effects. In the case of the index on its own the unstandardized index slope is $B = 3.61$ and 2.42 ($p< .01$) for raw scores and deviations from class average respectively. Using dummies for match again suggests that only one demographic match is not a significant improvement but larger and statistically significant gains above no match of approximately 5.5%-7.5% in raw scores ($p <.01$) if there is match in two demographics and up to 9.01% - 10.22% in deviations on class average. Figure 4-6 and Figure 4-7 show these regression results in path diagram form.



N = 359. $^{***} = p < .01$, $^{**} = p < .05$, $^{*} = p < .10$.

Figure 4-6: Match index effect on Institution 2 raw scores (non-Black teachers)



N = 359. *** = *p < .01,* ** = *p < .05,* * = *p < .10.*

Figure 4-7: Match index effect on Institution 2 difference from average (non-Black teachers)

This analysis may suggest an association between demographic match and academic performance, but does not at this stage identify the exact type of match that may lead to the gains. Such possibilities are explored further using comparison on means in the next section.

	Raw Scores				Difference from Class Ave.			
	Match index		**Match dummies**		**Match index**		**Match dummies**	
	B	**95% CI**	**B**	**95% CI**	**B**	**95% CI**	**B**	**95% CI**
Intercept	248.33***	168.03 to 328.62	38.79**	7.06 to 70.53	-25.39*	-51.18 to 0.4	-27.03*	-54.71 to 0.65
LogAge	-6.48***	-94.39 to -42.58	.90	-7.41 to 9.21	4.4	-2.17 to 10.96	5.01	-2.24 to 12.26
Year 1	37.1***	19.64 to 54.56	38.61***	19.58 to 57.64	15.99*	-0.19 to 32.17	14.78*	-1.82 to 31.37
MatchIndex	3.61***	2.16 to 5.06			2.42***	1.05 to 3.78		
Match Dummies								
• *1 Match*			.31	-3.18 to 3.8			1.71	-1.33 to 4.75
• *2 Match*			7.26***	2.87 to 11.64			5.09***	1.26 to 8.91
• *3 Match*			10.22***	2.61 to 17.83			9.01***	2.37 to 15.65

Notes. N = 359. *** *= p < .01,* *** *= p < .05,* * *= p < .10.*

Table 4-54 Regression analyses of match/mismatch as an index for the non-Black teachers in the Institution 2 data

4.2.2.3.b.1.3 Comparisons of means

The following formal comparisons of means further assesses differences between groups in the single score dataset.

4.2.2.3.b.1.3.1 T-tests for basic match versus non-match comparisons

The results of undertaking T-Tests of the differences between match/mismatch within each demographic separately are presented in Table 4-55 and Table 4-56 for Institution 1 and 2 respectively. In both the Institution 1 and Institution 2 samples there are general albeit contradictory effects.

		95% T-Test Confidence Intervals			
		Means		**Differences (Match-Mismatch)**	
		Match	**Mismatch**	**Pooled**	**Satterthwaite**
Race					
•	*To class ave*	-3.37 to -1.11	0.42 to 2.14	-4.92 to -2.12**	-4.94 to -2.10**
•	*Raw difference*	50.86 to 53.53	56.46 to 58.42	-6.87 to -3.63**	-6.9 to -3.59**
Gender					
•	*To class ave*	-1.76 to 0.12	-0.37 to 1.66	-2.85 to -0.09**	-2.85 to -0.09**
•	*Raw difference*	52.56 to 54.74	56.06 to 58.4	-5.18 to -1.99**	-5.18 to -1.98**
Home Language					
•	*To class ave*	0.34 to 3.07	-1.38 to 0.21	0.57 to 4.00**	0.71 to 3.86**
•	*Raw difference*	58.17 to 61.28	53.33 to 55.16	3.5 to 7.46**	3.67 to 7.29**

Notes. *** = $p < .01$, ** = $p < .05$, * = $p < .10$.

Table 4-55: T-test differences between match/mismatch Institution 1 sample

Specifically, in the Institution 1 sample racial mismatch is associated with higher performance on average, while the opposite may be true for the Institution 2 data (looking at the differences from average). For the Institution 1 data gender mismatch also seems to lead to better performance, while language match is preferential. In the Institution 2 data, neither gender nor language differences significantly affect differences from class average.

	95% T-Test Confidence Intervals			
	Means		Differences (Match-Mismatch)	
	Match	Mismatch	Pooled	Satterthwaite
Race				
To class ave	-0.24 to 2.22	-3.3 to -0.03	0.64 to 4.68**	0.62 to 4.71**
Raw difference	61.71 to 64.80	68.12 to 71.83	-9.12 to -4.32**	-9.13 to -4.30**
Gender				
To class ave	-1.87 to 0.77	-1.49 to 1.69	-2.71 to 1.4	-2.71 to 1.41
Raw difference	61.73 to 64.8	69.06 to 72.87	-10.12 to -5.27**	-10.14 to -5.25
Home Language				
To class ave	-1.65 to 1.22	-1.77 to 1.1	-1.91 to 2.15	-1.91 to 2.15
Raw difference	61.63 to 64.76	67.93 to 71.58	-8.96 to -4.16**	-8.96 to -4.16**

Notes. *** = $p < .01$, ** = $p < .05$, * = $p < .10$.

Table 4-56: T-test differences between match/mismatch Institution 2 sample

4.2.2.3.b.1.3.2 ANOVA tests for within-demographic analyses (Institution 1)

Testing specific directions of within-demographic results for match/mismatch (e.g. Female/Male versus Male/Female) requires an ANOVA-type approach. A general structural equation framework was used for the analysis. However, stability depends partly on cell sizes and normality. Given the small data cell sizes (a number of the classes of students in the samples were small in terms of student numbers), General Linear Modelling (GLM) and nonparametric analyses were attempted.

4.2.2.3.b.1.3.2.1 Within-gender differences

Table 4-51 and Table 4-52 suggest some within-demographic results.

GLM-type tests that were initially employed for analysis of within-gender differences for single-score students in Institution 1 controlled for student age (which is noted due to significant kurtosis) and module level (dummy variables reflecting first and second year students). However, outlier analysis indicated significant outliers. Therefore, the SAS PROC ROBUSTREG implementation of ANOVA was employed, specifically implementing Huber's M-estimator which is stable and appropriate for ANOVA since there cannot be high leverage in categorical dummy variable predictors of this nature (Huber, 1981).

For both dependent variables (raw student scores and deviations from class average), both the initial and robust results revealed the same pattern: there were no significant gender effects or gender interactions. However, it was noted that both age and module level had significant effects. In the effects for deviation from average, younger students tended to perform worse ($B = -13.92$, $p < .01$, i.e. a 1% increase in age was associated with a decline of .14% compared to class average) and students in lower level classes performed on average significantly worse than higher levels (-6% for first years and -8.2% for second years compared to high level classes). The age effect was very similar in the case of raw student scores, with first year students performing 11% worse than high level students. Second year students do not perform significantly worse.

4.2.2.3.b.1.3.2.2 Within-race differences

There existed limited racial matches between student and teacher in the single-score Institution 1 data, with mostly White and Indian teachers. Nonetheless, this did allow for match/mismatch comparisons.

For instance, Table 4-51 suggests that Black, Zulu speaking students significantly underperform the class average when taught by the Indian females specifically. Likewise, Black male Zulu speakers significantly underperformed when taught by White females. Conversely, Indians taught by Indians over-performed class averages in many cases, specifically when the teachers were female.

Initial GLM ANOVAs that controlled for student age and year of study did not find significant interactions between student and teacher race (other results were as for gender above). However, outlier analysis shows large outliers (as for gender). Therefore the SAS PROC ROBUSTREG implementation of ANOVA was used. Here, the interaction is significant at the 5% level of analysis.

4.2.2.3.b.1.3.2.3 Within-language differences

Unfortunately, all teachers associated with single-score students in Institution 1 spoke English, so little cross-comparison was enabled. However, one-way ANOVAs allowed comparison between student languages. There were only two Afrikaans speakers in the Institution 1 sample, and so these were dropped from the analysis. Moreover, since there were significantly different cell sizes in the other languages (English = 304, Zulu = 298, Other African Languages = 42), Dunn's nonparametric analysis of one-way group differences was utilised. Table 4-57 and Table 4-58 show these results for raw scores and deviations from class average respectively, in which English speaking students consistently and significantly outperformed other languages. It is possible that this supports the match/mismatch hypothesis since all the teachers for this group spoke English as their home language. However, this cannot be shown with any rigor since comparison to non-English speaking teachers is not possible.

Compare	**Difference**	**SE**	**Q**	**q(.05)**	**Conclusion**
English vs. Zulu	132.73	15.16	8.76	2.394	Reject
English vs. Other African	77.89	30.61	2.54	2.394	Reject
Other African vs. Zulu	54.84	30.65	1.79	2.394	No not reject

Group sample sizes not equal, and tied ranks present, Dunn's test used with alpha=0.05.

Table 4-57: Comparison of raw student scores between Institution 1 students

Compare	**Difference**	**SE**	**q**	**q(.05)**	**Conclusion**
English vs. Zulu	135.78	15.17	8.95	2.394	Reject
English vs. Other African	88.94	30.62	2.90	2.394	Reject
Other African vs. Zulu	46.84	30.66	1.53	2.394	No not reject

Group sample sizes not equal, and tied ranks present, Dunn's test used with alpha=0.05.

Table 4-58: Comparison of deviations from means between Institution 1 students

Similar analyses in Institution 2 did not, however, find any effects (see *Appendix G: Race TCTSE Moderation (Institution 2) output (SAS), Appendix H: Home Language TCTSE Moderation (Institution 2) output (SAS)* and *Appendix I: Gender TCTSE Moderation (Institution 2) output (SAS)*).

4.2.2.3.b.2 Part 2: Repeated measures analysis

One major problem with the above single-score analyses is that the student's own level of ability is not taken into account. However, where there exist multiple scores for each student (that is, scores for multiple classes) it is possible to account for the student's own innate ability by examining within-student changes over different teachers. Accordingly, repeated measures analysis was undertaken to ascertain whether, over multiple classes, a change in teacher demographics is seemingly associated with changes in scores.

It is important to note that in the repeated measures analysis the difference between raw student scores and deviations from class averages does become particularly important. Since each treatment is a different class, the relative difficulty of the course can be expected to affect raw scores. Accordingly, in repeated measures it makes far more sense to standardize for difficulty by analyzing deviations from class averages, since ubiquitous difficulty levels will be reflected in the entire class's performance and therefore screened out in the scores via the differencing procedure.

4.2.2.3.b.2.1 Repeated measures over exact, partial and no match

In this analysis, all students were extracted for whom there were at least three types of teachers, viz. a) a teacher of an exact demographic match, b) a teacher of a partial demographic match, and c) a teacher with no demographic match. Obviously, this limits the sample, specifically to a sample size of only 278 students in the Institution 1 dataset and 243 students in the Institution 2 dataset.

Initially, structural equation modeling (SEM) was attempted, specifically using a latent growth modelling specification that allows a test of change in student academic performance over the various levels of match (Kline, 2010). However, the data assumptions required for SEM (and indeed for parametric repeated measures ANOVA) were not met. The data proved to be substantially non-spherical, having serious non-normality even after outlier deletion. Transformation was attempted to ameliorate the problem, but multivariate normality as indicated by Mardia's multivariate kurtosis score was substantial. This problem persisted over all iterations of repeated measures analyses. Neither structural equations nor parametric repeated measures ANOVA should be attempted under such conditions (Kline, 2010).

Accordingly, the Friedman K-Way Related ANOVA procedure was utilized (Conover, 1999, Friedman, 1937, Friedman, 1940) to assess statistical evidence of differences in student scores, with the multiple comparison procedure suggested by Holm (1979). This procedure allows for non-normal data with outliers since it converts to ranks, including the adjustment for tied ranks of which there were several in the dataset. The classical test statistic is:

$$S = \frac{12\sum_{j=1}^{k}\left(R_{.j} - nR_{..}\right)^2}{nk(k+1) - \dfrac{\sum_{i=1}^{n}\left(\sum_{j=1}^{g_i} t_{i,j}^3 - k\right)}{k-1}}$$

where n = number of students, k = number of repeated measures, $R_{.j}$ = average rank at measurement, $R_{..}$ = (k + 1)/2, g_i = number of tied groups in block i, $t_{i,j}$ = size of the j^{th} tied group in block i, and untied ranks are treated as ties of size 1. In a large sample S is Chi-square distributed, with multiple comparison finding trait $u < v$ if:

$$\left|R_u - R_v\right| \geq q(\alpha, k, \infty)\sqrt{\frac{nk(k+1)}{12}}$$

where values of q are given in tables (Conover's (1980) F approximation for comparison).

Table 4-59 below shows the overall ANOVA results for raw score and deviations from class average. As can be seen, in both samples raw scores did seem to differ across classes, but deviations from class averages do not.

Test	Test/Sample	N	K	Classical F	Conover's F
Raw scores	Institution 1	278	3	144.18^{***}	96.98^{***}
Raw scores	Institution 2	243	3	6.17^{**}	3.11^{**}
Deviations from average	Institution 1	278	3	4.23^{ns}	2.13^{ns}
Deviations from average	Institution 2	243	3	$.03^{ns}$	$.01^{ns}$

Notes. $^{***} = p < .01$, $^{**} = p < .05$, $^{*} = p < .10$.

Table 4-59: Nonparametric Repeated Measures ANOVA

These results would seem to indicate that student-teacher demographics do not, in repeated measures, affect the class placement of students, after controlling for relative difficulty of classes.

Despite the relative disadvantages of unadjusted raw scores, since these were significant in the above analysis, the between treatment differences were also analysed. Table 4-60 gives the average ranks across the three levels of match, where the data analyses raw student scores. As can be seen, in neither sample was the average rank lowest (i.e. best) with complete student-teacher demographic match. Indeed, in the Institution 1 sub-sample complete match led to demonstrably worse student performance, while some match provided the best scores. In the Institution 2 analysis some match was the inferior combination.

	Institution 1		Institution 2	
	Mean Rank	**SD**	**Mean Rank**	**SD**
No Match	1.98	.79	1.93	.88
Some Match	1.50	.69	2.13	.80
Complete match	2.52	.62	1.94	.75

Table 4-60: Mean ranks across levels of match index for raw student scores

Table 4-61 gives the associated Holm (1979) multiple comparisons. As seen there, all levels are significantly different from one another in Institution 1 data (so some match was significantly best, complete match significantly worst), while in Institution 2 data only the relatively worse performance of students with some demographic match is significant.

	P-values	
	Institution 1	**Institution 2**
Some match vs. complete match	.00	.01
No match vs. some match	.00	.16
No match vs. complete match	.00	.41

Notes. Multiple comparison analysis based on the procedure of Holm (1979)

Table 4-61: Holm (1979) multiple comparisons for (overall) raw student scores

However, these results should perhaps be treated with caution, since relative difficulty of the classes themselves appears to be creating some of these findings.

4.2.2.3.b.2.2 Repeated measures based on change in race

Repeated measures analyses were also carried out just for a change in race (i.e. where the student was taught by his/her own race, then for classes where the teacher was of a different race). The only significant differences were for black students in the Institution 1 group, as seen in Table 4-62. Table 4-63 furthermore shows that these students tended to perform better (with a lower average rank) when their teacher was of the same race.

Test	Test/Sample	N	K	Classical F	Conover's F
Raw scores	Institution 1	553	2	44.09^{***}	47.82^{***}
Raw scores	Institution 2	468	2	2.07^{ns}	2.07^{ns}
Deviations from average	Institution 1	553	2	4.70^{**}	4.74^{**}
Deviations from average	Institution 2	468	2	$.855^{ns}$	$.854^{ns}$

Notes: *** *= p < .01,* ** *= p < .05,* * *= p < .10.*

Table 4-62: Nonparametric Repeated Measures ANOVA in Institution 1 (Black students)

	Raw scores		Deviation from class ave.	
	Mean Rank	**SD**	**Mean Rank**	**SD**
Match	1.36	.48	1.45	.50
Mismatch	1.64	.48	1.55	.50

Table 4-63: Mean ranks across treatments in Institution 1 (Black students)

4.2.2.4 Summary of findings for cohorts two and three

The GEE analyses (phase 1) above consistently show highly significant results for race and home language matched students that suggest a positive relationship between teacher student match and student test scores for both cohorts two and three, as well as the combined dataset (see Table 4-36 to Table 4-44). Teacher student gender match effects were not significant for the GEE analyses (see Table 4-42 to Table 4-44).

Furthermore, Table 4-45 to Table 4-47 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 4-47) 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.

Further analyses (phase 2) using higher order statistical methods (see *4.2.2.3.b Phase 2: Further analysis of match mismatch effects using higher order statistical methods*) provided some support for these findings and present a more nuanced view of the results.

For example, Table 4-48 presents descriptive statistics for a variety of combinations of demographic match/mismatch for students with a single test score. While, perfect demographic match is shown in Table 4-48 to have a significant positive effect on the Institution 1 sample, this improvement effect is amplified when only race mismatches ($M = 3.24$, $p < .05$). For Institution 2, the same analysis reveals significantly positive race match effects (Table 4-48).

Table 4-49 disaggregates the data used for Table 4-48 by teacher race group (excluding Black teachers) and shows that race and home language matches produce significantly higher average outperformance of class averages for non-Black teachers. For Institution 1, a mismatch in all demographics leads to underperformance of class average by -3.15% on average ($p < .01$), and a match in all demographics outperforms class average by 4.42% on average ($p < .01$). Once again, a match on language alone seems to mitigate other mismatch effects ($M = -.42$, ns), and a mismatch on race alone is not a significant deviation from average. For Institution 2, a match in all demographics accounts for an 8.99% outperformance of class average.

Table 4-53 and Table 4-54 support the results of the GEE analyses that showed a positive relationship between indexes of match and test score results. Figure 4-4 to Figure 4-7 further illustrate that incremental values of the match index have highly significant effects on test scores. For Institution 1, each match index increment produces a raw score improvement of 2.81% ($p<.05$) (figure 4-1) and a 2.83% ($p<.05$) improvement in deviation from class average (Figure 4-5). For Institution 2, each match index increment results in a 3.61% ($p<.01$) raw score improvement (Figure 4-6) and a 2.42% ($p<.01$) improvement in deviation from class average (figure 4-4). Although only one demographic match is not a significant improvement, larger and statistically significant gains above no match of approximately 5.5% - 7.5% in raw scores ($p <.01$) occur if there is match in two demographics, and up to 9.01% - 10.22% in deviations on class average (Table 4-53 and Table 4-54).

4.2.3 Student perceptions of collective self-efficacy

4.2.3.1 Overview

The third of the research questions (and sub-questions) this study sought to investigate was:

Research question 3(RQ3): *"Do student perceptions of collective self-efficacy (in respect of teacher capability), vary among cultural groupings?"*

> Sub-question 3.1(SQ3.1): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among race groupings?"*
>
> Sub-question 3.2(SQ3.2): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among home language groupings?"*
>
> Sub-question 3.3(SQ3.3): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among gender groupings?"*
>
> Sub-question 3.4(SQ3.4): *"How does culture-based variation in student perceptions of collective self-efficacy (in respect of teacher capability) relate to culture-based differences in the impact of teacher student congruence on student cognitive test performance in information systems and technology education?"*

4.2.3.2 Cohort one

4.2.3.2.a Results

The results of the component of the study addressing student perceptions of collective self-efficacy are presented below for cohort one. It should be noted that the term 'Asian' is in this context synonymous with 'Indian'.

For each of the 'teacher' questions, and for each of the demographic variable categories, a Chi-square goodness-of-fit test was applied to investigate whether responses were selected with approximately the same frequency or whether some response options were selected significantly more/less often than others. The results are summarised as follows (in each case, the value that is expected if all options were selected equally is represented by the horizontal line):

4.2.3.2.a.1 Results by race

Student perceptions of the impact of teacher student gender match

The following figures present the survey results in respect of student perceptions of the impact of teacher student gender match (the results are separated by student race):

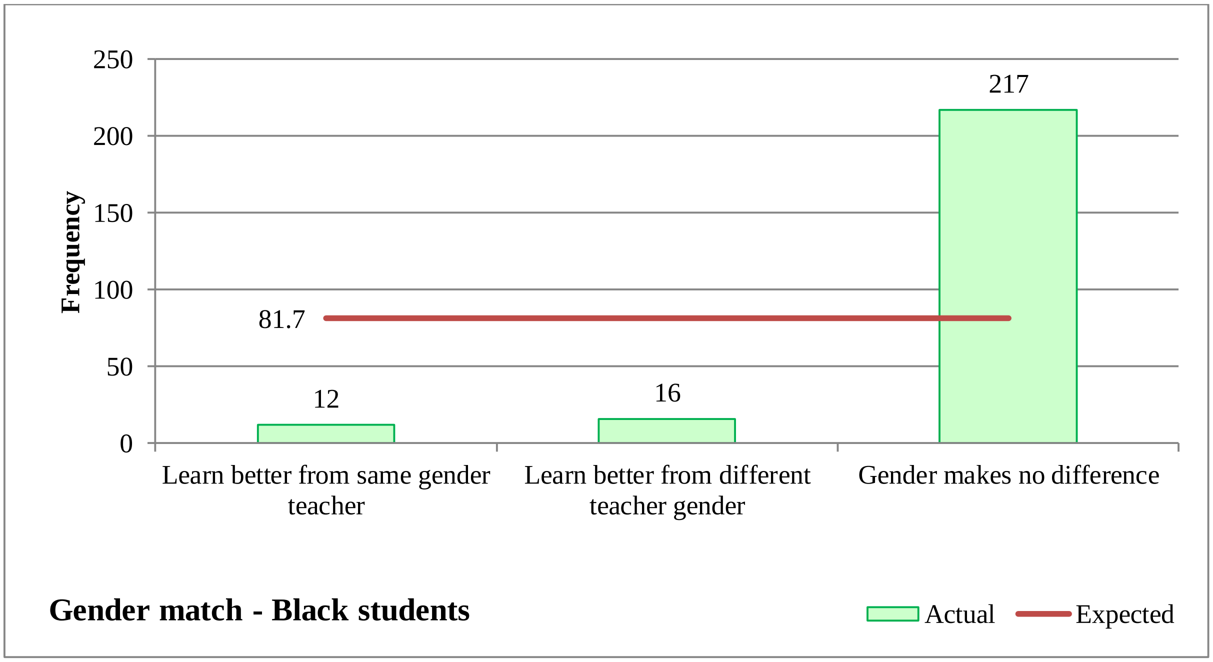


Figure 4-8 Black student perceptions of the impact of teacher student gender match

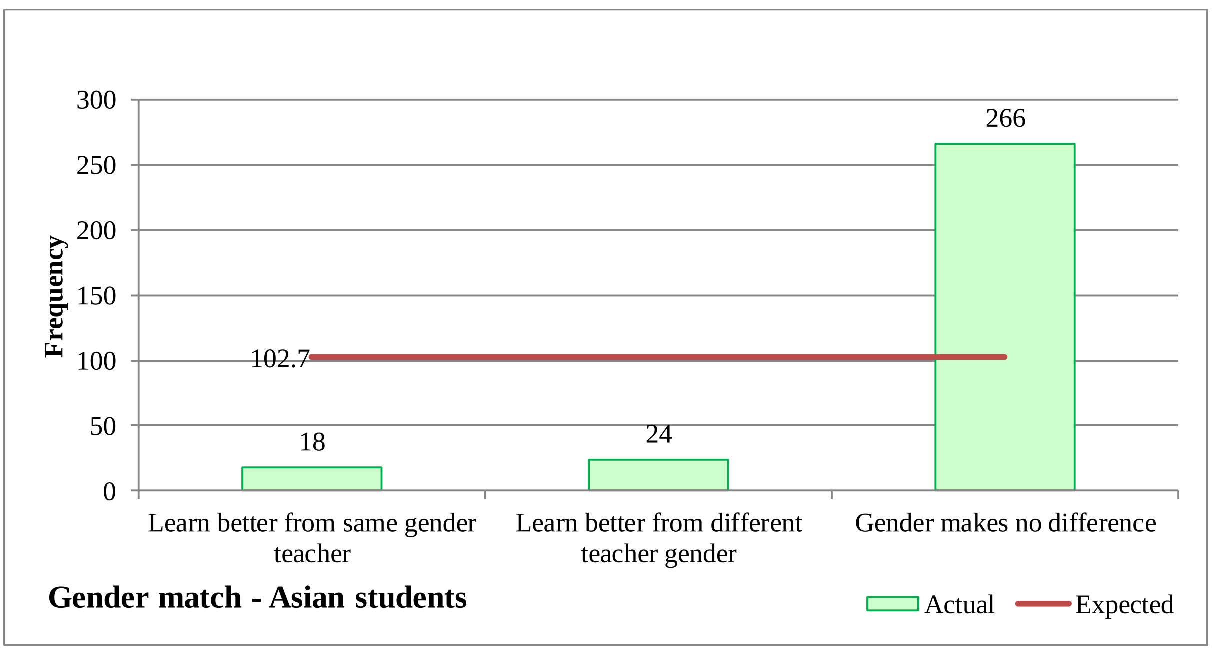


Figure 4-9 Asian student perceptions of the impact of teacher student gender match

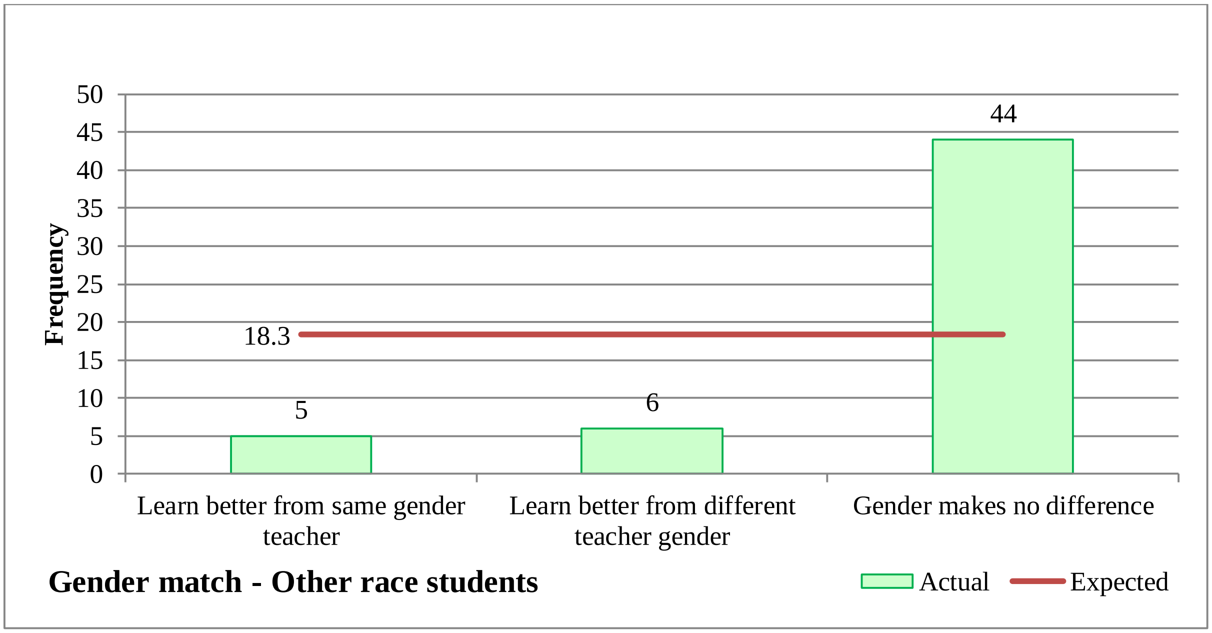


Figure 4-10 Other race student perceptions of the impact of teacher student gender match

For each of the above, options were selected with significantly different frequencies. Clearly, most students from all race groupings believe that the gender of their teacher does not make a difference ($p<.0005$ in all cases).

Student perceptions of the impact of teacher student race match

The following figures present the survey results in respect of student perceptions of the impact of teacher student race match (the results are separated by student race):

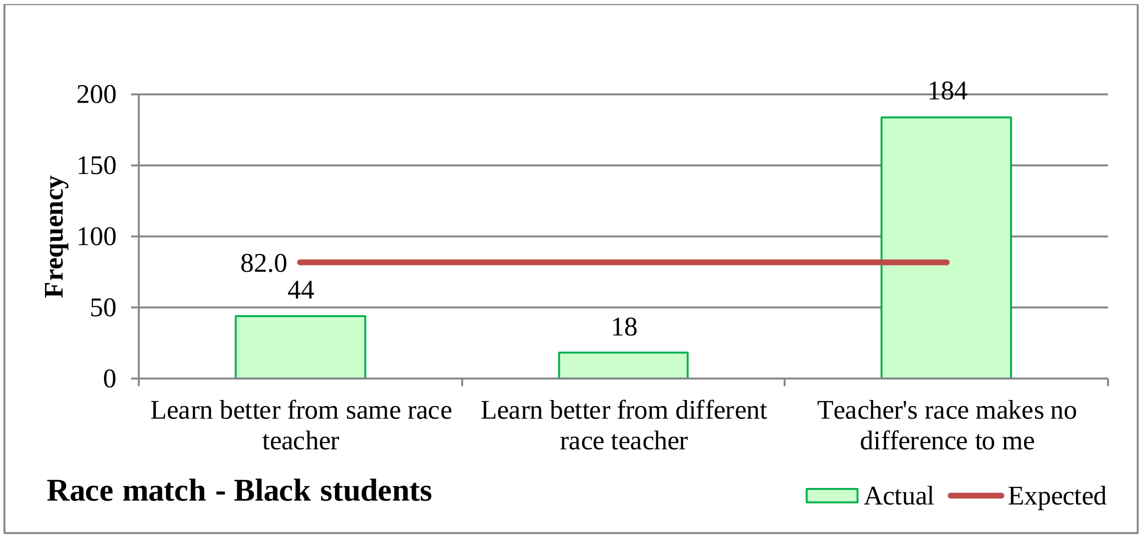


Figure 4-11 Black student perceptions of the impact of teacher student race match

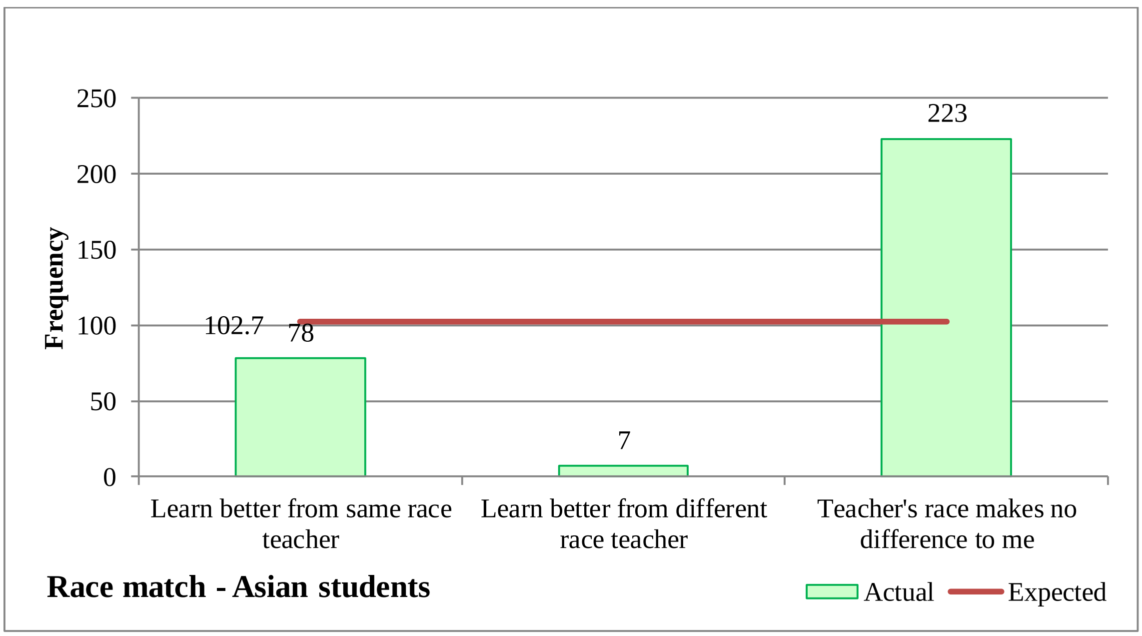


Figure 4-12 Asian student perceptions of the impact of teacher student race match

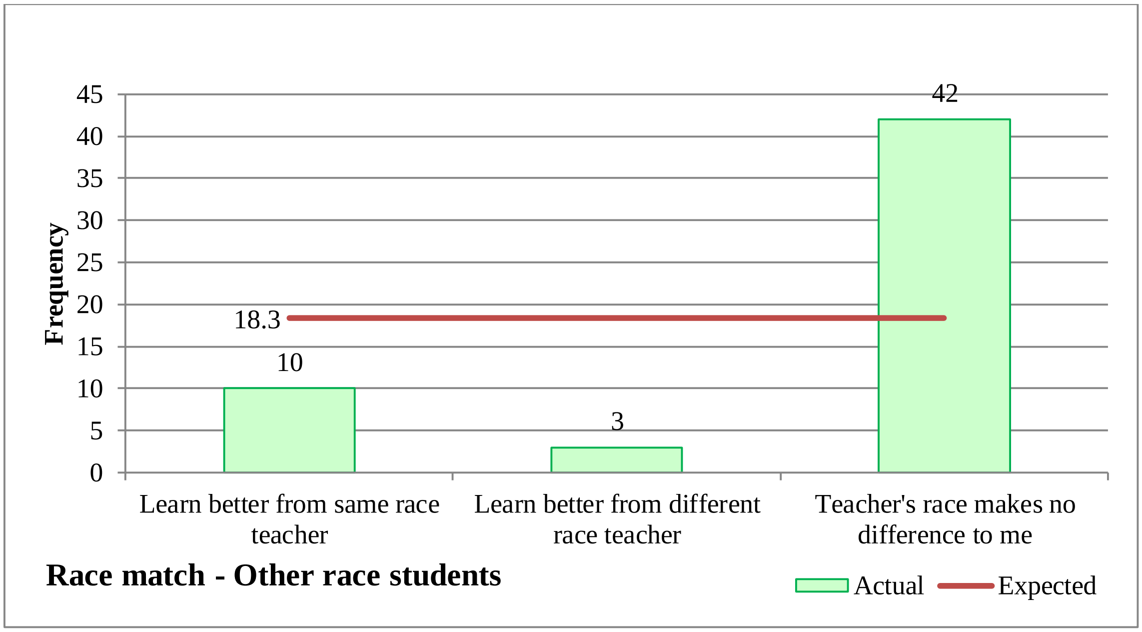


Figure 4-13 Other race student perceptions of the impact of teacher student race match

For each of the above, options were selected with significantly different frequencies. Clearly, most students from all race groupings believe that the race of their teacher does not make a difference ($p<.0005$ in all cases).

Student perceptions of the impact of teacher student home language match

The following figures present the survey results in respect of student perceptions of the impact of teacher student home language match (the results are separated by student race):

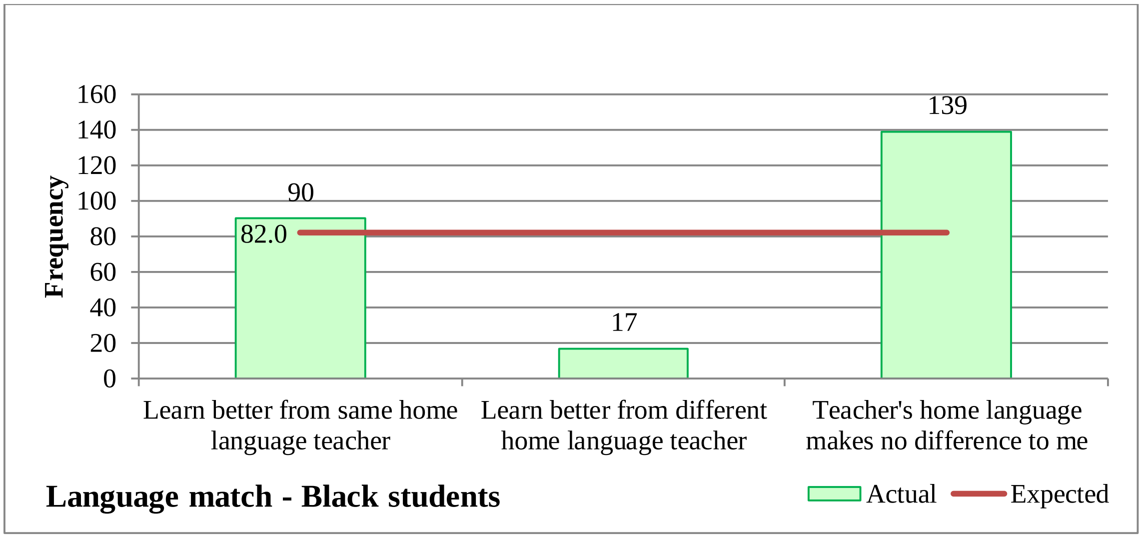


Figure 4-14 Black student perceptions of the impact of teacher student home language match

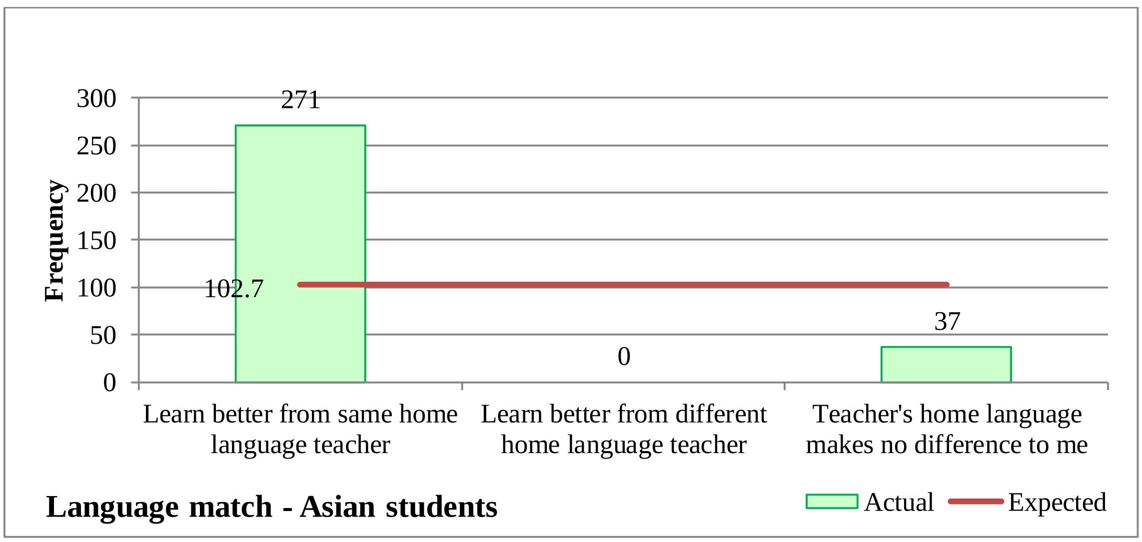


Figure 4-15 Asian student perceptions of the impact of teacher student home language match

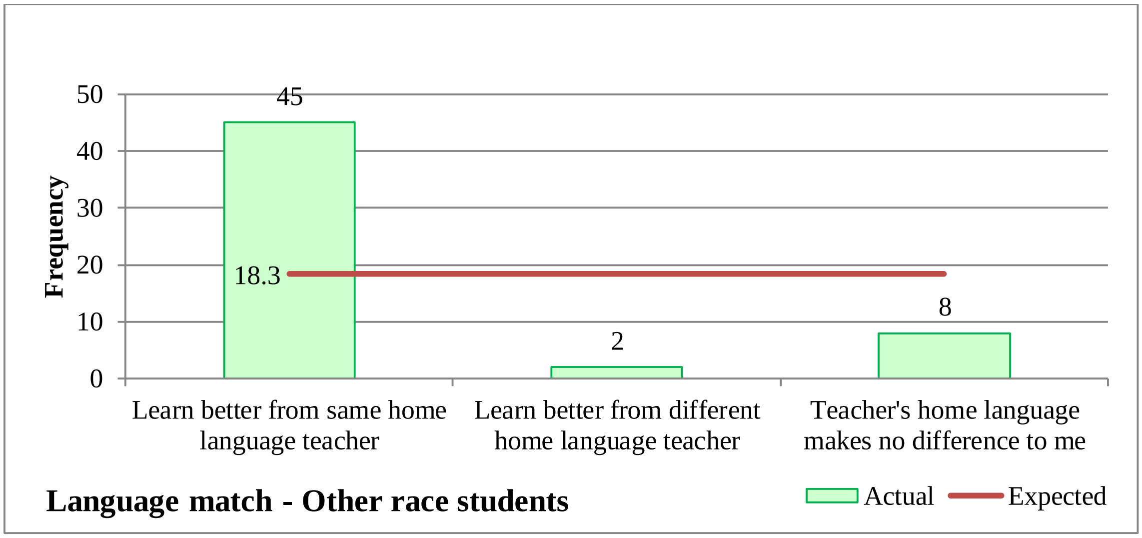


Figure 4-16 Other race student perceptions of the impact of teacher student home language match

Significantly ($p<.0005$) more than expected (139) of the Black students indicated that teacher's home language made no difference. Fewer than expected said they would learn better from a different home language teacher. The Asian and Other race students selected the 'better from same home language teacher' option significantly ($p<.0005$, $p<.0005$ respectively) more often than expected.

Student perceptions of the impact of being taught in the student's home language

The following figures present the survey results in respect of student perceptions of the impact of being taught in the student's home language (the results are separated by student race):

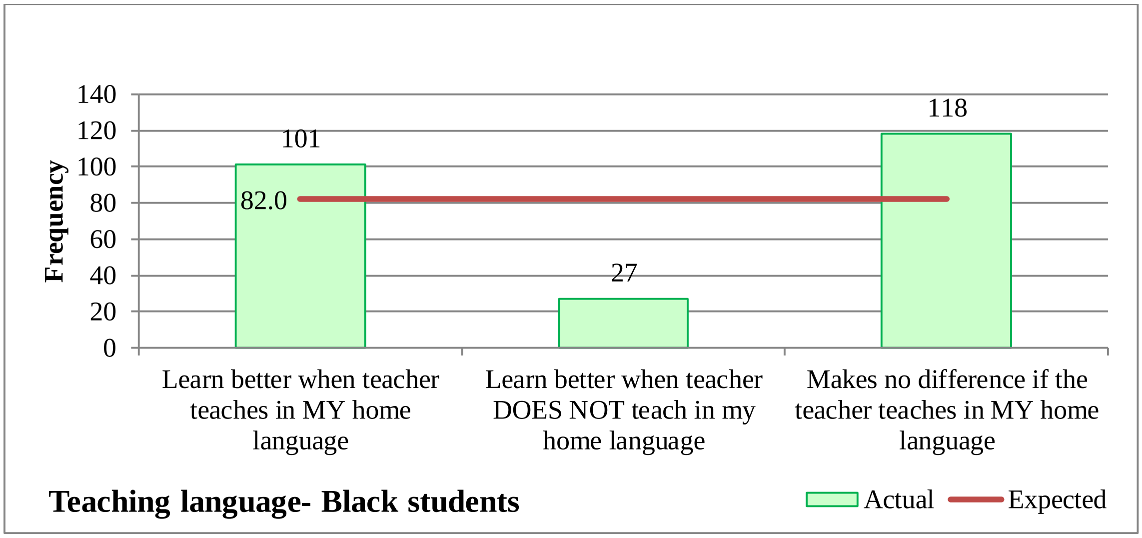


Figure 4-17 Black student perceptions of the impact of being taught in the student's home language

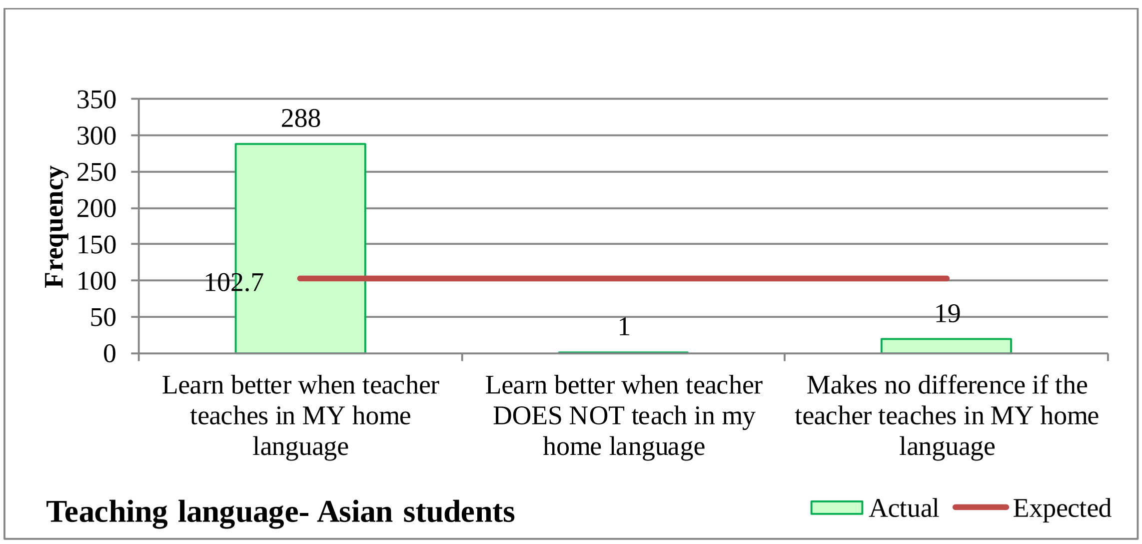


Figure 4-18 Asian student perceptions of the impact of being taught in the student's home language

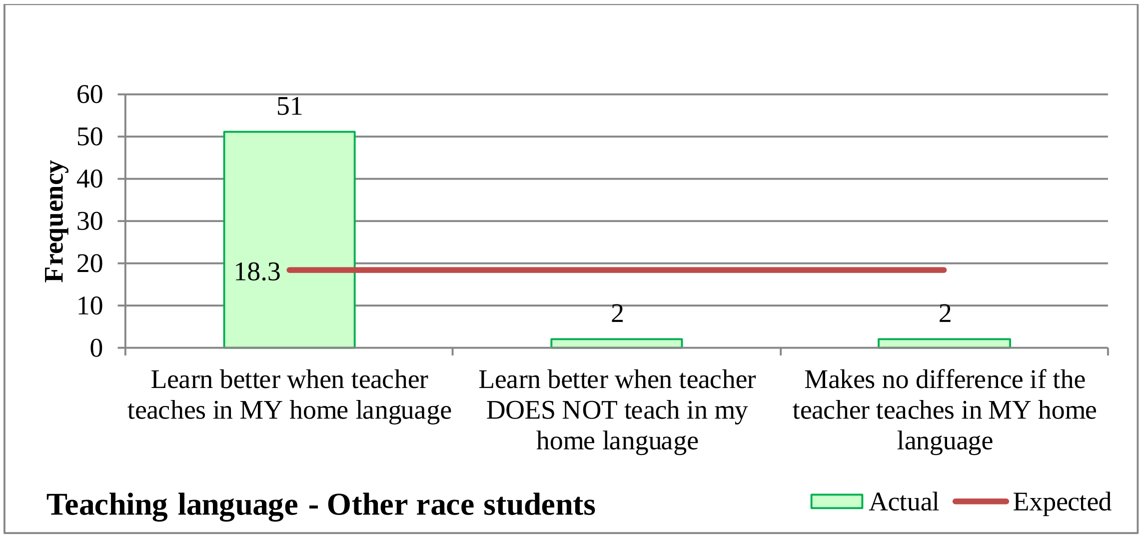


Figure 4-19 Other race student perceptions of the impact of being taught in the student's home language

It is very clear that the Asian and Other race students prefer to be taught in their own home languages ($p<.0005$, $p<.0005$ respectively). However, it is not quite as clear for the Black students who have a proportionately higher number of 'learn better when teacher does not teach in my home language' responses than the other race groups.

4.2.3.2.a.2 Results by home language

Student perceptions of the impact of teacher student gender match

The following figures present the survey results in respect of student perceptions of the impact of teacher student gender match (the results are separated by student home language):

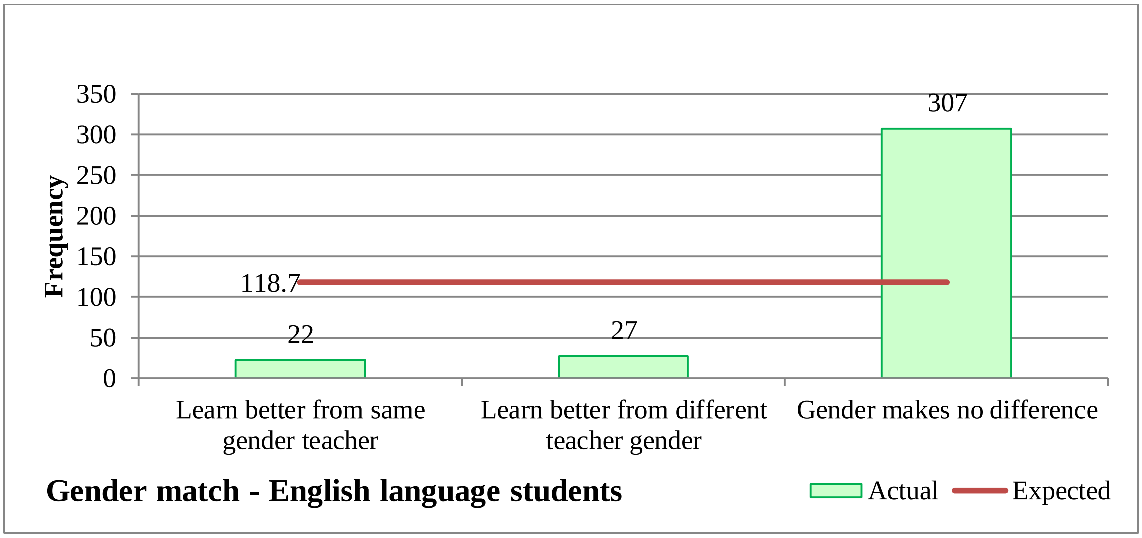


Figure 4-20 English language student perceptions of the impact of teacher student gender match

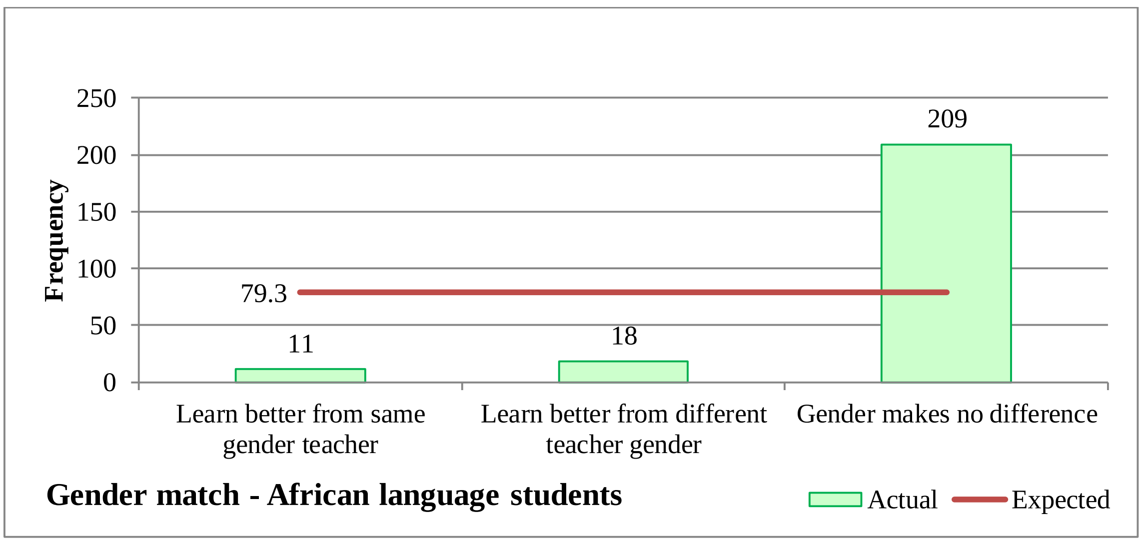


Figure 4-21 African language student perceptions of the impact of teacher student gender match

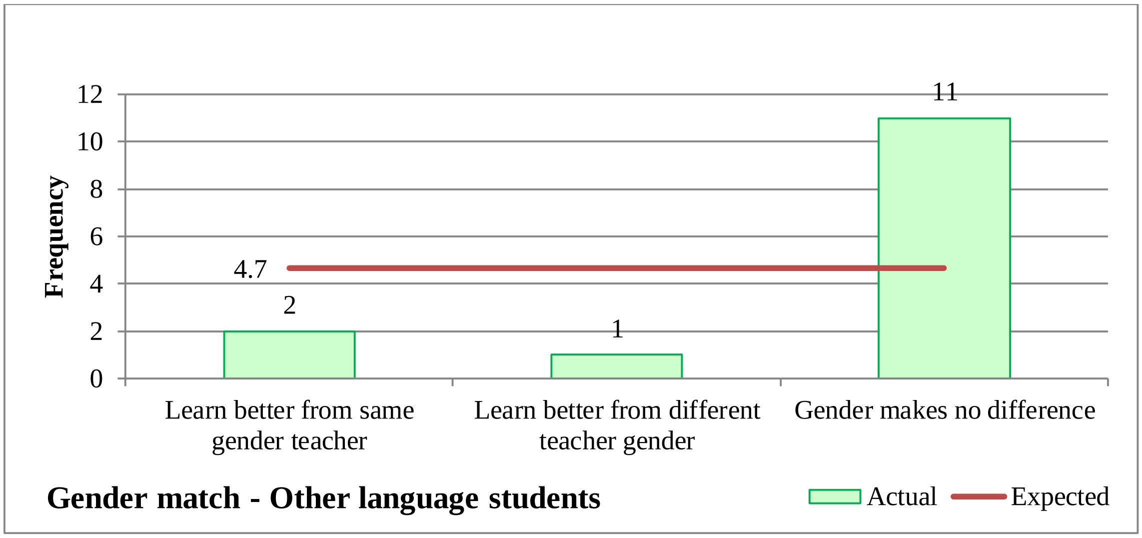


Figure 4-22 Other language student perceptions of the impact of teacher student gender match

Clearly, the different groups of students (English, African Language and Other) do not think gender is an issue (p<.0005, p<.0005 and p=.002, respectively).

Student perceptions of the impact of teacher student race match

The following figures present the survey results in respect of student perceptions of the impact of teacher student race match (the results are separated by student home language):

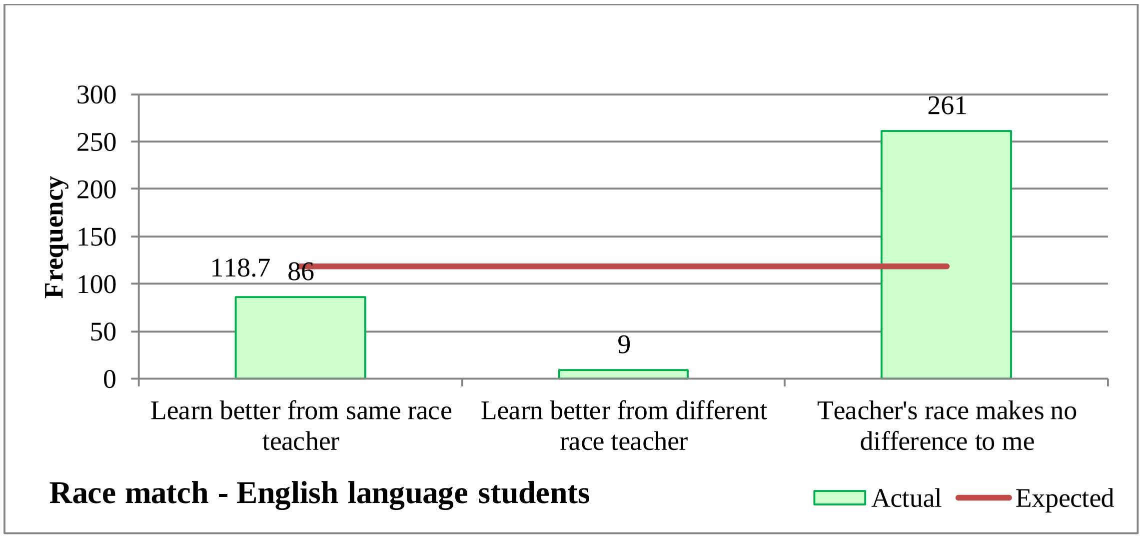


Figure 4-23 English language student perceptions of the impact of teacher student race match

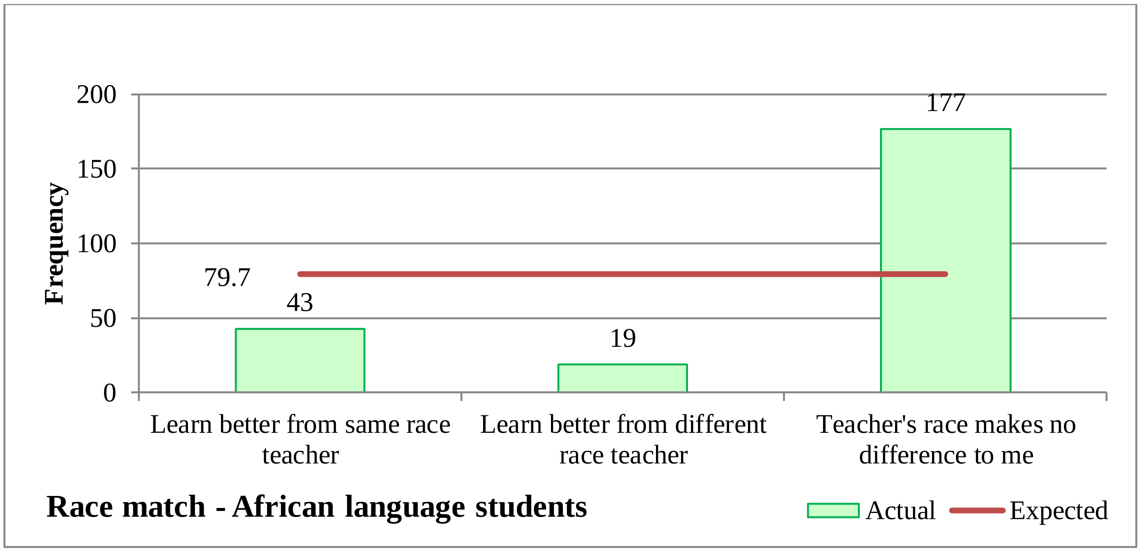


Figure 4-24 African language student perceptions of the impact of teacher student race match

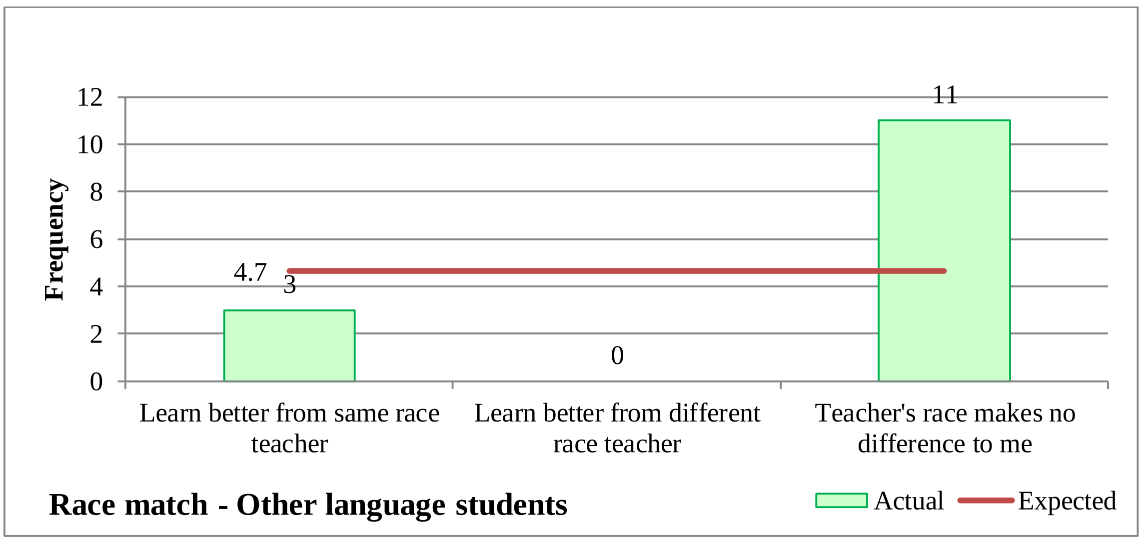


Figure 4-25 Other language student perceptions of the impact of teacher student race match

Each group of students (English, African Language and Other) indicated that the race of the teacher is not important ($p<.0005$, $p<.0005$, $p=.001$, respectively).

Student perceptions of the impact of teacher student home language match

The following figures present the survey results in respect of student perceptions of the impact of teacher student home language match (the results are separated by student home language):

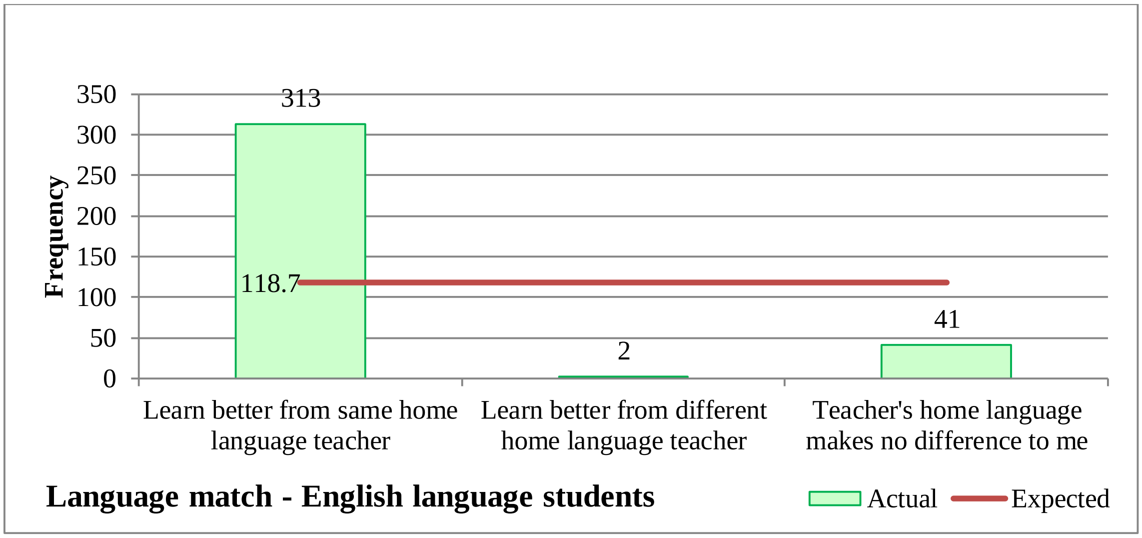


Figure 4-26 English language student perceptions of the impact of teacher student home language match

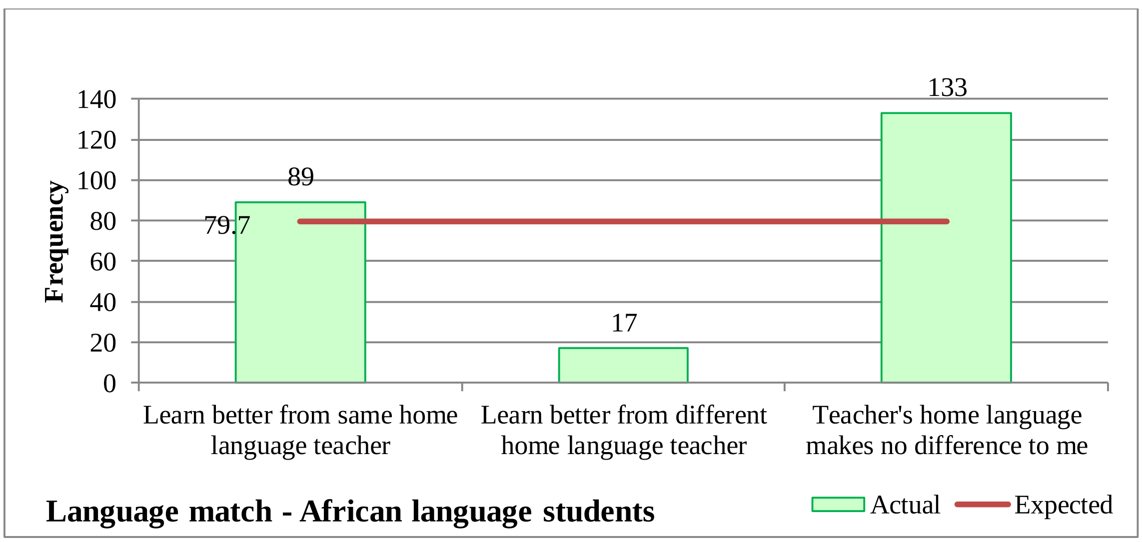


Figure 4-27 African language student perceptions of the impact of teacher student home language match

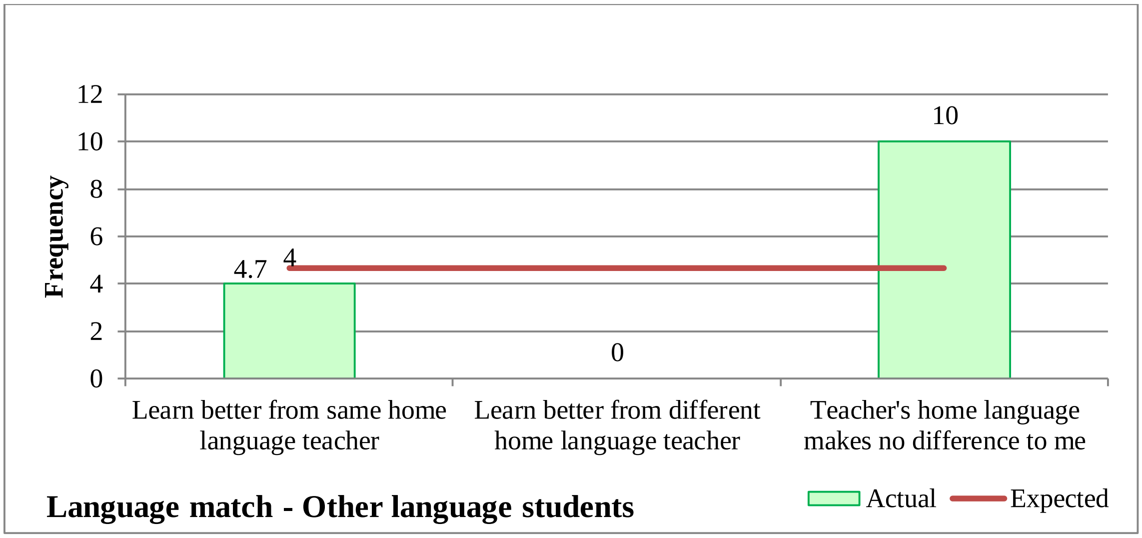


Figure 4-28 Other language student perceptions of the impact of teacher student home language match

For the English home language students, learning from a same home language teacher is clearly important (p<.0005).

African home language students selected ‘learn better from different home language teacher’ significantly less often than expected and ‘no difference’ significantly more often than expected (p<.0005).

Other language students selected ‘no difference’ significantly more often than expected (p=.003).

Student perceptions of the impact of being taught in the student’s home language

The following figures present the survey results in respect of student perceptions of the impact of being taught in the student’s home language (the results are separated by student home language):

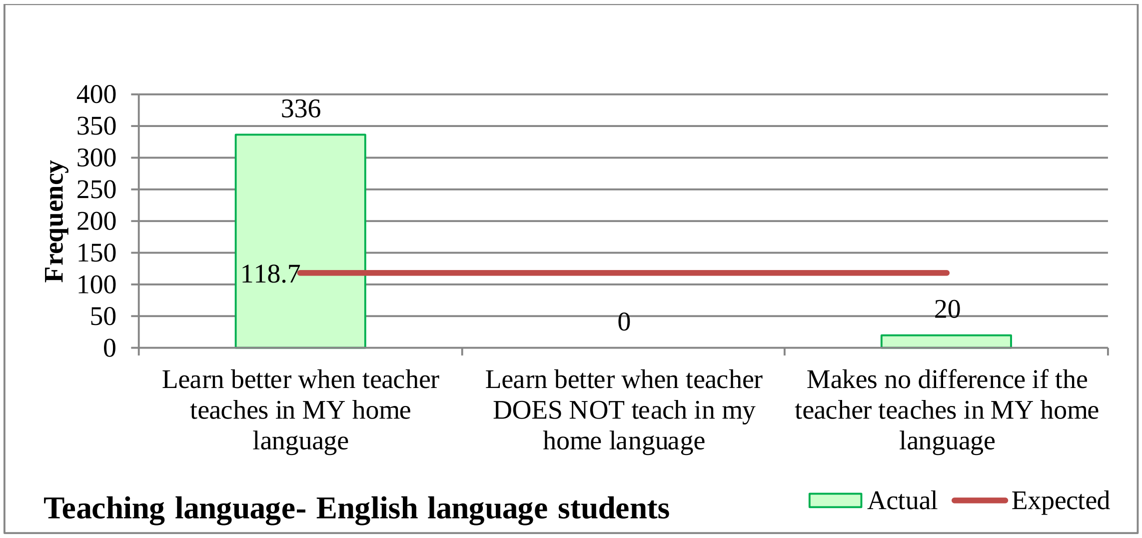


Figure 4-29 English language student perceptions of the impact of being taught in the student's home language

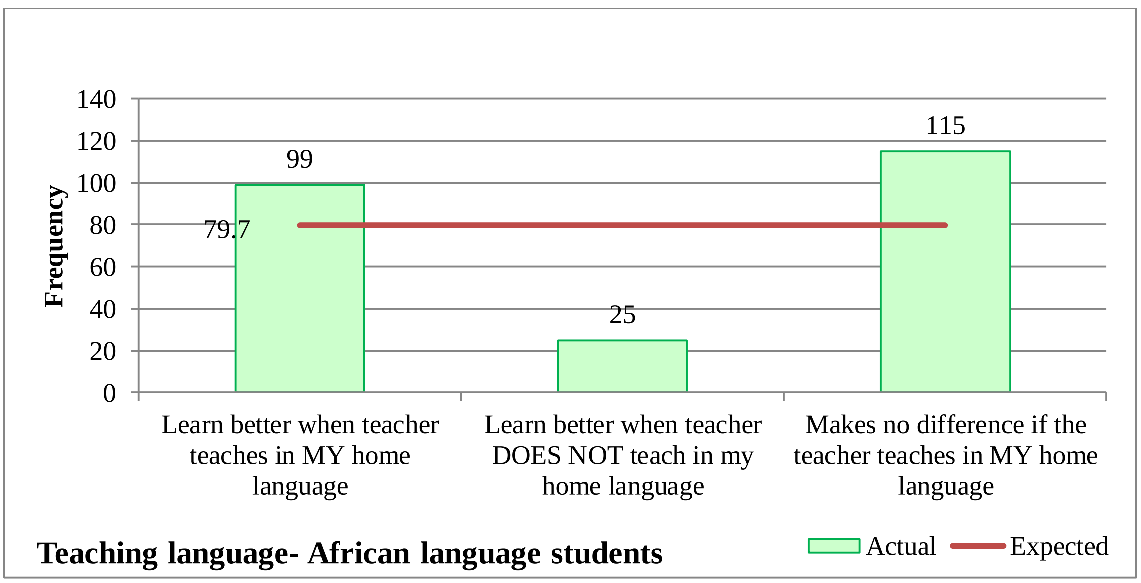


Figure 4-30 African language student perceptions of the impact of being taught in the student's home language

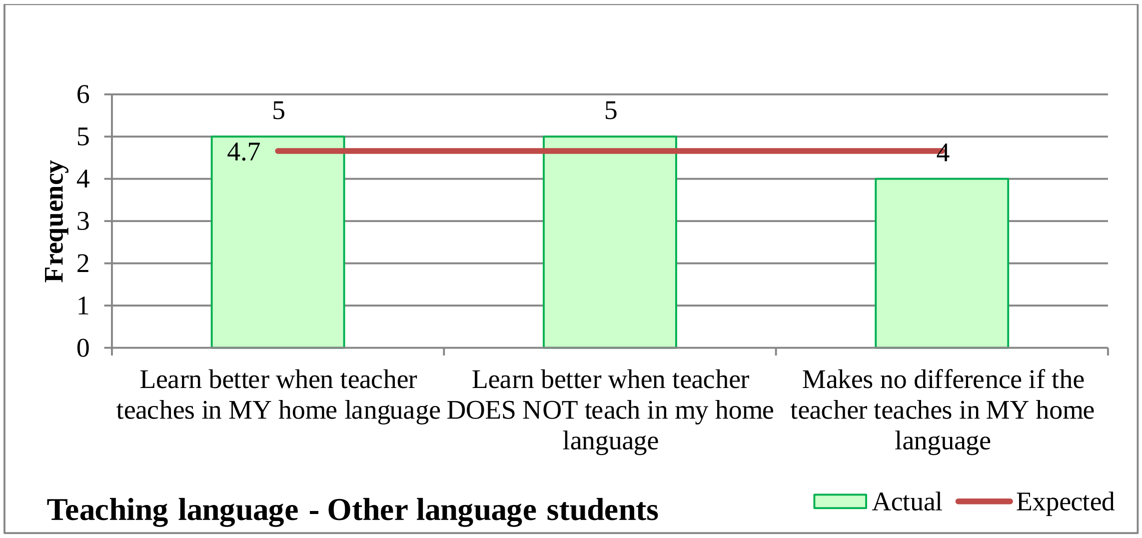


Figure 4-31 Other language student perceptions of the impact of being taught in the student's home language

English home language students selected 'better in my home language' significantly ($p<.0005$) more often than expected. African language students selected 'better not in home language' significantly more often than expected ($p<.0005$). Other language students did not select any of the options significantly more than the others ($p=.931$).

4.2.3.2.a.3 Results by gender

Student perceptions of the impact of teacher student gender match

The following figures present the survey results in respect of student perceptions of the impact of teacher student gender match (the results are separated by gender):

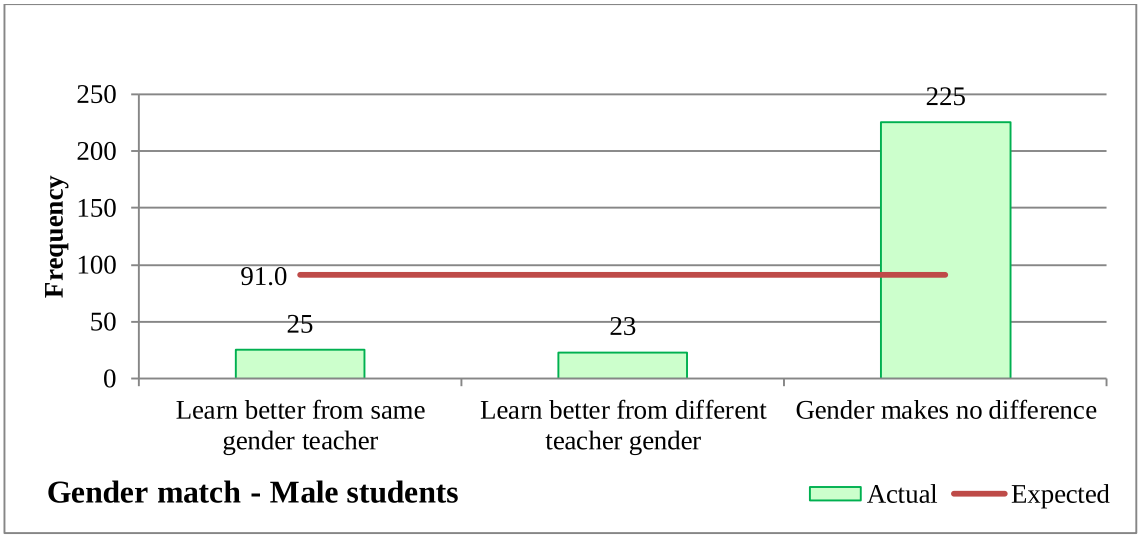


Figure 4-32 Male student perceptions of the impact of teacher student gender match

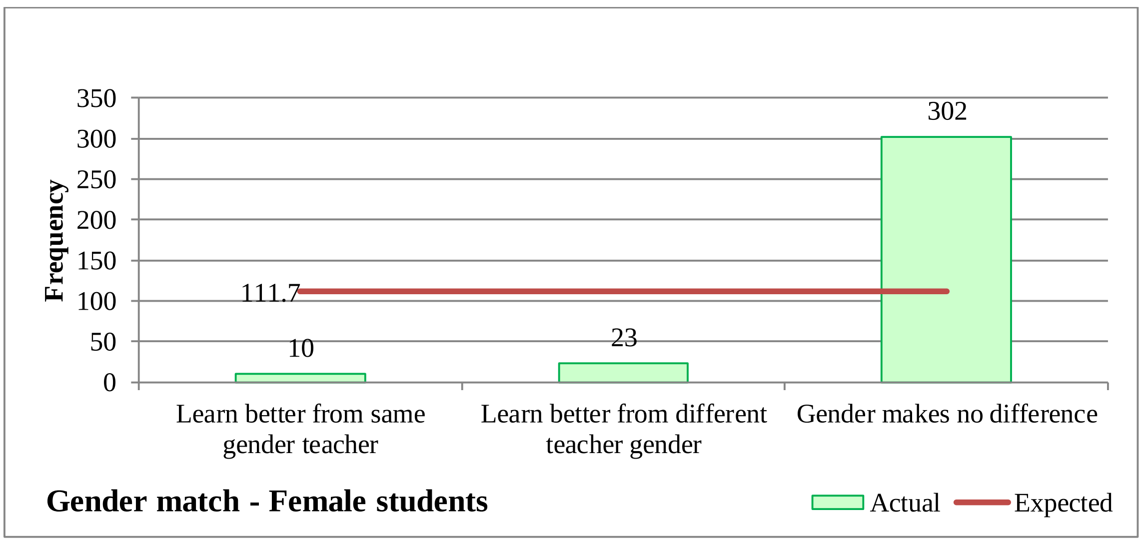


Figure 4-33 Female student perceptions of the impact of teacher student gender match

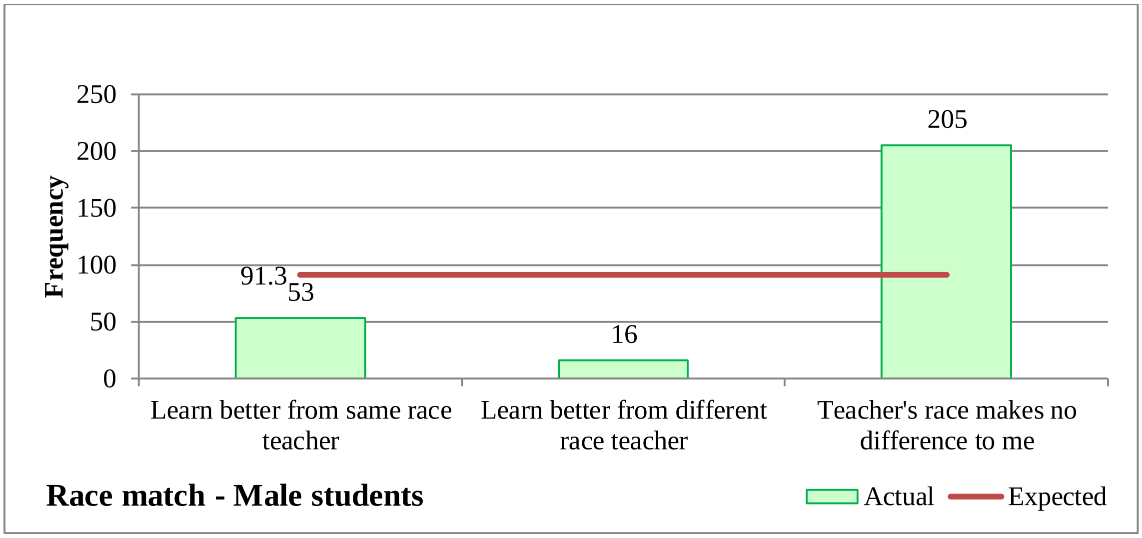


Figure 4-34 Male student perceptions of the impact of teacher student race match

Both male and female significantly selected ‘gender makes no difference’ more often than expected ($p<.0005$; $p<.0005$).

Student perceptions of the impact of teacher student race match

The following figures present the survey results in respect of student perceptions of the impact of teacher student race match (the results are separated by student gender):

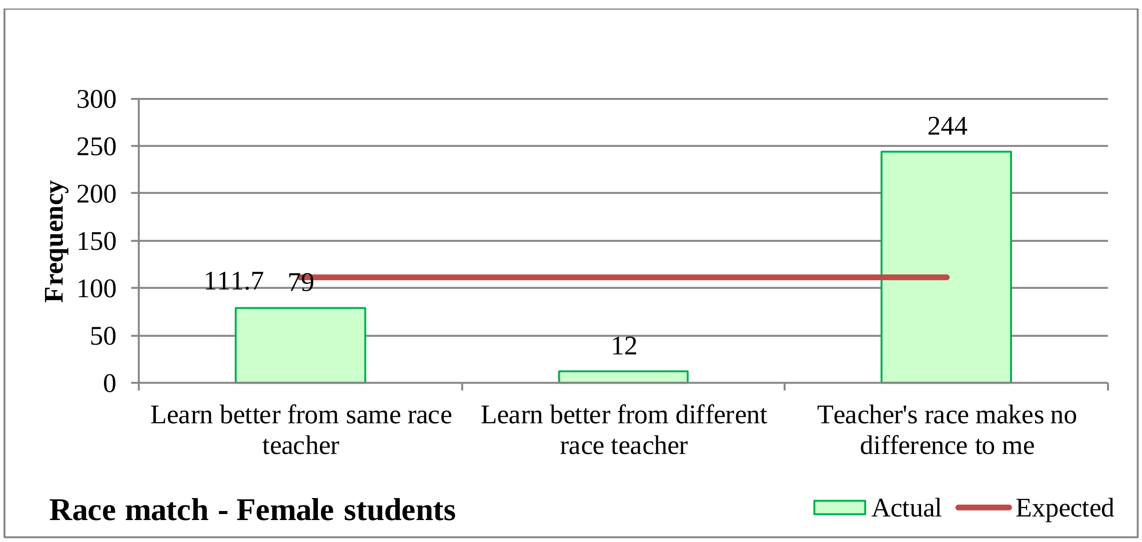


Figure 4-35 Female student perceptions of the impact of teacher student race match

Both male and female significantly selected ‘race makes no difference’ more often than expected ($p<.0005$; $p<.0005$).

Student perceptions of the impact of teacher student home language match

The following figures present the survey results in respect of student perceptions of the impact of teacher student home language match (the results are separated by gender):

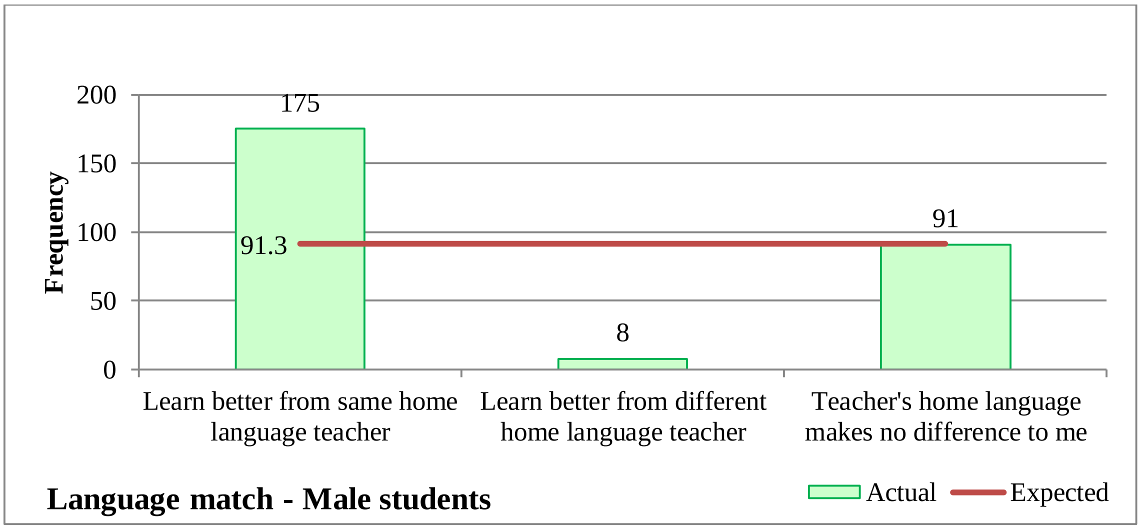


Figure 4-36 Male student perceptions of the impact of teacher student home language match

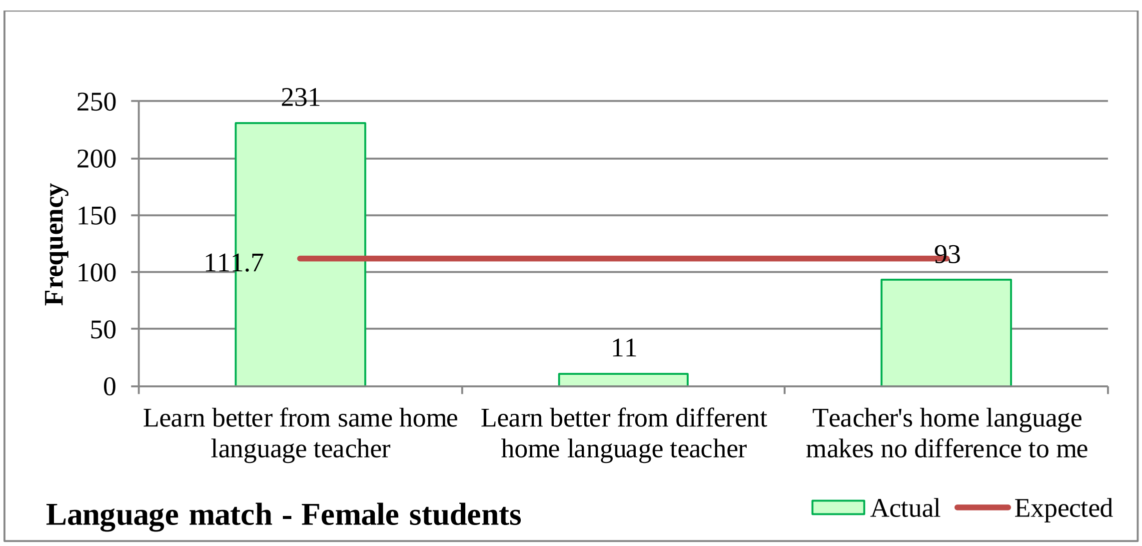


Figure 4-37 Female student perceptions of the impact of teacher student home language match

Both male and female significantly selected ‘learn better from same home language teacher’ more often than expected ($p<.0005$; $p<.0005$).

Student perceptions of the impact of being taught in the student’s home language

The following figures present the survey results in respect of student perceptions of the impact of being taught in the student’s home language (the results are separated by gender):

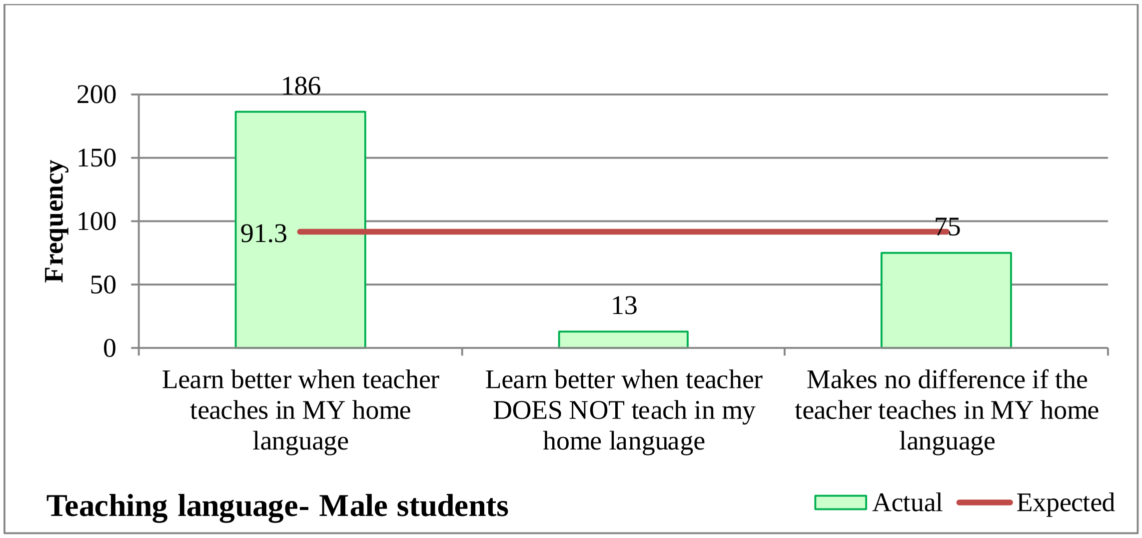


Figure 4-38 Male student perceptions of the impact of being taught in the student’s home language

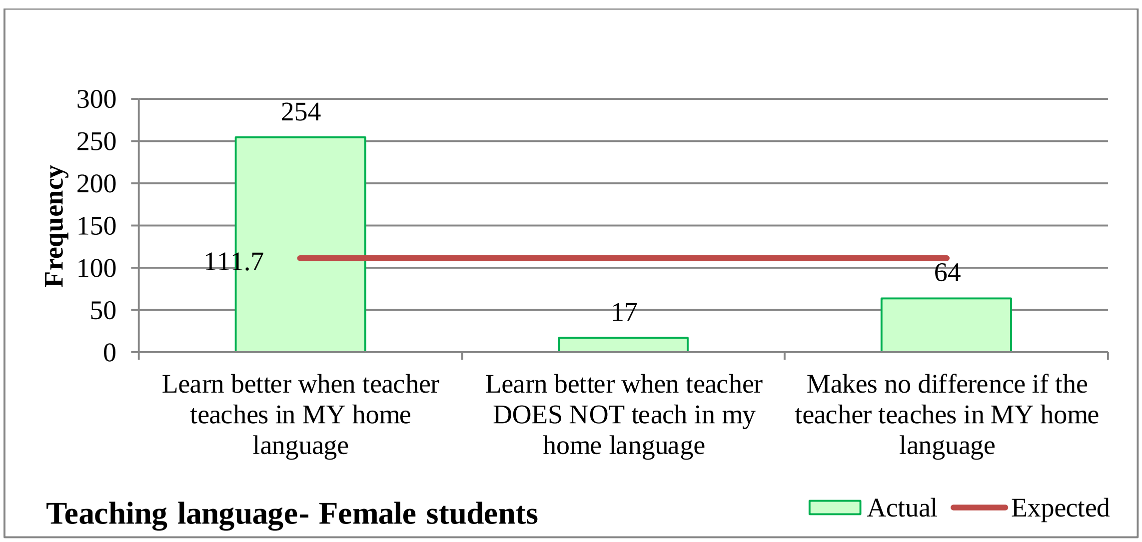


Figure 4-39 Female student perceptions of the impact of being taught in the student’s home language

Both male and female significantly selected 'learn better when taught in my home language' more often than expected (p<.0005; p<.0005).

4.2.3.2.b Analysis

Relationships between demographic variables and 'teacher' questions

A Chi-square test of independence was applied to the cross-tabulation of student gender, race and home language with each of the four 'teacher' questions in order to ascertain whether a significant relationship exists between the demographic variable and the responses to the specific 'teacher' question. Under the null hypothesis, there is no relationship between the two variables.

An analysis of the relationships between demographic variables and 'teacher' questions are presented below for each question:

'Which of the following is true about your teacher's gender?'

By Gender

		True about teacher's gender			
% within Gender		Learn better from same gender teacher	Learn better from different teacher gender	Gender makes no difference	Total
Gender	Male	9.2%	8.4%	82.4%	100.0%
	Female	3.0%	6.9%	90.1%	100.0%
Total		5.8%	7.6%	86.7%	100.0%

Table 4-64 Student perceptions of impact of teacher's gender on learning (by gender)

With reference to Table 4-64, a significant (p=.003) relationship existed between student gender and the responses to this question. In terms of expected proportions (Total), significantly more males (and fewer females) than expected selected the first response option ('I learn better from a teacher who is of the same gender as me.').

By Race

% within Race - grouped		True about teacher's gender: Learn better from same gender teacher	Learn better from different teacher gender	Gender makes no difference	Total
Race - grouped	Black	4.9%	6.5%	88.6%	100.0%
	Asian	5.8%	7.8%	86.4%	100.0%
	Other	9.1%	10.9%	80.0%	100.0%
Total		5.8%	7.6%	86.7%	100.0%

Table 4-65 Student perceptions of impact of teacher's gender on learning (by race)

With reference to Table 4-65, no significant relationship existed between student race and responses to this question (p=.567).

By Home Language

% within Home Language		True about teacher's gender: Learn better from same gender teacher	Learn better from different gender teacher	Gender makes no difference	Total
Home Language	English	6.2%	7.6%	86.2%	100.0%
	African Languages	4.6%	7.6%	87.8%	100.0%
	Other	14.3%	7.1%	78.6%	100.0%
Total		5.8%	7.6%	86.7%	100.0%

Table 4-66 Student perceptions of impact of teacher's gender on learning (by home language)

With reference to Table 4-66, no significant relationship existed between student home language and responses to this question (p=.663).

'Which of the following is true about your teacher's race?'

By Gender

% within Gender		True about teacher's race: Learn better from same race teacher	Learn better from different race teacher	Teacher's race makes no difference to me	Total
Gender	Male	19.3%	5.8%	74.8%	100.0%
	Female	23.6%	3.6%	72.8%	100.0%
Total		21.7%	4.6%	73.7%	100.0%

Table 4-67 Student perceptions of impact of teacher's race on learning (by gender)

With reference to Table 4-67, no significant relationship existed between student gender and responses to this question (p=.223).

By Race

% within Race - grouped		True about teacher's race: Learn better from same race teacher	Learn better from different race teacher	Teacher's race makes no difference to me	Total
Race - grouped	Black	17.9%	7.3%	74.8%	100.0%
	Asian	25.3%	2.3%	72.4%	100.0%
	Other	18.2%	5.5%	76.4%	100.0%
Total		21.7%	4.6%	73.7%	100.0%

Table 4-68 Student perceptions of impact of teacher's race on learning (by race)

With reference to Table 4-68, a significant (p=.003) relationship existed between student race and the responses to this question. More than expected Black students chose option 2 ('I learn better from a teacher who is not of the same race as me'). More than expected Asians chose option 1 ('I learn better from a teacher who is of the same race as me.'). Fewer than expected Asians chose option 2 ('I learn better from a teacher who is not of the same race as me').

By Home Language

% within Home Language		True about teacher's race: Learn better from same race teacher	Learn better from different race teacher	Teacher's race makes no difference to me	Total
Home Language	English	24.2%	2.5%	73.3%	100.0%
	African Languages	18.0%	7.9%	74.1%	100.0%
	Other	21.4%		78.6%	100.0%
Total		21.7%	4.6%	73.7%	100.0%

Table 4-69 Student perceptions of impact of teacher's race on learning (by home language)

With reference to Table 4-69, a significant (p=.015) relationship existed between student home language and the responses to this question. More than expected African Language students chose option 2 ('I learn better from a teacher who is not of the same race as me'). Fewer than expected English speakers chose option 2 ('I learn better from a teacher who is not of the same race as me').

'Which of the following is true about your teacher's home language?'

By Gender

% within Gender		True about teacher's Home Language: Learn better from same Home Language teacher	Learn better from different Home Language teacher	Teacher's Home Language makes no difference to me	Total
Gender	Male	63.9%	2.9%	33.2%	100.0%
	Female	69.0%	3.3%	27.8%	100.0%
Total		66.7%	3.1%	30.2%	100.0%

Table 4-70 Student perceptions of impact of teacher's home language on learning (by gender)

With reference to Table 4-70, no significant relationship existed between student gender and responses to this question (p=.345)

By Race

% within Race - grouped		True about teacher's Home Language: Learn better from same Home Language teacher	Learn better from different Home Language teacher	Teacher's Home Language makes no difference to me	Total
Race - grouped	Black	36.6%	6.9%	56.5%	100.0%
	Asian	88.0%		12.0%	100.0%
	Other	81.8%	3.6%	14.5%	100.0%
Total		66.7%	3.1%	30.2%	100.0%

Table 4-71 Student perceptions of impact of teacher's home language on learning (by race)

With reference to Table 4-71, a significant ($p<.0005$) relationship existed between student race and the responses to this question. More than expected Black students chose option 2 ('I learn better from a teacher whose home language is not the same as mine'). More than expected Asians chose option 1 ('I learn better from a teacher whose home language is the same as mine'). Fewer than expected Asians chose option 2 ('I learn better from a teacher whose home language is not the same as mine).

By Home Language

% Home Language		True about teacher's Home Language: Learn better from same Home Language teacher	Learn better from different Home Language teacher	Teacher's Home Language makes no difference to me	Total
Home Language	English	87.9%	.6%	11.5%	100.0%
	African Languages	37.2%	7.1%	55.6%	100.0%
	Other	28.6%		71.4%	100.0%
Total		66.7%	3.1%	30.2%	100.0%

Table 4-72 Student perceptions of impact of teacher's home language on learning (by home language)

With reference to Table 4-72, a significant ($p<.0005$) relationship existed between student home language and the responses to this question. More than expected African language students chose option 2 ('I learn better from a teacher whose home language is not the same as mine'). More than expected English speakers chose option 1 ('I learn better from a teacher whose home language is the same as mine'). Fewer than expected English speakers chose option 2 ('I learn better from a teacher whose home language is not the same as mine).

'Which of the following is true about your teacher speaking your home language while teaching you?'

By Gender

% within Gender		True about teacher speaking Home Language while teaching			
		Learn better when teacher speaks my Home Language	Learn better when teacher does not speak my Home Language	Makes no difference if the teacher teaches in my Home Language	Total
Gender	Male	67.9%	4.7%	27.4%	100.0%
	Female	75.8%	5.1%	19.1%	100.0%
Total		72.2%	4.9%	22.8%	100.0%

Table 4-73 Student perceptions of impact of language of instruction on learning (by gender)

With reference to Table 4-73, no significant relationship existed between student gender and responses to this question (p=.053).

By Race

% within Race - grouped		True about teacher speaking Home Language while teaching			
		Learn better when teacher speaks my Home Language	Learn better when teacher does not speak my Home Language	Makes no difference if the teacher teaches in my Home Language	Total
Race - grouped	Black	41.1%	11.0%	48.0%	100.0%
	Asian	93.5%	.3%	6.2%	100.0%
	Other	92.7%	3.6%	3.6%	100.0%
Total		72.2%	4.9%	22.8%	100.0%

Table 4-74 Student perceptions of impact of language of instruction on learning (by race)

With reference to Table 4-74, a significant (p<.0005) relationship exists between student race and the responses to this question. Fewer than expected Black students chose option 1 ('I learn better when my teacher speaks my home language while teaching me'). More than expected Asians chose option 1 ('I learn better when my teacher speaks my home language while teaching me'). Fewer than expected Asians chose option 2 ('I learn better when my teacher does not speak my home language while teaching me').

By Home Language

% within Home Language		True about teacher speaking Home Language while teaching: Learn better when teacher speaks my Home Language	Learn better when teacher does not speak my home language	Makes no difference if the teacher teaches in my Home Language	Total
Home Language	English	94.4%		5.6%	
	African Languages	41.4%	10.5%	48.1%	100.0%
	Other	35.7%	35.7%	28.6%	100.0%
Total		72.2%	4.9%	22.8%	100.0%

Table 4-75 Student perceptions of impact of language of instruction on learning (by home language)

With reference to Table 4-75, a significant (p<.0005) relationship exists between student home language and the responses to this question. Fewer than expected African language students chose option 1 ('I learn better when my teacher speaks my home language while teaching me'). More than expected English speakers chose option 1 ('I learn better when my teacher speaks my home language while teaching me'). Fewer than expected English speakers chose option 2 ('I learn better when my teacher does not speak my home language while teaching me').

4.2.3.2.c Summary of findings for cohort one

Gender - Male and Female

- Although a significant number of males and females indicated that the gender of the teacher is not important, when analysing males and females together, more males than were expected said they preferred to be taught by a male.
- Neither males nor females showed any significant preference in terms of teacher race and home language, or the language of instruction.

Race - Blacks, Asians and Others

- All race groups indicated significantly that the gender of the teacher is not important. When analysed together, there was no difference in their responses regarding gender.
- All race groups indicated significantly that the race of the teacher was not important. However, when analysed together, significantly more than expected Black students indicated they learnt better from a teacher of a different race, and more than expected Asians indicated they learnt better from a teacher of Asian race and not from a different race.
- Black students indicated that their teacher's home language made no difference to them. Asians and Other Race students preferred teachers who spoke their home language. When analysing the races together, more than expected Black students did not mind about the home language, and more than expected Asians preferred teachers whose home language was the same as theirs.
- Asian and Other Race students definitely preferred to be taught in their home language. A higher than expected number of Black students responded that they either preferred not to be taught in their home language or that being taught in their home language made no difference. A significantly lower proportion of Black students compared to Asian and Other Race students responded that they preferred to be taught in their home language. In short, Black students did not believe they learnt better in their home language.

Home language – English, African Languages and other

- All home language groups indicated significantly that the gender of the teacher is not important. When analysed together, there was no difference in their response regarding gender.
- All home language groups indicated significantly that the race of the teacher was not important. When analysed together, more than expected English speaking students said they did not learn better from a teacher of a different race and more than expected African speaking students did believe they learn better from a teacher of a different race.
- English home language students preferred to learn from an English speaking teacher. African students did not think they learnt better from teachers of a different home language to them, but some also believed that home language is not important. Other home language students did not think home language matters. Analysed together, more than expected English speaking students indicated they learnt better from a teacher with their own home language,

and more than expected African language students said the teacher's home language is not important.

- English students definitely wanted to be taught in English. African students preferred not to be taught in their home language. Analysed together, English students preferred to be taught in English whereas African students did not mind what language they were taught in. Fewer than expected African Language speaking students said they wanted to be taught in their own home language and Other Language students said they learn better when they were not taught in their home language.

4.2.3.3 Cohorts two and three

The following sections present the results of employing GEE models to investigate the effects of CTSE on student test scores (phase 1), followed by a further analysis of the CTSE data using higher order statistical methods (phase 2).

4.2.3.3.a Phase 1: GEE analysis

The following analyses (Table 4-76 to Table 4-84) present the results of applying a Generalized Estimating Equations (GEE) model to the datasets representing cohorts two and three (Institutions 1 and 2 respectively) to explore the effects of both student and teacher collective teaching self-efficacy (CTSE) on student test scores, both as a direct independent variable and as a moderating variable that affects the strength of the match → test score effect.

For the analyses that follow, a subset of the total dataset for cohorts two and three were extracted on the basis of those students and teachers who completed the collective teaching self-efficacy surveys from each institution. Two separate analyses are conducted- one with the total collective teaching self-efficacy (CTSE) score as independent variable and the student's z-score as the dependent variable (see *Figure 3-7 CTSE as a direct predictor of test score*); the other with the CTSE score acting as a moderating variable to the match → z-score effect (see *Figure 3-8 CTSE as a moderating variable*).

Direct effect of collective teaching self-efficacy on student scores

First, the direct effect of student and teacher collective teaching self-efficacy on student academic performance is explored (as per *Figure 3-7 CTSE as a direct predictor of test score*).

Table 4-76 to Table 4-84 show the results from Institutions 1 and 2 of applying the GEE model to identify the direct effect of student and teacher collective teaching self-efficacy on student academic performance.

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.402	.1717	-.739	-.066	5.494	1	.019
Race Match	.073	.0573	-.040	.185	1.608	1	.205
Race Mismatch	0[b]	.	.	.	.	.	.
StCTSER	.064	.0280	.010	.119	5.309	1	.021*
TCTSER	.041	.0299	-.018	.099	1.856	1	.173 ns
(Scale)	.933						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchRace, StCTSER, TCTSER
a. Institution_ID = Institution 1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-76 CTSE direct effect on test score (Institution 1, race)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.074	.1403	-.201	.349	.276	1	.600
Race Match	.002	.0604	-.117	.120	.001	1	.975
Race Mismatch	0[b]	.	.	.	.	.	.
StCTSER	.055	.0243	.007	.103	5.099	1	.024*
TCTSER	-.009	.0196	-.047	.030	.195	1	.659 ns
(Scale)	.674						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchRace, StCTSER, TCTSER
a. Institution_ID = Institution 2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-77 CTSE direct effect on test score (Institution 2, race)

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.108	.1059	-.315	.100	1.039	1	.308
Race Match	.072	.0416	-.010	.153	2.981	1	.084
Race Mismatch	0[a]	.	.	.	.	.	.
StCTSER	.049	.0188	.012	.086	6.672	1	.010**
TCTSER	.006	.0159	-.025	.037	.151	1	.697 [ns]
(Scale)	.829						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchRace, StCTSER, TCTSER
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-78 CTSE direct effect on test score (combined institutions, race)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.295	.1799	-.648	.057	2.691	1	.101
Home Language Match	.328	.0587	.212	.443	31.082	1	.000
Home Language Mismatch	0[b]	.	.	.	.	.	.
StCTSEHL	.085	.0286	.029	.141	8.748	1	.003**
TCTSEHL	-.032	.0323	-.096	.031	.996	1	.318 [ns]
(Scale)	.910						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchHomeLanguage, StCTSEHL, TCTSEHL
a. Institution_ID = Institution 1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-79 CTSE direct effect on test score (Institution 1, home language)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.024	.1253	-.222	.269	.036	1	.849
Home Language Match	.059	.0602	-.059	.177	.967	1	.326
Home Language Mismatch	0[b]	.	.	.	.	.	.
StCTSEHL	.066	.0263	.015	.118	6.318	1	.012*
TCTSEHL	-.011	.0172	-.045	.023	.416	1	.519[ns]
(Scale)	.672						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchHomeLanguage, StCTSEHL, TCTSEHL
a. Institution_ID = Institution 2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-80 CTSE direct effect on test score (Institution 2, home language)

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.045	.1034	-.248	.158	.190	1	.663
Home Language Match	.199	.0427	.115	.282	21.610	1	.000
Home Language Mismatch	0[a]	.	.	.	.	.	.
StCTSEHL	.054	.0196	.015	.092	7.558	1	.006**
TCTSEHL	-.024	.0159	-.055	.007	2.318	1	.128 [ns]
(Scale)	.822						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchHoeLanguage, StCTSEHL, TCTSEHL
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-81 CTSE direct effect on test score (combined institutions, home language)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	-.177	.1985	-.566	.212	.794	1	.373
Gender Match	.029	.0524	-.073	.132	.312	1	.576
Gender Mismatch	0[b]	.	.	.	.	.	.
StCTSEG	.040	.0262	-.012	.091	2.284	1	.131 [ns]
TCTSEG	.012	.0392	-.065	.089	.099	1	.753 [ns]
(Scale)	.937						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchGender, StCTSEG, TCTSEG
a. Institution_ID = Institution 1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-82 CTSE direct effect on test score (Institution 1, gender)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.198	.1247	-.046	.443	2.534	1	.111
Gender Match	-.123	.0520	-.224	-.021	5.564	1	.018
Gender Mismatch	0[b]	.	.	.	.	.	.
StCTSEG	.052	.0235	.006	.098	4.995	1	.025*
TCTSEG	-.020	.0171	-.053	.014	1.347	1	.246 [ns]
(Scale)	.670						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchGender, StCTSEG, TCTSEG
a. Institution_ID = Institution 2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-83 CTSE direct effect on test score (Institution 2, gender)

Parameter Estimates

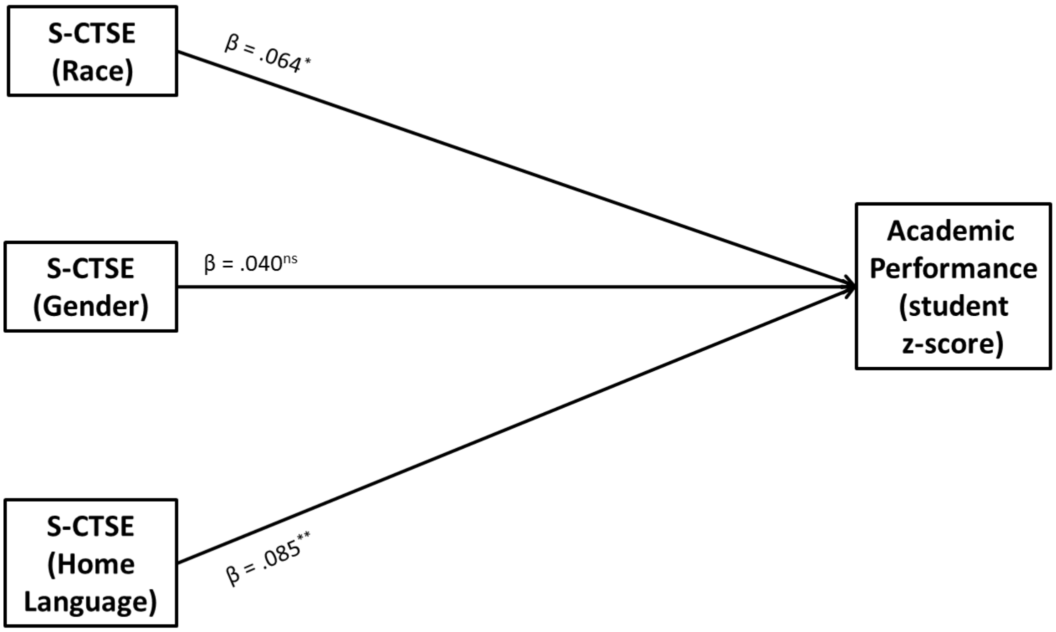
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	.022	.1018	-.177	.222	.048	1	.827
Gender Match	-.007	.0377	-.081	.066	.038	1	.845
Gender Mismatch	0[a]	.	.	.	.	.	.
StCTSEG	.045	.0180	.010	.080	6.302	1	.012*
TCTSEG	-.016	.0158	-.047	.015	1.029	1	.310 [ns]
(Scale)	.830						

Dependent Variable: Student Test Score (z-Score)
Model: (Intercept), TeacherStudentMatchGender, StCTSEG, TCTSEG
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-84 CTSE direct effect on test score (combined institutions, gender)

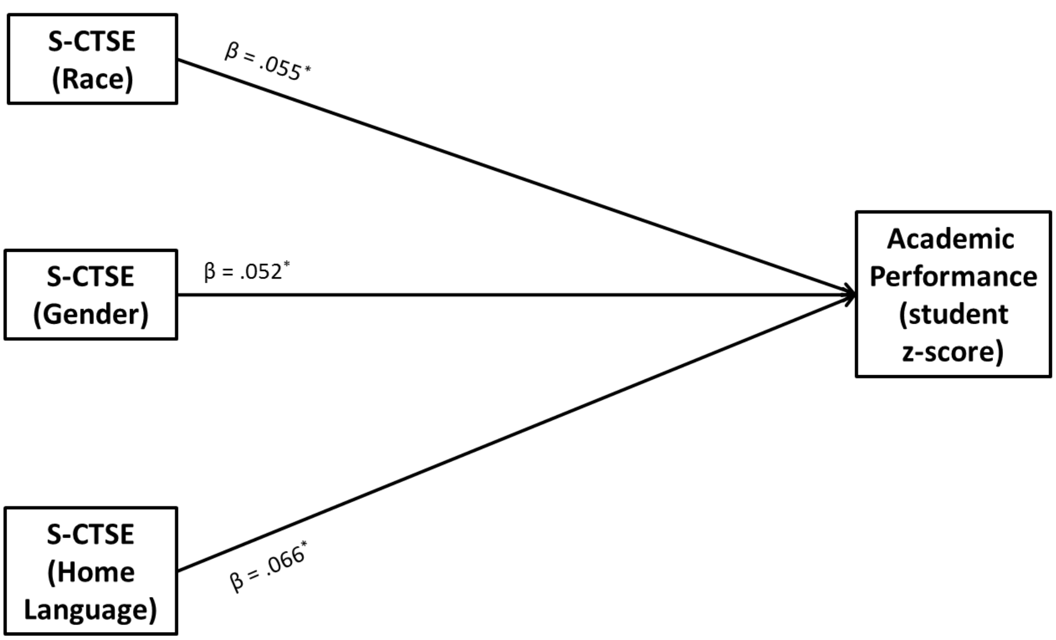
Table 4-76 to Table 4-84 indicate statistically significant effects on test score for student collective teaching self-efficacy. Teacher collective teaching self-efficacy scores did not seem to be significant.

Figure 4-40 to Figure 4-45 show the match effects from Table 4-76 to Table 4-84 in the form of path diagrams.



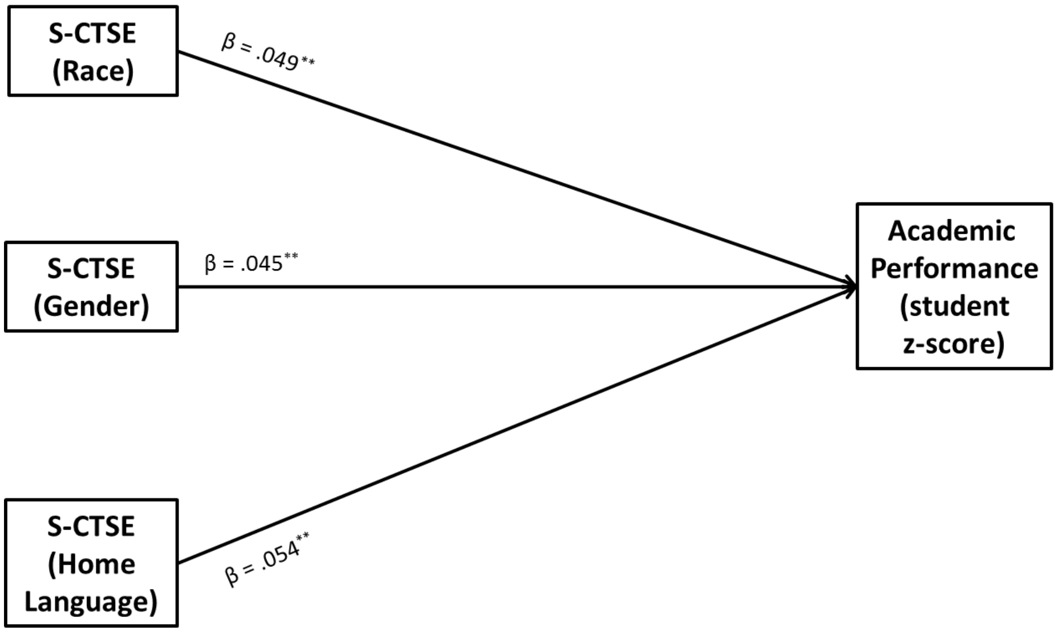
Notes:
-Institution 1
-All paths are standardised betas.
*** = p < .001, ** = p < .01, * = p <.05, ns = not significant (p > .05)

Figure 4-40 S-CTSE direct effect on test score (Institution 1)



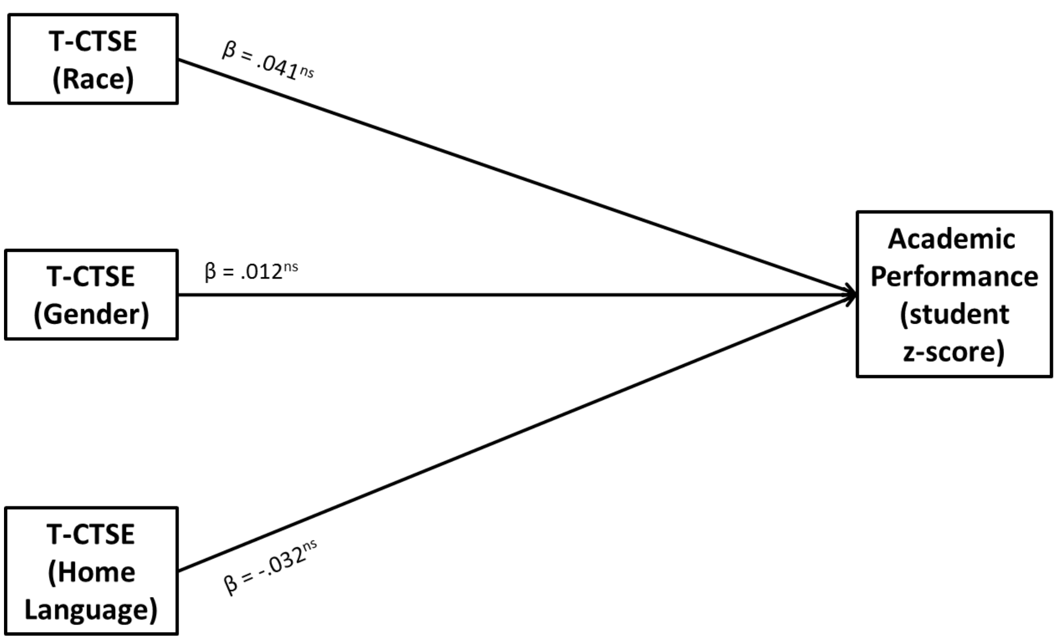
Notes:
-Institution 2
-All paths are standardised betas.
*** = p < .001, ** = p < .01, * = p <.05, ns = not significant (p > .05)

Figure 4-41 S-CTSE direct effect on test score (Institution 2)



Notes:
-Combined Institutions
-All paths are standardised betas.
*** = p < .001, ** = p < .01, * = p <.05, ns = not significant (p > .05)

Figure 4-42 S-CTSE direct effect on test score (combined institutions)



Notes:
-Institution 1
-All paths are standardised betas.
*** = p < .001, ** = p < .01, * = p <.05, ns = not significant (p > .05)

Figure 4-43 T-CTSE direct effect on test score (Institution 1)

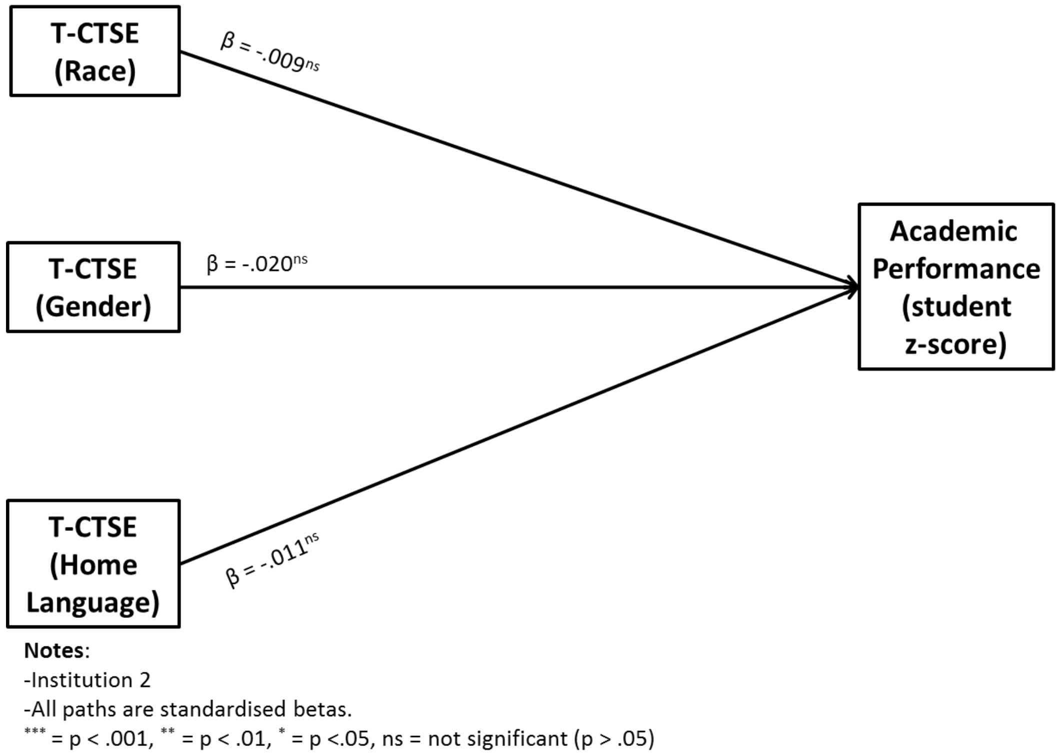


Figure 4-44 T-CTSE direct effect on test score (Institution 2)

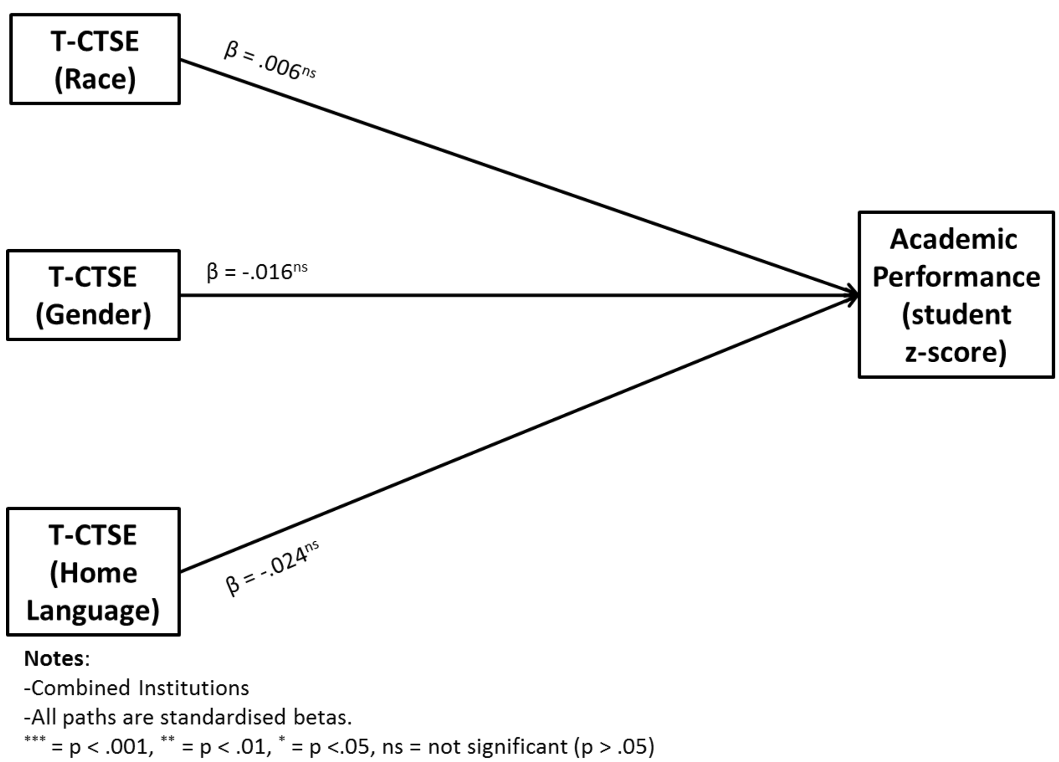


Figure 4-45 T-CTSE direct effect on test score (combined institutions)

The foregoing examined the direct effect of total student and teacher collective teaching self-efficacy (CTSE) scores on academic performance (see *Figure 3-7 CTSE as a direct predictor of test score*). The following explores the potential moderating effect of the CTSE score on the teacher student match → z-score effect (see *Figure 3-8 CTSE as a moderating variable*).

Collective teaching self-efficacy as a moderating variable on the match → student score effect

Table 4-85 to Table 4-93 show the results from Institutions 1 and 2 of applying the GEE interaction model (see *3.5.2.3 Data analysis models)* to explore the potential moderating effect of the CTSE score on the teacher student match → z-score effect.

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Race Match	-1.041	.2753	-1.581	-.502	14.301	1	.000
Race Mismatch	.141	.2014	-.253	.536	.494	1	.482
StCTSER	.052	.0333	-.014	.117	2.406	1	.121
TCTSER	-.082	.0374	-.155	-.008	4.759	1	.029
Race Match * StCTSER	.037	.0571	-.075	.149	.429	1	.512[ns]
Race Mismatch * StCTSER	0[b]	.	.	.	.	.	.
Race Match * TCTSER	.286	.0600	.168	.403	22.645	1	.000***
Race Mismatch * TCTSER	0[b]	.	.	.	.	.	.
(Scale)	.920						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchRace, StCTSER, TCTSER, TeacherStudentMatchRace * StCTSER, TeacherStudentMatchRace * TCTSER
a. Institution_ID = Institution1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-85 CTSE as a moderating variable (Institution 1, race)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Race Match	.054	.1491	-.239	.346	.130	1	.719
Race Mismatch	.122	.2054	-.281	.524	.351	1	.554
StCTSER	.056	.0367	-.016	.128	2.283	1	.131
TCTSER	-.020	.0281	-.075	.035	.518	1	.472
Race Match * StCTSER	-.001	.0483	-.096	.093	.001	1	.977 [ns]
Race Mismatch * StCTSER	0[b]	.	.	.	.	.	.
Race Match * TCTSER	.020	.0390	-.057	.096	.259	1	.611 [ns]
Race Mismatch * TCTSER	0[b]	.	.	.	.	.	.
(Scale)	.675						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchRace, StCTSER, TCTSER, TeacherStudentMatchRace * StCTSER, TeacherStudentMatchRace * TCTSER
a. Institution_ID = Institution2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-86 CTSE as a moderating variable (Institution 2, race)

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Race Match	-.164	.1359	-.431	.102	1.464	1	.226
Race Mismatch	.053	.1457	-.232	.339	.135	1	.714
StCTSER	.039	.0253	-.010	.089	2.401	1	.121
TCTSER	-.023	.0227	-.068	.021	1.068	1	.301
Race Match * StCTSER	.021	.0377	-.053	.094	.300	1	.584 [ns]
Race Mismatch * StCTSER	0[a]	.	.	.	.	.	.
Race Match * TCTSER	.054	.0318	-.008	.117	2.916	1	.088 [ns]
Race Mismatch * TCTSER	0[a]	.	.	.	.	.	.
(Scale)	.829						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchRace, StCTSER, TCTSER, TeacherStudentMatchRace * StCTSER, TeacherStudentMatchRace * TCTSER
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-87 CTSE as a moderating variable (combined institutions, race)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Home Language Match	-.302	.3361	-.961	.357	.809	1	.368
Home Language Mismatch	-.168	.2251	-.609	.273	.559	1	.455
StCTSEHL	.077	.0366	.005	.149	4.417	1	.036
TCTSEHL	-.057	.0371	-.130	.016	2.366	1	.124
Home Language Match * StCTSEHL	.014	.0591	-.102	.129	.053	1	.817 [ns]
Home Language Mismatch * StCTSEHL	0[b]	.	.	.	.	.	.
Home Language Match * TCTSEHL	.096	.0759	-.052	.245	1.610	1	.205 [ns]
Home Language Mismatch * TCTSEHL	0[b]	.	.	.	.	.	.
(Scale)	.909						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchHomeLanguage, StCTSEHL, TCTSEHL, TeacherStudentMatchHomeLanguage * StCTSEHL, TeacherStudentMatchHomeLanguage * TCTSEHL
a. Institution_ID = Institution1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-88 CTSE as a moderating variable (Institution 1, home language)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Home Language Match	-.153	.3099	-.761	.454	.245	1	.620
Home Language Mismatch	.081	.1374	-.189	.350	.344	1	.558
StCTSEHL	.047	.0297	-.011	.106	2.527	1	.112
TCTSEHL	-.006	.0186	-.043	.030	.113	1	.737
Home Language Match * StCTSEHL	.089	.0625	-.033	.212	2.049	1	.152 ns
Home Language Mismatch * StCTSEHL	0[b]	.	.	.	.	.	.
Home Language Match * TCTSEHL	-.017	.0462	-.108	.073	.141	1	.707 ns
Home Language Mismatch * TCTSEHL	0[b]	.	.	.	.	.	.
(Scale)	.672						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchHomeLanguage, StCTSEHL, TCTSEHL, TeacherStudentMatchHomeLanguage * StCTSEHL, TeacherStudentMatchHomeLanguage * TCTSEHL
a. Institution_ID = Institution2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-89 CTSE as a moderating variable (Institution 2, home language)

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Home Language Match	-.154	.2167	-.578	.271	.503	1	.478
Home Language Mismatch	.054	.1204	-.182	.290	.201	1	.654
StCTSEHL	.035	.0236	-.012	.081	2.168	1	.141
TCTSEHL	-.030	.0177	-.064	.005	2.794	1	.095
Home Language Match * StCTSEHL	.071	.0416	-.011	.152	2.899	1	.089 ns
Home Language Mismatch * StCTSEHL	0[a]	.	.	.	.	.	.
Home Language Match * TCTSEHL	.025	.0399	-.053	.103	.400	1	.527 ns
Home Language Mismatch * TCTSEHL	0[a]	.	.	.	.	.	.
(Scale)	.821						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchHomeLanguage, StCTSEHL, TCTSEHL, TeacherStudentMatchHomeLanguage * StCTSEHL, TeacherStudentMatchHomeLanguage * TCTSEHL
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-90 CTSE as a moderating variable (combined institutions, home language)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Gender Match	-.155	.2701	-.685	.374	.330	1	.565
Gender Mismatch	-.092	.2932	-.667	.482	.099	1	.753
StCTSEG	.082	.0363	.011	.153	5.153	1	.023
TCTSEG	-.055	.0636	-.180	.070	.745	1	.388
Gender Match * StCTSEG	-.081	.0518	-.182	.021	2.416	1	.120 ns
Gender Mismatch * StCTSEG	0[b]	.	.	.	.	.	.
Gender Match * TCTSEG	.110	.0803	-.048	.267	1.869	1	.172 ns
Gender Mismatch * TCTSEG	0[b]	.	.	.	.	.	.
(Scale)	.935						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchGender, StCTSEG, TCTSEG, TeacherStudentMatchGender * StCTSEG, TeacherStudentMatchGender * TCTSEG
a. Institution_ID = Institution1
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-91 CTSE as a moderating variable (Institution 1, gender)

Parameter Estimates[a]

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Gender Match	.153	.1361	-.114	.420	1.264	1	.261
Gender Mismatch	.007	.2169	-.418	.432	.001	1	.975
StCTSEG	.122	.0407	.042	.202	8.972	1	.003
TCTSEG	-.044	.0303	-.103	.016	2.078	1	.149
Gender Match * StCTSEG	-.102	.0493	-.199	-.006	4.293	1	.038*
Gender Mismatch * StCTSEG	0[b]	.	.	.	.	.	.
Gender Match * TCTSEG	.039	.0367	-.033	.111	1.154	1	.283 ns
Gender Mismatch * TCTSEG	0[b]	.	.	.	.	.	.
(Scale)	.668						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchGender, StCTSEG, TCTSEG, TeacherStudentMatchGender * StCTSEG, TeacherStudentMatchGender * TCTSEG
a. Institution_ID = Institution2
b. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-92 CTSE as a moderating variable (Institution 2, gender)

Parameter Estimates

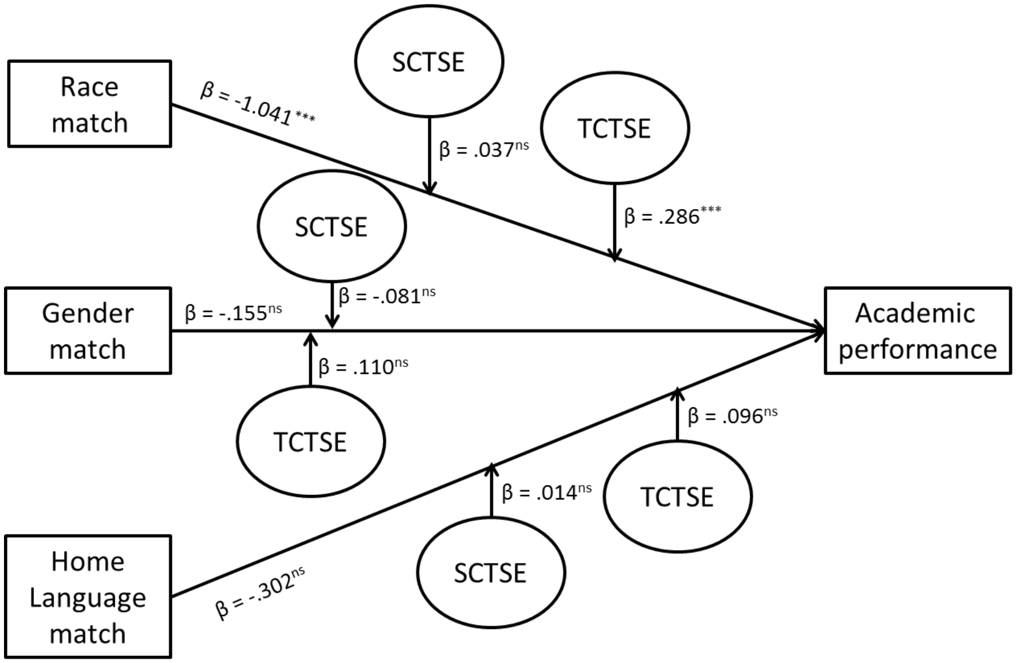
Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
Gender Match	.114	.1211	-.123	.351	.887	1	.346
Gender Mismatch	-.135	.1671	-.463	.193	.652	1	.419
StCTSEG	.100	.0278	.046	.155	12.943	1	.000
TCTSEG	-.034	.0286	-.090	.022	1.389	1	.239
Gender Match * StCTSEG	-.090	.0361	-.161	-.019	6.253	1	.012*
Gender Mismatch * StCTSEG	0[a]	.	.	.	.	.	.
Gender Match * TCTSEG	.030	.0342	-.037	.097	.772	1	.380 [ns]
Gender Mismatch * TCTSEG	0[a]	.	.	.	.	.	.
(Scale)	.829						

Dependent Variable: Student Test Score (z-Score)
Model: TeacherStudentMatchGender, StCTSEG, TCTSEG, TeacherStudentMatchGender * StCTSEG, TeacherStudentMatchGender * TCTSEG
a. Set to zero because this parameter is redundant.
ns = not significant at p=.05, * = significant at p<.05, ** = significant at p<,.01, *** p = significant at p<.001

Table 4-93 CTSE as a moderating variable (combined institutions, gender)

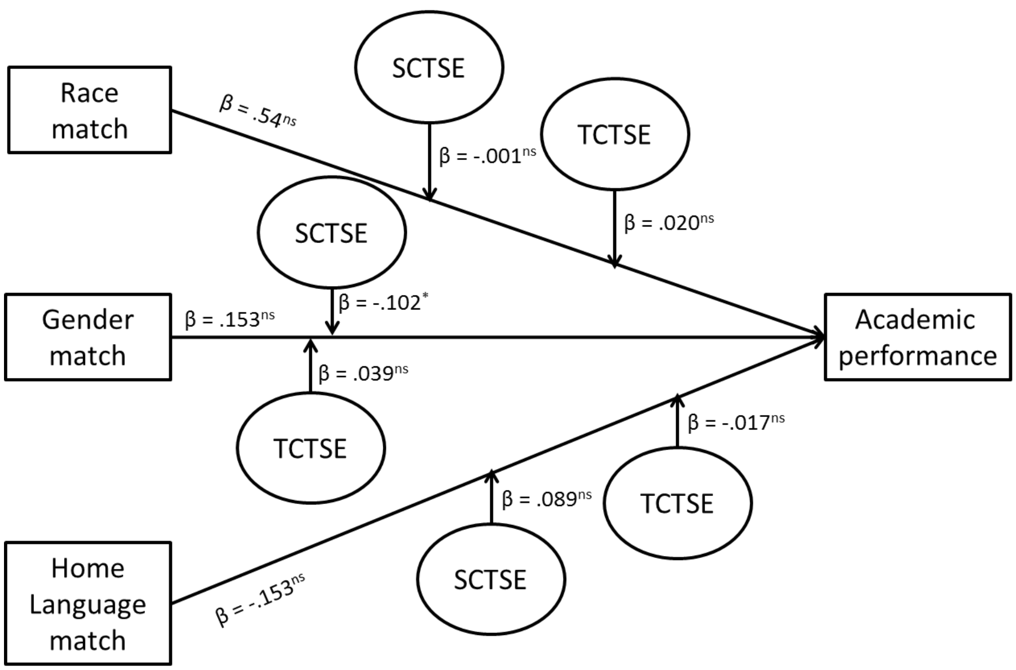
As shown in Table 4-85 to Table 4-93, applying the GEE interaction model to the cohort two and three data does not appear to show any significant interaction (moderation) effect of either S-CTSE or T-CTSE on the match → student z-score effect. This interaction effect will be explored further in the next section below using higher order statistical methods.

Figure 4-46 to Figure 4-48 show the match effects from Table 4-85 to Table 4-93 in the form of path diagrams.



Notes:
-Institution 1
-All paths are standardised betas.
*** = p < .001, ** = p < .01, * = p <.05, ns = not significant (p > .05)

Figure 4-46 CTSE as a moderating variable (Institution 1)



Notes:
-Institution 2
-All paths are standardised betas.
*** = p < .001, ** = p < .01, * = p <.05, ns = not significant (p > .05)

Figure 4-47 CTSE as a moderating variable (Institution 2)

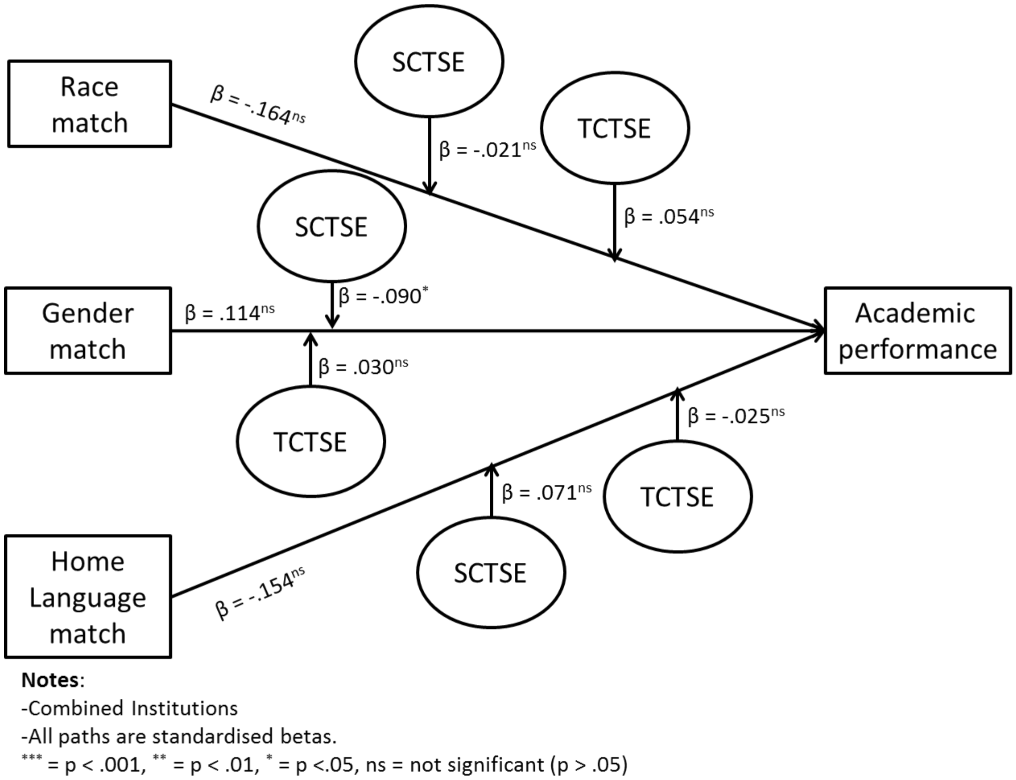


Figure 4-48 CTSE as a moderating variable (combined institutions)

The foregoing analyses utilized robust GEE models to show the effects of both student and teacher collective teaching self-efficacy (CTSE) on student test scores, both as a direct independent variable and as a moderating variable that affects the strength of the match → test score effect.

To further explore and confirm some of the results achieved in the foregoing analyses, the following section applies a variety of higher order statistical models to the cohort two and three datasets, including confirmatory factor analysis, structural equation modelling, and moderation analysis using variable interaction.

4.2.3.3.b Phase 2: Further analysis of the collective teaching self-efficacy effect using higher order statistical methods

The refined collective teaching self-efficacy (CTSE) measures were multi-item scales and therefore benefitted from analysis of factor structure (see Table 3-11). The following describes the analysis approach adopted in respect of both the student collective teaching self-efficacy (S-CTSE) and the teacher collective teaching self-efficacy (T-CTSE) data.

Factor structure for student collective teaching self-efficacy (S-CTSE) data

For the student data, confirmatory factor analysis (CFA) was employed to test the underlying factor structure. Diagnostic analysis indicated no serious issues with collinearity or heteroskedasticity and all univariate variables were normally distributed.

However, there existed substantial multivariate non-normality as indicated by the Mardia multivariate kurtosis score. Further analysis showed a straight Q-Q plot, with some large multivariate outliers causing the issues. Therefore, robust covariance analysis was employed using the SAS ROBCOV macro which successfully creates a robust Minimum Covariance Distance matrix (Rousseeuw & Van Driessen, 1990) for input into the structural equation model.

The resultant covariance matrix student data was shown to fit the confirmatory factor analysis model acceptably, as seen in Table 4-94 with Chi-square = 539.64(46) $p < .01$, SRMSR = .03, RMSEA = .088 (90% CI = .082-.095), CFI = .97, NNFI/TLI = .96. Table 4-94 also gives commonly used albeit debatable cut-offs for these fit indices, against which fit appears good. (Note that the significant chi-square is generally ignored due to large sample power effects, which would apply in this case given the sample of 1371).

		Commonly used Benchmarks for Index		
Index	**Index in CFA**	**Good**	**Acceptable**	**Bad**
χ^2	$539.64(46)^{***}$	Not sig	Sig in large sample	Sig in small sample
SRMSR	.03	< .05	< .08	> .10
RMSEA	.088	< .05	< .08	> .10
CFI	.97	> .95	> .90	< .90
TLI / NNFI	.96	> .95	> .90	< .90

Notes. N = 1371. Cut offs based on many SEM texts, e.g. Kline (2010). $^{***} = p < .01$

Table 4-94 Confirmatory factor analysis fit results

The PROC SCORE routine in SAS was subsequently employed to extract factor scores for each of the sub-factors (see *Appendix E: Student CFA output (SAS)*).

Factor structure for teacher collective teaching self-efficacy (T-CTSE) data

As indicated in Table 3-2, there were only 52 teachers in the combined group (cohort two and three) and twelve manifest variables. This was not enough to perform structural Kline (equation modelling (SEM) type analysis (Kline, 2010), as confirmed when attempted (unstable results ensued with Heywood cases- see *Appendix F: Teacher CFA output (SAS)*). Even when bounded to eliminate

Heywood cases, the analysis furthermore suggested extremely high inter-factor covariances, suggesting possibility of a one-factor solution (see *Appendix F: Teacher CFA output (SAS)*).

Instead of the CFA (Confirmatory Factor Analysis) approach, the stable and robust variable clustering technique was attempted (Anderberg, 1973, Harman, 1976, Harris & Kaiser, 1964). This technique also suggested a one-factor solution. Finally, the Cronbach alpha for all variables was .99, again suggesting a single factor.

Accordingly, a single teacher collective self-efficacy variable was produced using a simple arithmetic mean of the manifest variables (see *Appendix F: Teacher CFA output (SAS)*).

4.2.3.3.b.1 Self-efficacy across demographics

Table 4-95 shows the differences in student collective teaching self-efficacy (S-CTSE) scores across different demographics in students from this subset (those who completed the CTSE survey) for both cohorts.

Institution	Variable	Gender		Race			Languages	
		Female	Male	Black	White	Indian	English	African
1	SEX	-0.09	-0.01	-0.06	0.18	0.03	0.04	-0.07
1	IS	-0.08	-0.02	-0.02	0.04	-0.02	-0.01	-0.02
1	CM	-0.09	-0.01	-0.03	-0.02	-0.08	-0.07	-0.03
1	SEN	-0.08	-0.03	0.00	-0.16	-0.10	-0.09	0.00
2	SEX	-0.05	-0.28	-0.27	0.05	-0.15	-0.21	-0.23
2	IS	-0.04	-0.28	-0.25	0.01	-0.10	-0.20	-0.22
2	CM	-0.05	-0.29	-0.23	-0.10	-0.38	-0.30	-0.20
2	SEN	-0.05	-0.27	-0.18	-0.12	-0.29	-0.28	-0.16

Note: SEX=Subject Expertise, IS=Instructional Strategies, CM=Classroom Management, SEN=Student Engagement
[a] *African* refers to grouping of Zulu, Xhosa, Swazi, Ndebele, Southern Sotho, Northern Sotho, Tsonga, Tswana and Venda.

Table 4-95: Demographic differences in student collective teaching self-efficacy (S-CTSE) scores

In the case of teachers, only one summary collective teaching self-efficacy (T-CTSE) factor was extracted since sub-items are so strongly related (see *3.5.2.2.b Investigating student and teacher perceptions of collective self-efficacy*). Table 4-96 shows the scores for these between demographics.

Institution	Gender		Race			Languages	
	Female	Male	Black	White	Indian	English	African[a]
1	4.03	4.28	3.28	3.81	4.48	4.32	3.28
2	4.56	4.00	3.55	4.50	4.69	4.31	4.15

[a] *African* refers to grouping of Zulu, Xhosa, Swazi, Ndebele, Southern Sotho, Northern Sotho, Tsonga, Tswana and Venda.

Table 4-96: Demographic differences in teacher collective teaching self-efficacy (T-CTSE) scores

As is seen, differences do seem to exist. Recalling that the scale for this measure is 1-6, in both the samples Indian teachers scored highest and Black teachers lowest, while English speakers had higher efficacy. Gender effects differed, with males higher in Institution 1 but lower in Institution 2.

4.2.3.3.b.2 Self-efficacy as a predictor

Table 4-97, shows the effects of regressions using demographics and the sub-dimensions of student collective teaching self-efficacy as predictors of performance. As can be seen, there were no significant effects for either of the two institutions.

	Institution 1		Institution 2	
	B	SE	B	SE
Intercept	8.36*	4.45	18.21	10.11
Student age	-0.30	0.24	-.54	.50

Gender	-0.10	0.93	-2.06	1.31
Race	-3.93***	0.95	-1.42	1.77
Sex	2.92	1.78	-2.11	2.13
Is	-2.48	2.22	4.02	2.91
Cm	0.98	2.19	-2.56	2.92
Sen	0.67	1.85	1.86	2.31

Table 4-97: Regressions using student collective teaching self-efficacy (S-CTSE) factors as predictors of performance

Similar analyses using teacher collective teaching self-efficacy likewise found no significant effects either (see *Appendix G: Race TCTSE Moderation (Institution 2) output (SAS)*, *Appendix H: Home Language TCTSE Moderation (Institution 2) output (SAS)* and *Appendix I: Gender TCTSE Moderation (Institution 2) output (SAS)*). It does not appear that either student or teacher collective teaching self-efficacy affects academic performance to any great degree.

4.2.3.3.b.3 Self-efficacy as a moderating variable

Research question 3 asks whether student collective teaching self-efficacy (S-CTSE) moderates the relationships between demographic match/mismatch and academic performance. The potentially moderating effects of each of the S-CTSE factors (viz. subject expertise, classroom management, instructional strategies and student engagement) are tested using a restricted structural equation modeling approach (Kline, 2010). Once again, however, almost no moderation effects are found for efficacy – it appears that this variable does not affect the model much with one exception discussed below.

As discussed in the methods chapter, student efficacy is factored into a four-factor solution using confirmatory factor analysis. Each is tested as a moderator separately, but controlling for the other three efficacy dimensions.

The first result, in which the four dimensions of student efficacy are tested for a moderating effect on the race match → academic performance relationship for Institution 1, is shown in Figure 4-49. No significant interaction effects could be found in this case.

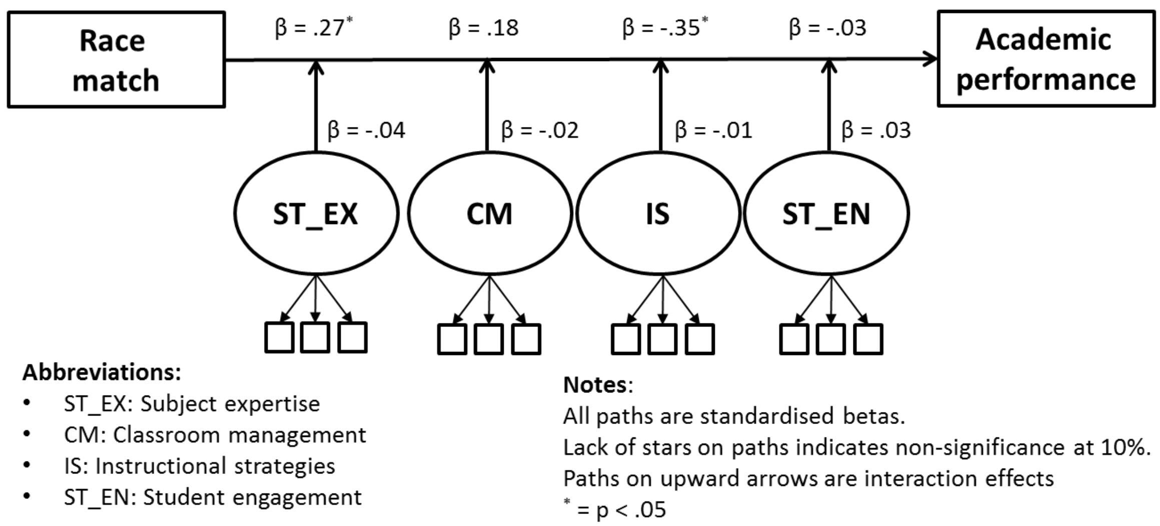


Figure 4-49: Student efficacy moderating the race-performance relationship (Institution 1)

Similarly, Figure 4-50 shows the moderating effect on the gender match → academic performance relationship. As seen there, the interaction between S-CTSE (Subject Expertise) and the gender match → academic performance relationship is statistically significant.

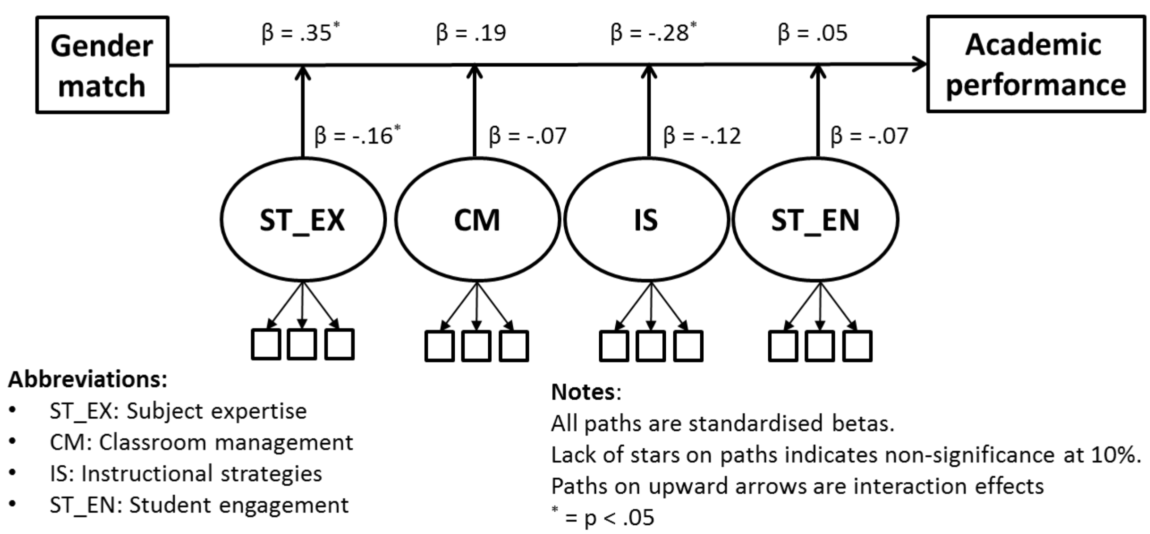


Figure 4-50: Student efficacy moderating the gender-performance relationship (Institution 1)

Figure 4-51 shows the only significant interaction, namely between subject expertise and the gender match → academic performance effect.

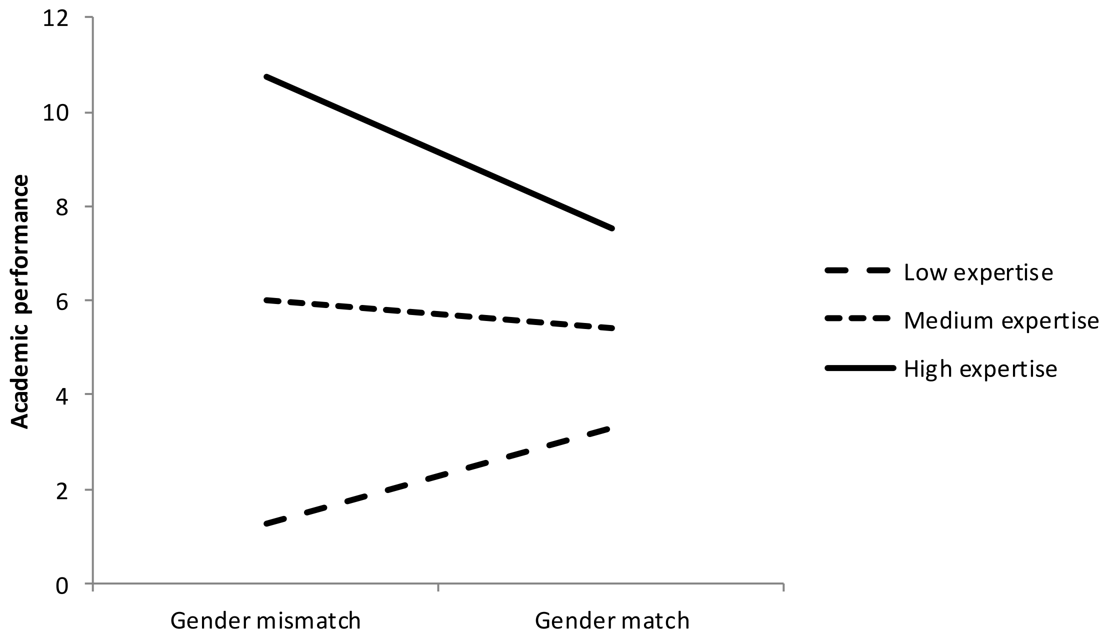


Figure 4-51: Representation of the interaction of S-CTSE (subject expertise) and gender

Figure 4-51 is somewhat counterintuitive, suggesting that low subject expertise efficacy leads to a positive effect of gender match on academic performance, while high subject expertise efficacy leads to higher academic scores when there is gender mismatch.

Finally, Figure 4-52 shows the interaction effects for S-CTSE on the home language match → academic performance effect, none of which are statistically significant.

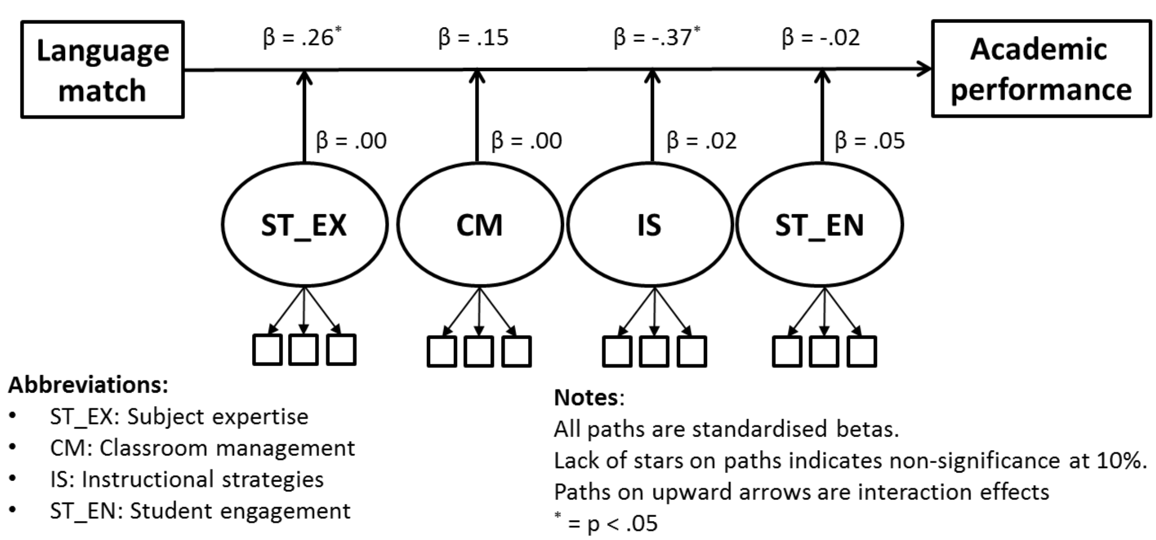


Figure 4-52: Student efficacy moderating the language-performance relationship (Institution 1)

Teacher collective teaching self-efficacy (T-CTSE) shows stronger effects than student efficacy in the case of Institution 1, as seen in Figure 4-53 which presents the interaction between the total T-CTSE variable and the respective match → student academic performance effects.

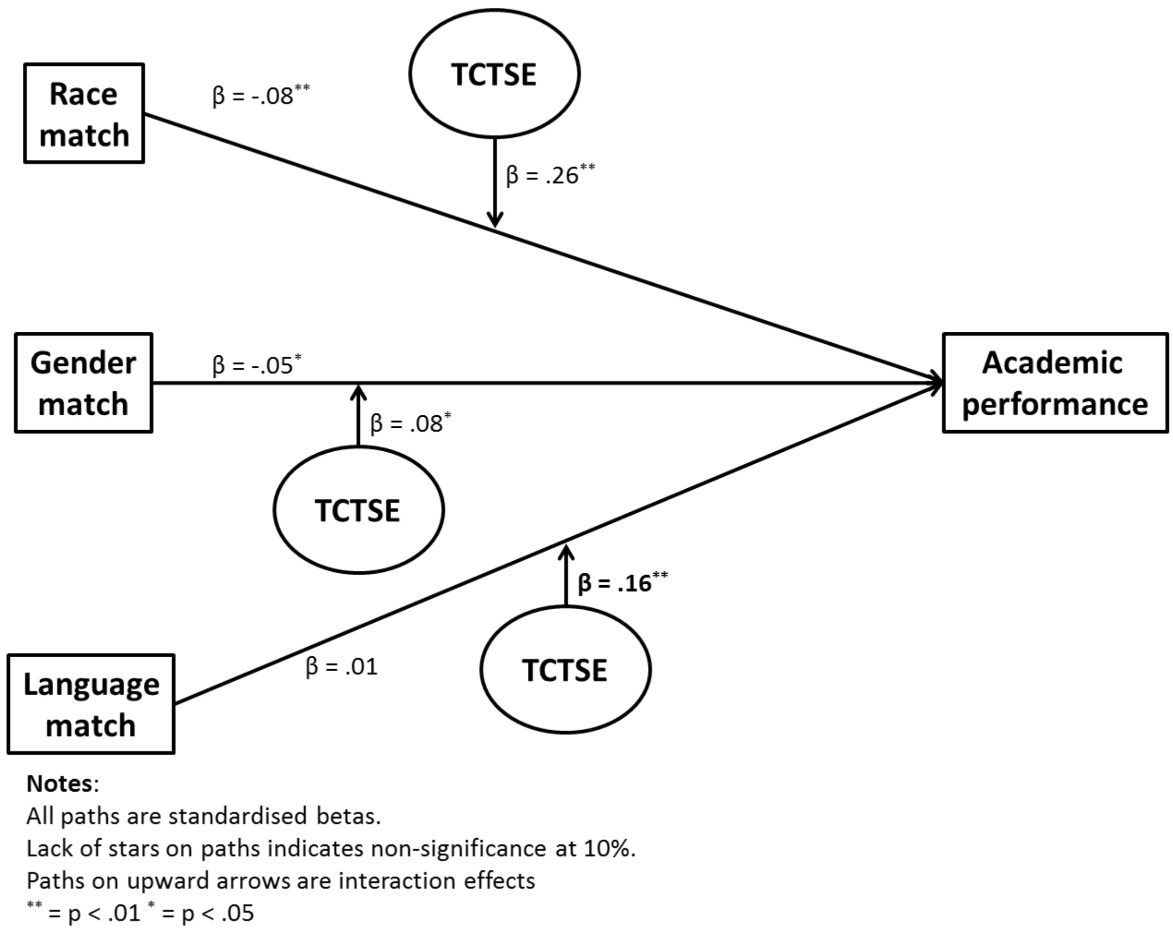


Figure 4-53 Interaction effects of T-CTSE (Institution 1)

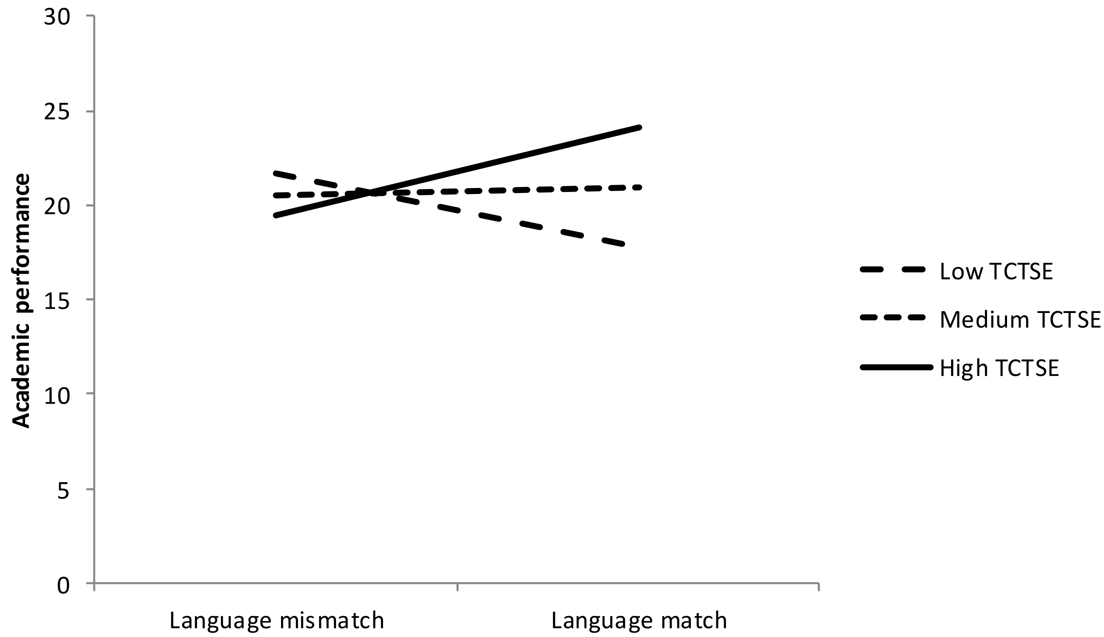


Figure 4-54 Moderation results of teacher efficacy on language match (Institution 1)

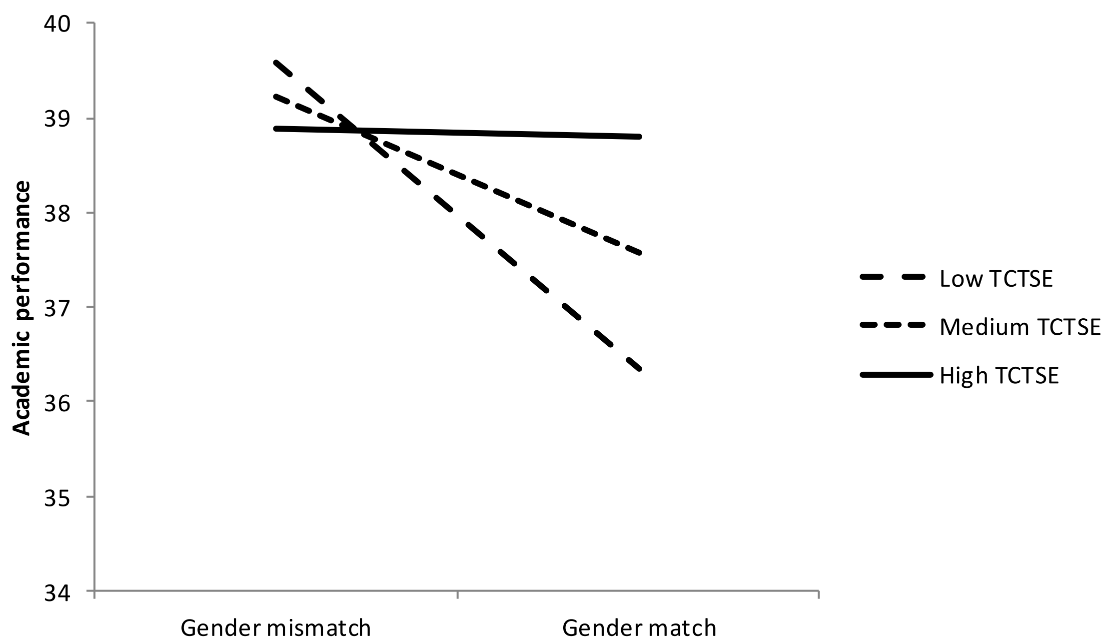


Figure 4-55: Moderation results of teacher efficacy on gender match (Institution 1)

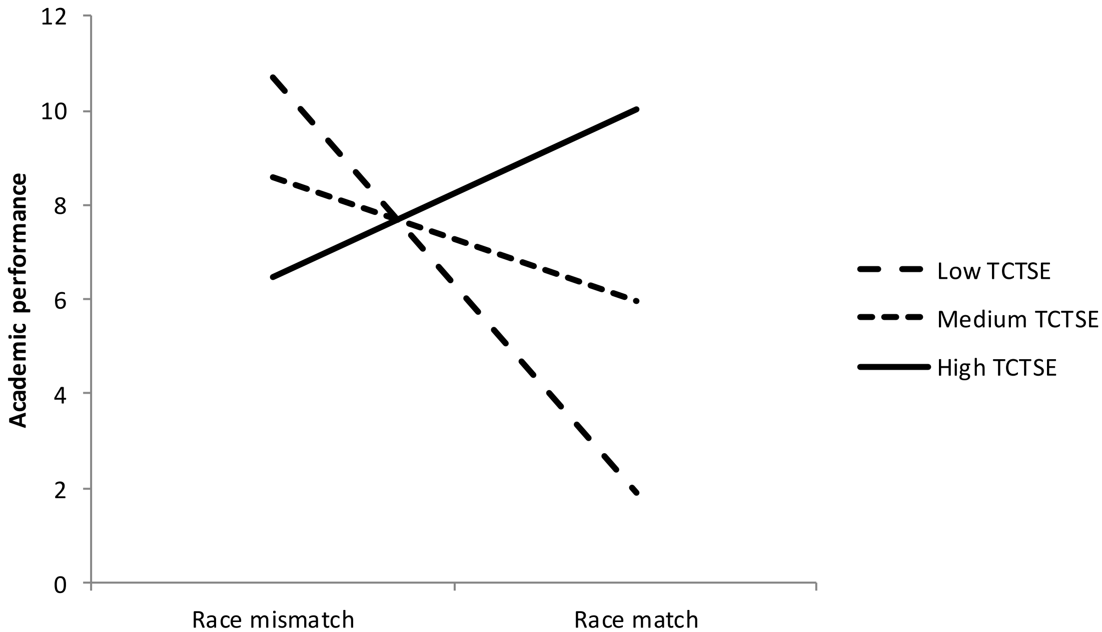


Figure 4-56: Moderation results of teacher efficacy on race match (Institution 1)

Applying these analysis models, both student and teacher collective teaching self-efficacy had weak and non-significant effects on Institution 2 data, as seen in *Appendix G: Race TCTSE Moderation (Institution 2) output (SAS)*, *Appendix H: Home Language TCTSE Moderation (Institution 2) output (SAS)* and *Appendix I: Gender TCTSE Moderation (Institution 2) output (SAS)*).

4.2.3.3.c Summary of findings for cohorts two and three

The GEE analyses (phase 1) above consistently suggest a positive and significant relationship between race and home language student collective teaching self-efficacy (S-CTSE) scores and student test scores for matched students in both cohorts two and three (see tables 4-76 to 4-81) with home language S-CTSE showing the strongest effect on test scores for the combined institution analysis (table 4-81). Gender based S-CTSE was significant for Institution 2 and the Combined Institution analysis (tables 4-83 and 4-84), but not for Institution 1 (table 4-82). Teacher collective teaching self-efficacy (T-CTSE) scores did not seem to be a significant predictor of student test scores using GEE (tables 4-76 to 4-84).

Applying the GEE interaction model (see *3.5.2.3 Data analysis models*) to the cohort two and three data (Table 4-85 to Table 4-93) produced inconsistent results. Most of the analyses did not show any significant interaction (moderation) effects for either S-CTSE or T-CTSE on the match → student z-score effect. However, Race T-CTSE was highly significantly related ($p<.001$) to test scores for Institution 1 (Table 4-85), and Gender S-CTSE was significantly related to test scores for Institution 2 and for the Combined Institution analysis (Table 4-92 and Table 4-93).

Further analysis of the CTSE component of the study (phase 2) using a variety of higher order statistical methods provided inconsistent results (see *4.2.3.3.b Phase 2: Further analysis of the collective teaching self-efficacy effect using higher order statistical methods*). For example, testing the moderating effects of each of the S-CTSE and T-CTSE factors using a restricted structural equation modelling approach (Kline, 2010) did not yield any significant results, with the exception of the S-CTSE (Subject Expertise) factor in the gender/academic performance interaction shown in Figure 4-50. Interestingly, for Institution 1, T-CTSE showed statistically significant interactions on the match → academic performance effect for all three factors (race, home language and gender) (see Table 4-41). Given that SEM (structural equation modelling) as a statistical modelling technique requires large datasets for robust analysis (Kline, 2010), it is possible that SEM (structural equation modelling) may have produced more significant results for cohort two (Institution 1) had the sample been larger and this should be the subject of future research.

4.3 Conclusion

This chapter has presented the results of the three components of this study, viz.

- Race, home language and gender as predictors of cognitive test performance;
- Teacher student congruence as a predictor of cognitive test performance;
- Student perceptions of collective self-efficacy and the impact of this construct on the teacher student congruence effect on cognitive test performance.

The following section concludes the thesis with a summary of key findings, a discussion of limitations of the study, and implications and recommendations for further research.

Chapter 5: Conclusions and recommendations

5.1 Introduction

This thesis has made a thorough examination of the impact of matching teachers and students by race, home language and gender on academic performance in IS&T classrooms. This examination has proceeded along three related lines (as per the three research questions for the study- see *1.3 Objectives and research questions*)- one, differences in student academic performance by race, home language and gender were considered (RQ1) (see 4.2.1); two, the effect of matching teacher and student by race, home language and gender on academic performance was investigated (RQ2) (see 4.2.2); and three, the potential interactions of collective self-efficacy with the match → academic performance effect was explored (RQ3) (see 4.2.3).

The key findings of this study are presented below in respect of each of the study's research questions.

5.2 Summary of key findings

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?"*

Finding of study

> *Race, home language and gender are each significant predictors of cognitive test performance in information systems and technology education and training.*

Cohort one

The analysis of the data for cohort one 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.

It is interesting that while Black students were significantly 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 leveled’ at university.

Cohorts two and three

In support of the results from cohort one, Table 4-17 suggests that there is some evidence for demographic effects for cohorts two and three. In cohort two (Institution 1), age is significantly negatively related to scores, White students outperform other races, and English speaking students perform better on average than other language groups. In cohort three (Institution 2), White students outperform other races and men underperform women.

Research question 2 (RQ2): *“Does matching teacher and student in respect of cultural factors impact student cognitive test performance in information systems and technology education?”*

> Sub-question 2.1 (SQ2.1): *“Does matching teacher and student in respect of race impact student cognitive test performance in information systems and technology education?”*
>
> Sub-question 2.2(SQ2.2): *“Does matching teacher and student in respect of home language impact student cognitive test performance in information systems and technology education?”*

Sub-question 2.3 (SQ2.3): *"Does matching teacher and student in respect of gender impact student cognitive test performance in information systems and technology education?"*

Findings of study

Matching teacher and student in terms of race or home language significantly improves student cognitive test performance in information systems and technology education and training. Gender match does not appear to yield significant results.

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

Cohort one

In short, the results from cohort one are inconclusive on these questions. The multiple regression analysis with pre-test score as a covariate indicated that for some of the courses teacher student congruence was indeed significant as a predictor of cognitive test performance.

However, these results were inconsistent and sometimes contradictory. For example, whereas race matched students scored higher marks than race mismatched students in Courses A (Databases) and C (Spreadsheets), race mismatched students scored higher than race matched students in Course B (Networks).

This race congruence example is particularly interesting and warrants further discussion, since it sheds light on the possible reason for these apparently conflicting results. In both cases where race matched students performed better than race mismatched students (viz. Course A and Course C), the race of the teacher was Indian. Course B (for which the race mismatched students performed better) was taught by a Black teacher. The race matched students for Courses A and C were therefore Indian students. The majority of the race mismatched students in Course B were also Indian. Thus it is reasonable to suggest that the reason for results achieved had less to do with teacher student congruence and more to do with the simple fact that Indian students out-perform Black students in cognitive testing, regardless of the race of the teacher. This is consistent with the results relating to race, home language and gender as predictors of cognitive test performance above, which showed that Indian students scored consistently higher in cognitive testing than Black students.

Cohorts two and three

The *teacher student match* → *academic performance* results from cohorts two and three are more consistent than for cohort one. The Generalized Estimating Equation based analyses show consistent and highly significant positive relationships between teacher student match and student test performance for race and home language match, but not for gender match.

In terms of research question 2, the results from cohorts two and three strongly suggest, therefore, that matching teacher and student in respect of race and home language 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 (Table 4-53 and Table 4-54). In other words, the greater the level of match, the more positive the match effect on test scores.

Phillips' ROI analysis

Figure 5-1, Figure 5-2 and Figure 5-3 present the improvement score results for each of the three courses from cohort one in terms of Phillips' ROI analysis framework. Although the focus of this study is on level 2 ('Learning'), the graphic also shows the other levels in Phillips' model so as to contextualise the results. According to Phillips, a 'chain of impact' occurs whereby the impact of a training intervention at lower levels inevitably results in impact at higher levels in the model. Thus, if factors influencing the impact achieved at level 2 can be identified and controlled, it is expected that the overall return on training investment can be improved (Phillips, 1997, Phillips and Stone, 2002).

Taken at face value (using only the raw test scores), the results presented in Figure 5-1, Figure 5-2 and Figure 5-3 in terms of Phillips' model suggest the following:

- Course A:
    - ROI is maximised when teacher and student are matched in terms of race or gender.
- Course B:
    - ROI is maximised when teacher and student are matched in terms of race.
    - ROI is maximised when teacher and student are mismatched in terms of gender or home language.
- Course C:
    - ROI is maximised when teacher and student are mismatched in terms of race or home language.

- ROI is maximized when teacher and student are matched in terms of gender.

Phillips' approach to ROI analysis typically utilises raw pre- and post-test scores in determining improvement at level 2, whereas statistical models (such as multiple regression) take cognisance of other factors, such as covariate values (pre-test score, in the case of this study), which ensure statistically significant analysis. Thus, whereas the raw mean scores shown in Figure 5-1, Figure 5-2 and Figure 5-3 suggest, for example, that teacher student race match for Course B resulted a higher improvement score (6.76%) than for race mismatched students (6.00%), applying multiple regression with pre-test score as a covariate showed that race mismatch was in fact the better performer in this case when sound statistical models were applied (see *A note on the multiple regression based analysis* in *4.2.2.2.c Summary of findings for cohort one*). It is therefore suggested that while Phillips' framework for ROI analysis is useful as a means of contextualising performance gains as a result of training and their impact at the various levels outlined in the model, analysis of performance gain data should be statistically sound. As demonstrated in the foregoing, raw test performance scores do not always present the full picture (Phillips, 1997, Phillips and Stone, 2002).

In the light of the above, the interpretation of improvement scores when appropriate statistical analysis models are applied, would have to be as follows (despite the impression created by the raw scores):

- Course A:
    - There were no statistically significant differences in performance scores between the matched and the mismatched students in terms of any of the cultural factors. Therefore, teacher student congruence in terms of race, home language and gender cannot be said to contribute to improving ROI in training in this particular instance.
- Course B:
    - ROI is maximised when teacher and student are mismatched in terms of gender or race.
- Course C:
    - ROI is maximised when teacher and student are matched in terms of race, home language or gender.

The example above illustrates the insertion of results from cohort one (Courses A-C) into the Phillips framework that are statistically significant, but not necessarily significant at a practical level. For example, for Course B (Network Skills), race matched students score .74% higher on average than mismatched students. Although statistically significant, it is unlikely this potential for improvement would be of practical value to human resource practitioners. However, the results from cohorts two and three indicate that improvements to test score as a result of match factors can be in the order of 10% (see Table 4-49, Table 4-53 and Table 4-54). For example, Table 4-49 shows that for classes with non-Black teachers in cohort three, a match in all three factors (race, home language and gender) results in a statistically highly significant improvement in test score of the order of 8.99%, which is also of practical significance, while a complete mismatch results in a -1.16% improvement. This represents a difference of 10.52% between completely matched and completely mismatched students. Clearly, form a Phillips ROI framework perspective, return on investment in ICT training in this specific case is maximized in real terms at level 2 of the ROI model by matching teachers and students by race, home language and gender.

Level	Objectives	Independent Variables	Baseline Performance	Post-Training Performance	Performance Improvement
1. Reaction					
2. Learning	Database Skills (Course A)	Teacher Student Match (Race)	52.79	70.86	18.07
		Teacher Student Mismatch (Race)	49.06	66.76	17.70
		Teacher Student Match (Home Language)	-	-	-
		Teacher Student Mismatch (Home Language)	51.68	69.64	17.96
		Teacher Student Match (Gender	53.18	71.32	18.14
		Teacher Student Mismatch (Gender)	50.62	68.46	17.84
3. Application					
4. Impact					
5. ROI%					

Figure 5-1 Phillips' ROI analysis (Course A)

Level	Objectives	Independent Variables	Baseline Performance	Post-Training Performance	Performance Improvement
1. Reaction					
2. Learning	Network Skills (Course B)	Teacher Student Match (Race)	51.86	58.60	6.74
		Teacher Student Mismatch (Race)	67.16	73.16	6.00
		Teacher Student Match (Home Language)	66.67	71.67	5.00
		Teacher Student Mismatch (Home Language)	62.95	69.17	6.22
		Teacher Student Match (Gender	61.37	67.10	5.73
		Teacher Student Mismatch (Gender)	65.34	72.21	6.87
3. Application					
4. Impact					
5. ROI%					

Figure 5-2 Phillips' ROI analysis (Course B)

Level	Objectives	Independent Variables	Baseline Performance	Post-Training Performance	Performance Improvement
1. Reaction					
2. Learning	Spread-sheet Skills (Course C)	Teacher Student Match (Race)	48.93	60.23	11.30
		Teacher Student Mismatch (Race)	43.50	55.06	11.56
		Teacher Student Match (Home Language)	48.99	60.24	11.25
		Teacher Student Mismatch (Home Language)	42.53	54.25	11.72
		Teacher Student Match (Gender	48.82	60.38	11.56
		Teacher Student Mismatch (Gender)	46.20	57.44	11.25
3. Application					
4. Impact					
5. ROI%					

Figure 5-3 Phillips' ROI analysis (Course C)

Research question 3 (RQ3): *"Do student perceptions of collective self-efficacy (in respect of teacher capability), vary among cultural groupings?"*

Sub-question 3.1 (SQ3.1): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among race groupings?"*

Sub-question 3.2 (SQ3.2): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among home language groupings?"*

Sub-question 3.3 (SQ3.3): *"Do student perceptions of collective self-efficacy (in respect of teacher capability specifically), vary among gender groupings?"*

Sub-question 3.4 (SQ3.4): *"How does culture-based variation in student perceptions of collective self-efficacy (in respect of teacher capability) relate to culture-based differences in the impact of teacher student congruence on student cognitive test performance in information systems and technology education?"*

Findings of study

Student perceptions of collective teaching self-efficacy vary among race, home language and gender groupings and appear to relate to culture-based differences in the impact of teacher student congruence on information systems and technology related learning outcomes.

Students' collective teaching self-efficacy (for race, home language and gender) is significantly positively related to academic performance.

Teachers' collective teaching self-efficacy (for race, home language and gender) does not appear to be significantly related to student academic performance.

Neither students' nor teachers' collective teaching self-efficacy (for race, home language and gender) significantly moderate the teacher student match → academic performance effect.

Cohort one

The results from cohort one suggest that student perceptions of collective self-efficacy (in respect of teacher capability) do indeed vary among cultural groupings. Moreover, there is evidence to suggest that these perceptions relate significantly to cognitive test performance.

Gender based differences were not significant, whereas the results related to race and home language differed significantly for Black and Indian students. For example, significantly more than expected

Black and African Language speaking students felt they would learn better from teachers who were of a different race and did not speak their home language. This contrasts starkly with Asian students who speak English and who clearly prefer to be taught by teachers of the same race and language. This would seem to align with some of the teacher student congruence results which indicated that Black students did not perform as well as their Indian counterparts when taught by a Black teacher (Course B). Interestingly, Black students performed worst in terms of post-test score in comparison with their Indian counterparts when they were taught by a Black teacher. Black students scored 14.56% less than Indian students when taught by a Black teacher in Course B, whereas Black students scored only 4.10% and 5.17% less than the Indian students when taught by an Indian teacher for Courses A and C respectively.

Although the foregoing would seem to suggest that Black students' perceptions of who they prefer to be taught by impacts their learning performance, there is no similar evidence that Indian students are affected in the same way by their perceptions of the impact of teacher student congruence factors.

Cohorts two and three

The GEE analyses for cohorts two and three consistently suggest a positive and significant relationship between race and home language student collective teaching self-efficacy (S-CTSE) scores and student test scores for race and home language matched students (see Table 4-76 to Table 4-81). Home language S-CTSE shows the strongest effect on test scores for the combined institution analysis (Table 4-81) and while gender based S-CTSE was significant for Institution 2 and the combined institution analysis (Table 4-83 and Table 4-84), gender based S-CTSE was not significant for Institution 1 (Table 4-82).

Teacher collective teaching self-efficacy (T-CTSE) scores did not seem to be a significant predictor of student test scores using GEE (Table 4-76 to Table 4-84).

Despite the aforementioned significant effects of race and home language S-CTSE on test scores (suggesting a possible interactive effect between levels of students' collective teaching self-efficacy and the match → academic performance effect), applying the GEE interaction model (see *3.5.2.3 Data analysis models*) to the cohort two and three data (Table 4-85 to Table 4-93), most of the analyses did not show any significant interaction (moderation) effects for either S-CTSE or T-CTSE on the match → student z-score effect.

Further analysis of the CTSE component of the study (phase 2) using a variety of higher order statistical methods (see *4.2.3.3.b Phase 2: Further analysis of the collective teaching self-efficacy* *effect using higher order statistical methods*) also provided inconsistent and inconclusive results. However, for Institution 1, T-CTSE showed statistically significant interactions on the match → academic performance effect for all three factors (race, home language and gender) (see Table 4-41), suggesting the possibility that teachers' own perceptions of their respective reference groups' teaching efficacy may be related to the academic performance of matched students.

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 2 (RQ2 and the related sub-questions, SQ2.1, SQ2.2 and SQ2.3), appear to be consistent with Bandura's theory of attention span as a contributor to observational learning. For cohort one, when using single post-test score as the dependent variable, students whose race matched that of the teacher performed better than those who were mismatched in two out of three courses (Course A and C). Similarly, both gender and home language teacher student match predicted performance for Course C. For cohorts two and three, race and gender matched students performed consistently better than mismatched students (see Table 4-36 to Table 4-44). 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).

Why then did the Black students in cohort one's Course A not also perform better than their Indian classmates when taught by a Black teacher? Why would racial congruence (model observer similarity) improve results for Indian students when matched with Indian teachers, but not for Black students when taught by Black teachers? According to SCT, it is not only 'similarity' of model to observer that affects a model's effectiveness, but also the model's 'perceived competence'. Thus, if Black students felt that Black teachers were not as competent as teachers of other races, it would negatively moderate the effects of observer-model similarity on learning effectiveness (see Figure 3-6 Research model).

Indeed, this interpretation would be consistent with the findings on collective self-efficacy for cohort one related to research question 3 (and specifically, sub-questions 3.1 and 3.2), which show that more than expected Black and African Language students prefer not to be taught by teachers of the same race or home language, thus demonstrating a low collective self-efficacy.

Conversely, the findings for cohort one on research question 3 in respect of Indian students show that a higher than expected proportion of Indian students prefer to be taught by teachers of the same race and home language, consistent with a high sense of collective self-efficacy. Similarly, cohorts two and three reveal a positive and significant relationship between race and home language student collective teaching self-efficacy (S-CTSE) and student test scores for matched students (see Table 4-76 to Table 4-81). This aligns with Bandura's (Bandura, 1977a, 1989) theory that 'observers' learn better from 'models' that they perceive as competent (or, in this case, that belong to a reference group (such as race) that the observer perceives as being competent).

Bandura also sheds light on the influencers of collective self-efficacy, pointing out that social models, social persuasion and mastery experiences all contribute to a reference group's sense of collective self-efficacy. Figure 3-6 suggests how cultural factors (such as an observer's race, home language or gender) can moderate the way in which social models, social persuasion and mastery experiences influence an observer's sense of collective self-efficacy. Certainly, this suggestion is not unreasonable in the South African context. There has historically been a dearth of Black and female South African academic role models for students from these reference groups to look up to and learn from (Badat, 2010, Reddy et al., 2010). Moreover, there has been no shortage of negative mastery experiences for Black South African students, who are not oblivious to the fact that, regardless of the underlying reasons, as a demographic grouping they have tended to perform worse than other races academically (Letseka and Maile, 2008, Badat, 2010, Department of Basic Education, 2010). In terms of Bandura's theory of social conditioning as an influencer of collective self-efficacy, it is not difficult to relate decades of coordinated racial (and language) discrimination to a negative sense of self-worth and capability on the part of the demographic grouping that bore the brunt of Apartheid- the Black, African Language speaking people (and students) of South Africa (Bandura, 2000, De Wet and Wolhuter, 2009).

Clearly, this combination of negative influencers will impact the sense of collective self-efficacy students have in respect of their race, home language or gender reference group. The resultant low collective self-efficacy rating is reflected in poor academic achievement, directly as a result, on one hand, of low self-efficacy (displayed as a direct linkage between the construct of 'collective self-efficacy' and 'observational learning' in Figure 3-6), and indirectly because of the effect low collective self-efficacy has on a model's credibility as an effective teacher (Bandura, 1977b, 1989, 2000). Thus, Bandura's theory on the effects of collective self-efficacy on learning, as discussed in the foregoing, provides a solid theoretical basis for understanding the findings of this study in respect of both RQ2 (related to the teacher student congruence) and RQ1 (including SQ1.1, SQ1.2 and SQ1.3, pertaining to disparities among race, home language and gender group performances respectively in cognitive testing).

5.3 Implications and recommendations

While it is understood that there is no quick fix to the culture-based educational challenges of South Africa, it is also suggested that the findings of studies such as this can contribute significantly to the efforts of educationalists who strive to find practical means of improving the learning experience for all South Africans and to identify strategies to maximise the return on investment in education and training for all stakeholders.

The following considers the implications of the findings of this study and presents specific recommendations that emerge from these findings, with a view to maximising return on investment in information and systems technology education and training.

Recommendation 1: Education and skills development strategy should be cognisant of any and all factors that contribute to improving learning and thereby maximizing return on investment.

The study has shown a significant positive relationship between matching teacher and student (in terms of race and home language) and student test scores (4.2.2.4). 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 (4.2.2.4). While the literal implication that it might be better to match teacher 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.

It is furthermore encouraging to note the findings of studies such as this when considering the fact that more Black teachers are being encouraged to become part of the educational system that comprises mainly Black students (Department of Basic Education, 2010). The findings from cohorts two and three that show that race and home language matched students perform better when taught by matched teachers are particularly significant in this context, given that the majority of students in that sample were Black (see Table 3-9 Student demographics for cohorts two and three).

Recommendation 2: Strategies to develop a positive sense of self-efficacy

According to Bandura (Bandura, 1977b, 1994, 1995, 2000), collective self-efficacy affects the learning performance of a reference group. This study has shown that there is a significant relationship between levels of collective self-efficacy and academic performance (4.2.3). This study has also specifically shown that Black students have a significantly lower sense of collective self-efficacy in terms of teaching ability than other races (4.2.3). This impacts Black students' academic performance directly, as well as indirectly, (as a mitigating factor in determining the level of credibility students ascribe teachers of the same race). This has serious implications for the furture of education in South Africa where the majority of students are Black and more Black teachers are being encouraged to enter the system. Moreover, this study has considered the effects of social modeling, social persuasion and mastery experiences in shaping the collective self-efficacy perceptions of various reference groups, as well as the implications of the historical South African socio-political context in respect of these factors. Bandura's Social Cognitive Theory, then, appears to shed light on the possible reasons behind the findings of this study in respect of culture-based academic performance disparities in IS&T education.

Negative experiences in terms of social modeling, mastery experiences and social persuasion have persisted for decades for certain cultural groupings, and the scars are deep and entrenched. Apart from describing culture-based differences in academic achievement, this study has as an underlying premise the idea that academic performance can be controlled and manipulated through research-based pedagogical strategies. In terms of Phillips' ROI framework, return on training investment can be improved by manipulating the factors that make a difference to the effectiveness of training and educational interventions (Phillips, 1997). Indeed, Bandura's Social Cognitive Theory has as a core tenet the ability of individuals (and collectives) to change how they respond to the environment and take charge of what they allow to impact their behaviour (including learning behaviour) and the extent to which their environment impacts their learning capability (Bandura, 1977a). The theory is empowering in this respect and is reason for optimism that teachers and students alike (individually and collectively in terms of cultural groupings), can be assisted to break the pattern of negative self-efficacy through both teacher and student education aimed at bolstering collective self-worth and pride.

The precise form these interventions aimed at building collective self-efficacy needs to take in order to be effective should be the subject of further research, but it is suggested that the injection of substantive programmes directed specifically at building culture-based sensitivity and respect into existing teacher education curricula could be of value. Similar programmes could be included as part of student curricula and could include show-casing of social models that are inspiring and highlighting successes and positive mastery experiences for each reference group. After summarising his findings showing that 'self-efficacy beliefs are a strong predictor of the collegiate achievement of African American males attending predominantly White research universities', Reid (2007), expresses optimism that interventions can succeed in improving collective self-efficacy perceptions, and by extension academic performance. Reid (2007) suggests that 'universities can directly impact the achievement levels of African-American students by raising their academic self-efficacy levels'. There is no reason to believe that similar enthusiasm and optimism would be misplaced in the South African context. There is no doubt that such an undertaking would be ambitious. Generations of oppression and conditioning under Apartheid have created a weak sense of collective self-efficacy for cultural groupings that represent the majority of South Africa's future workforce. It will require an equally sustained, concerted effort to redress these issues and build a positive sense of collective self-efficacy.

Recommendation 3: Address socio-economic factors that impact basic education

The study has demonstrated the lingering culture based gaps in academic performance in IS&T education (4.2.1). Despite the significant and well-intentioned efforts of government to date directed at redressing the educational inequities of South Africa's jaded past, the simple fact is that Black students continue to dramatically under-perform academically and are failing to take their rightful place in what should be a vibrant, productive workforce. Moreover, there is no credible indication that the inequitable state of schooling and the socio-economic challenges that negatively impact the ability of the basic education system to function as the feeder that it should be of quality students to the tertiary educational structures will be resolved adequately any time soon. Nevertheless, regardless of how unrealistic the hope that such mammoth and complex social ills can be cured to any appreciable degree in the near future, it would be entirely remiss of any set of recommendations on how to improve academic performance in the classroom not to dutifully take note of the need to address the single most influential factor in impeding academic progress for previously disadvantaged students, viz. the dire socio-economic conditions that South Africa's vast majority contend with on a daily basis.

Recommendation 4: Multicultural sensitivity training for educators

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 teachers of the same race and that in some cases teacher student racial congruence positively impacts academic performance (4.2.2.4). However, this fact does not necessarily recommend actually matching students with teachers 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 teacher 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 teachers bodes well for the future as more Black teachers 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 teachers is both impractical and unconstitutional, a reasonable 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 teachers to cultivate and nurture immediacy behaviours that are shown by research to appeal to the various students they teach, and which generally assist teachers 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).

5.4 Limitations, gaps and anomalies

Whereas international congruence studies have often identified different results depending on the subject matter, this study focused exclusively on first year IS&T subjects. It would be interesting to investigate the extent to which these findings apply to other subjects, (those not related to IS&T), to investigate whether the findings are duplicable across disciplines.

Moreover, although this study has identified interesting facts regarding the academic achievement disparities between cultures and provided useful insights into differing perceptions among students of different demographics relating to teacher preferences, it falls short of providing empirically sound recommendations on how to close the performance gap. For example, although based on sound logic and a thorough analysis of international experiences and precedent, the suggestion that sensitising teachers to the various aspects of multicultural pedagogy that have made a difference in other parts of the world would be effective in South Africa has not been tested. It would be useful and of practical value to conduct empirical research using control and focus groups to measure the actual impact of a culturally sensitive pedagogical strategy. In addition, it is suggested that such studies should include a formal analysis of immediacy factors that appeal to, and impact learning for, various cultural groupings of students.

Leading from this study, and to ensure the validity and credibility of such a programme of multicultural teacher education, it would be useful to further research the following:

- Whether the findings of this study extend appropriately across various academic disciplines;
- Culture-based student preferences for various teacher immediacy behaviours and teaching styles, and the extent to which these impact on academic performance.

5.5 Contribution to the body of knowledge

Given the multicultural nature of South African classrooms, the study contributes valuable insights into the perceptions of collective efficacy that influence how IS&T students react to teachers of certain race, home language and gender groupings, and how this potentially impacts academic performance (see 4.2.3). Furthermore, the study contributes a greater understanding of the nature and effects on student academic performance of teachers' own collective efficacy (see 3.5.2.2.b).

Additionally, this study and the outputs thereof make the following specific theoretical contributions to the general body of knowledge as follows:

1. *Adaptation of collective teacher self-efficacy construct for race, home language and gender reference groups (CTSE):* It is noted that in the literature reviewed on collective teacher self-efficacy as it applies in education, reference is typically made to school or university 'faculties' as the reference group that defines the 'collective' (Bandura, 1995, Oettingen, 1995, Tschannen-Moran and Barr, 2004). The theoretical design principles for faculty based collective teacher self-efficacy instruments found in the literature have been applied to adapt the construct for use with *culture-based reference groups* (race, home language and gender), rather than *faculties* to which teachers belong (see 3.5.2.2.b). The construct is referred to herein as teacher collective teaching self-efficacy, and refers to the perception a *teacher* has of the teaching capabilities of a culture-based reference group the teacher is a part of (such as race, home language or gender group). In this study, the teacher collective teaching self-efficacy construct is abbreviated to T-CTSE. T-CTSE is distinguished in this study from S-CTSE (student collective teaching self-efficacy), which is similarly a variation on the CTSE construct that refers to the perception a *student* has of the teaching capabilities of teachers from a culture-based reference group the student is a part of (such as race, home language or gender group).
2. *Formulation of a research model to test the direct effect of student perceptions of teacher collective efficacy on academic performance:* Similarly, while many studies in the literature focus on the teachers' own perceptions of collective teacher efficacy (Bandura, 1995, Oettingen, 1995, Tschannen-Moran and Barr, 2004) this study, in addition to researching the effect of teachers' own perceptions, also explores the effect on academic performance of student perceptions of the teaching efficacy of certain reference groups (viz. race, home language and gender groupings) (see 4.2.3.3). While there is some evidence in the literature of research related to student perceptions of individual teachers' knowledge, attitude and teaching skills as a predictor of academic performance (Adediwura et al. 2007), a review of

the literature found no evidence of research related specifically to student perceptions of collective teacher efficacy as a predictor of academic performance.

3. *Formulation of a research model to test the moderating effect of both student and teacher collective teaching self-efficacy (S-CTSE) on the teacher student match → academic performance effect:* This study presented a model for testing the interactive effect of S-CTSE and T-CTSE on the match → academic performance effect (and identified significant results) (see 4.2.3.3). A review of the literature found no evidence that student or teacher collective efficacy has previously been explored as a potential moderating variable for the teacher student match → academic performance effect.
4. *Formulation of a model to test the teacher student indexes of match → academic performance effect:* The parts of this study dealing with how teacher student match affects academic performance identified highly significant effects related to the combination of match factors, and showed that incremental indexes of teacher student match (in respect of race, home language and gender) were significantly related to higher student test scores (see 4.2.2). A review of the literature found no evidence of similar index of match type studies.

5.6 Conclusion

Both the review of international 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 university.

Whatever strategies are researched with a view to closing the culture-based academic achievement gap in information systems and technology education and skills development, it is recommended that the ongoing measurement of the effectiveness of these strategies becomes a core component of these studies with a view to ensuring that returns on investment in training and education are maximised and that precious budgets are spent appropriately. Phillips' ROI in training model can easily be adapted to provide a credible means, for example, of measuring the impact of training and education strategies and the ROI that the ICT sector is realising from its enormous skills development expenditure. Moreover, the real impact of any remedial interventions targeting the culture-based academic achievement gap (such as multicultural sensitivity training interventions for teachers or university lecturers) could comfortably be measured using the same Phillips' multi-level ROI model (Phillips and Stone, 2002).

Culture-based performance gaps in information systems and technology education do not have to be accepted as inevitable in view of the socio-economic challenges that plague South Africa. 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 ICT sector set to grow dramatically over the next decade and demanding more skilled professionals in the workforce, identifying factors that contribute positively to and 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. The findings of this study (and others referred to in the foregoing) provide reason for optimism that it is not only possible to identify the factors that impact learning, it is also possible to control these factors with a view to maximizing the return on investment that is realised in South Africa's multicultural information systems and technology classrooms.

The key findings of this study both confirm the existence of a race, home language and gender based academic achievement gap in information systems and technology education, and describe the nature of the gap in terms that allow educationalists to rethink with optimism pedagogical strategies to address these disparities. Clearly, maximising return on investment in information technology education and training in the South African context must take cognisance of cultural diversity. The findings of this study show that different cultures learn and currently perform differently in the information systems and technology classroom, and they respond differently to various pedagogical strategies. Teacher student congruence, as just one factor that influences the impact of information systems and technology education and training at the learning level (level 2 of Phillips' ROI in training framework (Phillips and Stone, 2002)), affects students of different cultural groupings in different ways. In this study, for example, while return on investment in training could be maximised for Indian students through teacher student ethnic congruence, the same was not shown to be true for black students, who seemed to prefer to be taught by teachers of other races.

In short, the findings of this study suggest that any attempt to maximise return on investment in information technology training (as investigated herein via manipulation of teacher student congruence factors at level 2 ('learning') of Phillips' ROI in training framework), must be responsive to the complexities and diversity of South Africa's information systems and technology student population. 'One response' does not 'fit all'. Bandura's Social Cognitive Theory (Bandura, 1977b, 2000), and in particular the construct of ‘collective self-efficacy’, helps us to make sense of this diversity in student perceptions and reactions to various pedagogical strategies. Our understanding as IS&T educators of the powerful role collective self-efficacy plays in effective learning in the multicultural context should inform the nature and content of interventions targeting both students and teachers at all levels and which have as their objective the bolstering of culture-based collective self-efficacy perceptions. Maximum returns on South Africa’s significant investments in education and training will only be fully realised when both students and teachers can break the psychological shackles of culture-based collective self-doubt.

References

ADEDIWURA, A. A. & TAYO, B. 2007. Perception of teachers' knowledge, attitude and teaching skills as redictor of academic performance in Nigerian secondary schools. *Educational Research and Review.* 2(7), 165-171.

AHMED, T., MOURATIDIS, H. & PRESTON, D. 2009. Website Design Guidelines: High Power Distance and High-Context Culture. *International Journal of Cyber Society and Education* 2**,** 47-60.

ALAVI, M., MARAKAS, G. M. & YOO, Y. 2002. A Comparative Study of Distributed Learning Environments on Learning Outcomes. *Information Systems Research,* 13**,** 404-415.

ALEXANDER, K. L., ENTWISLE, D. R. & THOMPSON, M. 1987. School Performance, Status Relations, and the Structure of Sentiment: Bring the Teacher Back In. *American Sociological Review,* 52**,** 665-682.

ALLEN, R. L. 2004. Whiteness and Critical Pedagogy. *Educational Philosophy and Theory,* 36**,** 121-136.

AMERICAN ASSOCIATION OF UNIVERSITY WOMEN EDUCATIONAL FOUNDATION. 2000. *Tech savvy: Educating girls in the new computer age.* [Online]. Available: http://www.aauw.org/learn/research/upload/TechSavvy.pdf [Accessed 18/2/2012].

ANASTASI, A. 1954. *Psychological Testing,* New York, Macmillan.

ANDERBERG, M. R. 1973. *Cluster Analysis for Applications*, New York: Academic Press.

ANDERSEN, J. 1979. Teacher immediacy as a predictor of teaching effectiveness. *In:* NIMMO, D. (ed.) *Communication in the classroom: Original essays.* New Brunswick, N.J.: Transaction Books.

ANDERSEN, J., NORTON, R. W. & NUSSBAUM, J. F. 1981. Three investigations exploring relationships between perceived teacher communication behaviors and student learning. *Communication Education,* 30**,** 377-392.

ANGLE, J. & MOSELEY, C. 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, J. D., HOVAV, A. & GALLETTA, D. 2009. User Awareness of Security Countermeasures and Its Impact on Information Systems Misuse: A Deterrence Approach. *Information Systems Research,* 20**,** 79-98.

ASHTON, P. & WEBB, R. 1986. *Making a difference: Teachers' sense of efficacy and student achievement.,* New York Longman.

ASTD. 2000a. *E-learning evaluation method gains support in Canada*. [Online]. Available: www.learningcircuits.org [Accessed 21/1/2012].

ASTD. 2000b. *Evaluating the Effectiveness and the Return on Investment of E-learning*. [Online]. Available: www.astd.org/virtual_community/research [Accessed].

AUSBURN, L. J., MARTENS, J., WASHINGTON, A., STEELE, D. & WASHBURN, E. 2009. A cross-case analysis of gender issues in desktop virtual reality learning environments. *Journal of Industrial Teacher Education,* 46**,** 51-89.

BADAT, S. 2010. *The challenges of transformation in higher education and training institutions in South Africa* [Online]. Development Bank of South Africa. Available: 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 11/11/2011].

BADROODIEN, A. 2005. Enterprise training in post-apartheid South Africa. *Journal of Education and Work,* 18**,** 85-110.

BAIN, C. D. & RICE, M. L. 2007. The influence of gender on attitudes, perception, and use of technology. *Journal of Research on Technology in Education,* 39**,** 119-132.

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. 1978. The self system in reciprocal determinism. *American Psychologist,* 33**,** 344-358.

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. 1991. Social cognitive theory of moral thought and action. *In:* KURTINES, W. M. & GERWITZ, J. L. (eds.) *Handbook of Moral Behavior and Development.* Hillsdale, NJ: Erlbaum.

BANDURA, A. 1994. Self-efficacy. *In:* RAMACHAUDRAN, V. S. (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 (Wiley-Blackwell),* 9**,** 75-78.

BANDURA, A. 2001. Social Cognitive Theory of Mass Communication. *Mediapsychology,* 3**,** 265-299.

BANDURA, A. 2002. Social Cognitive Theory in Cultural Context. *Applied Psychology,* 51**,** 269-290.

BARRON, T. 2001. *An e-learning industry update.* [Online]. Available: www.learningcircuits.org [Accessed 21/1/2012].

BASABE, N. & ROS, M. 2005. Cultural dimensions and social behavior correlates: Individualism-Collectivism and Power Distance. *International Review of Social Psychology,* 18**,** 189-225.

BELL, D. 2004. *Silent covenants: Brown v. Board of education an dthe unfulfilled hopes for racial reform.,* New York, Oxford University Press.

BELL, R. & DALY, J. A. 1984. The affinity-seeking function of communication. *Communication Momographs.,* 51**,** 91-115.

BEYER, S. 2006. Comparing Gender Differences in Computer Science and Management Information Systems Majors. *In:* TRAUTH, E. (ed.) *Encyclopedia of Gender and Information Technology.*

BEYER, S., RYNES, K., PERRAULT, J., HAY, K. & HALLER, S. Year. Gender differences in computer science students. *In:* 34th SIGCSE technical symposium on Computer science education, 2003. ACM Press, 49.

BLOCK, C. F. 1981. The relationship between student-teacher cognitive style distance and academic achievement. *Dissertation Abstracts International.,* 42**,** 1388.

BLOOM, B. S. 1956. Taxonomy of Educational Objectives, Handbook I: The Cognitive Domain. New York: David McKay Co Inc.

BREWER, D. J., EHRENBERG, R. G. & GOLDHABER, D. D. 1994. Do Teachers; race, gender, and ethnicity matter? Evidence from NELS 88. Paper presented at the National Bureau of Economic Research.

BURGOON, J. K., BULLER, D. B. & WOODALL, W. G. 1980. Nonverbal Communication: The Unspoken Dialogue. New York: Harper and Row Publishers.

BUSCH, T. 1995. Gender differences in self-efficacy and attitides toward computers. *Journal of Educational Computing Research,* 12**,** 147-158.

CAFFERTY, E. I. 1981. An analysis of student performance based upon the degree of matchbetween the educational cognitive style of the teacher and the educational cognitive style of the students. *Dissertation Abstracts International.,* 41**,** 2908.

CAFOLLA, R. 1987. Piagetian formal operations and other cognitive correlates of achievement in computer programming. *Journal of Educational Technology Systems,* 16**,** 45-55.

CALDER, A. M. & ASHBAUGH, E. L. 2005. Transfer of Learning through Gender and Ethnicity. *AIP Conference Proceedings,* 790**,** 39-41.

CANFIELD, A. A. 1988. *Learning styles inventory manual.,* Los Angeles, Western Psychological Services.

CATSAMBIS, S. 1995. Gender, race, ethnicity, and science education in the middle grades. *Journal of Research in Science Teaching,* 32**,** 243-257.

CENGIZ, M., SENEL, T., TERZI, Y., MURAT, N. & SAVAS, N. 2010. Comparing different sedation medications using generalized estimating equations approach. *African Journal of Pharmacy and Pharmacology,* 4(4), 130-134.

CENTRA, J. A. & GAUBATZ, N. B. 2000. Is there gender bias in student evaluation of teaching? *Journal of Higher Education,* 71**,** 17-33.

CHANG, D. F. & DEMYAN, A. 2007. Teachers' Stereotypes of Asian, Black, and White Students. *School Psychology Quarterly,* 22**,** 91-114.

CHAU, P. Y. K. & HU, P. J. H. 2002. Investigating healthcare professionals' decisions to accept telemedicine technology: An empirical test of competing theories. *Information & Management,* 39**,** 297-311.

CHAVOUS, T. M., BERNAT, D. H., SCHMEELK-CONE, K., CALDWELL, C. H., KOHN-WOOD, L. & ZIMMMERMAN, M. A. 2003. Racial Identity and Academic Attainment Among African American Adolescents. *Child Development,* 74**,** 1076-1090.

CHISHOLM, L., HOADLEY, U., WA KIVILU, M., BROOKES, H., PRINSLOO, C., KGOBE, A., MOSIA, D., NARSEE, H. & RULE, S. 2005. *Educator Workload in South Africa.,* Pretoria, HSRC.

CHRISTOPHEL, D. M. 1990. The relationship among teacher immediacy behaviors, student motivation, and learning. *Communication Education,* 37**,** 323-340.

CLEMENT, C. A., KURLAND, D. M., MAWBY, R. & PEA, R. D. 1986. Analogical reasoning and computer programming. *Journal of Educational Computing Research,* 2**,** 473-486.

CLEMENTZ, A. 2005. *Training Evaluation Management,* Gardenview, Zytek Publishing.

CLIFFORD, P. M. 2007. *The computer self-efficacy of African American and Hispanic American community college students as compared to their Caucasian counterparts*, Walden University.

COHEN, A. B. 2009. Many forms of culture. *American Psychologist,* 64**,** 194-204.

COLDWELL, D. & MOERDYK, A. 1981. Paradigms apart: black managers in a white man's world. *South African Journal of Business Management.*, 12**,** 70-76.

COLLIS, B. A. & WILLIAMS, R. L. 1987. Difference in adolescents' attitudes toward computers and selected school subjects. *Journal of Educational Research,* 8**,** 17-27.

COMPEAU, D. & HIGGINS, C. 1995. Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly,* 19**,** 189-211.

COMPEAU, D., HIGGINS, C. A. & HUFF, S. 1999. Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study. *MIS Quarterly,* 23**,** 145-158.

CONNOR, H., SUSSEX UNIV, B. I. F. E. S. & ET AL. 1996. Ethnic Minority Graduates: Differences by Degrees. Report 309.

CONOVER, W. J. 1999. *Practical Nonparametric Statistics*, Wiley Series in Probability and Statistics.

COOPER, J. 2006. The digital divide: The special case of gender. *Journal of Computer Assisted Learning,* 22**,** 320-334.

COUNCIL ON HIGHER EDUCATION. 2009. *The State of Higher Education in South Africa.* [Online]. Available: http://www.che.ac.za/documents/d000201/Higher_Education_Monitor_8.pdf [Accessed 01/12/2011].

CROMBIE, G., ABARBANEL, T. & ANDERSON, C. 2000. All-female computer science: The positive effects of single gender classes. *The Science Teacher,* March 2000**,** 40-43.

CROMBIE, G., ABARBANEL, T. & TRINNEER, A. 2002. All female classes in high school computer science: positive effects in three years of data. *Journal of Educational Computing Research,* 27**,** 385-409.

CRONJÉ, J. C. 2011. Using Hofstede’s cultural dimensions to interpret cross-cultural blended teaching and learning. *Computers & Education,* 56**,** 596-603.

CROSBIE-BRUNETT, M. & LEWIS, E. A. 1993. Theoretical contributions from social and cognitive behavioral psychology. *In:* BOSS, P. G., DOHETRY, W. J., LAROSSA, R., SCHUMM, W. R. & STREINMETZ, S. K. (eds.) *Sourcebook of Family Theories and Methods: A Contextual Approach.* New York: Plenum Press.

DE WET, C. & WOLHUTER, C. 2009. A transitiological study of some South African educational issues. *SOuth African Journal of Education,* 29**,** 359-376.

DEMPSEY, V. & NOBLIT, G. W. 1993. Cultural ignorance and school desegregation: Reconstructing a silenced narrative. *Educational Policy,* 7**,** 318-399.

DENNY, P. & MAHARAJ, M. S. 2011. Maximising Return on Investment in I.T. Training-An African Perspective. *In:* CUNNINGHAM, P. & CUNNINGHAM, M. (eds.) *IST Africa 2011*. Botswana.

DEPARTMENT OF BASIC EDUCATION 2010. Education Statistics in South Africa 2009. Pretoria: Department of Basic Education.

DEPARTMENT OF EDUCATION. 1995. *White Paper on Education and Training, Notice 196 of 1995* [Online]. Cape Town: Parliament of the Republic of South Africa. Available: http://www.info.gov.za/whitepapers/1995/education1.htm [Accessed 13 September 2011].

DEPARTMENT OF EDUCATION. 2001. *Education in South Africa: Achievements since 1994* [Online]. Available: http://www.info.gov.za/view/DownloadFileAction?id=70282 [Accessed].

DEPARTMENT OF EDUCATION. 2008. *Report of the Ministerial Committee on Transformation and Social Cohesion and the Elimination of Discrimination in Public Higher Education Institutions*. [Online]. Available: http://www.ukzn.ac.za/publications/ReportonHEandTransformation.pdf [Accessed 23/11/2011].

DIAZ, C. 1992. *Multicultural education for the 21" century.*, Washington, D.C., National Education Association.

DODGE, Y. 2003. *The Oxford Dictionary of Statistical Terms*. The Oxford University Press, Oxford.

DUBOW, W. 2011. NCWIT Scorecard: A report on the status of women in information technology. Boulder: NCWIT.

DUNN, R., GEMAKE, J., JALALI, F., ZENHAUSERN, R., QUINN, P. & SPIRIDAKIS, J. 1990. Cross-Cultural Differences in Learning Styles of Elementary-Age Students From Four Ethnic Backgrounds. *Journal of Multicultural Counseling & Development,* 18**,** 68-93.

DURNDELL, A. & HAAG, Z. 2002. Computer self efficacy, computer anxiety, attitudes towards the internet and reported experience with the internet, by gender, in an East European sample. *Computers in Human Behavior,* 18**,** 521-535.

DUVENHAGE, A. 2006. Politieke transformasie in Suid-Afrika - ’n konteksbepaling vir onderwys en moedertaalonderrig. *Tydskrif vir Geesteswetenskappe,* 46**,** 125-141.

ELKJÆR, B. 1992. Girls and information technology in Denmark - an account of a socially constructed problem. *Gender and Education,* 4.

EYBER, C., DYER, D. & VERSFELD, R. 1997. *Resisting racism: A teachers' guide to equality in education,* Cape Town and Johannesurg, TLRC.

FERGUSON, R. F. 1998. Teachers' Perceptions and Expectations and the Black-White Test Score Gap. *In:* JENCKS, C. & PHILLIPS, M. (eds.) *The Black-White Test Score Gap.* Washington, D.C.: Brookings Institution Press.

FERNANDEZ, D. R., CARLSON, D., STEPINA, L. P. & NICHOLSON, J. D. 1997. Hofstede's Country Classification 25 Years Later. *The Journal of Social Psychology,* 137**,** 43-54.

FISHER, A. & MARGOLIS, J. 2002. Unlocking the clubhouse: The Carnegie Mellon experience. *SIGCSE Bulletin,* 34**,** 79-83.

FOLEY, I. F. 1999. Teacher learning style preferences, student learning style preferences, and student reading achievement. *Dissertation Abstracts International.,* 60**,** 0995.

FOSTER, M. 1997. *Black teachers on teaching.,* New York, The New York Press.

FRIEDMAN, M. 1937. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American Statistical Association,* 32:675–701.

FRIEDMAN, M. 1940. A comparison of alternative tests of significance for the problem of m rankings. *Annals of Mathematical Statistics*, 11:86–92.

GALGUERA, T. 1998. Students' attitudes toward teachers' ethnicity, bilinguality and gender. *Hispanic Journal of Behavioral Sciences,* 20**,** 411-428.

GALLAGHER, K. & RIVIERE, D. 2004. Pink... With shades of grey:mediating moments of diversity in urban secondary classrooms. *Westminster Studies in Education.,* 27**,** 127-141.

GALLIVAN, M. J. 2006. Age, Gender, and Cognitive Style Differences in IS Professionals. *In:* TRAUTH, E. (ed.) *Encyclopedia of Gender and Information Technology.*

GALPIN, V., SANDERS, I., TURNER, H. & VENTER, B. 2003. Computer self-efficacy, gender, and educational background in South Africa. *Technology and Society Magazine,* 22**,** 43-48.

GILBERT, D., LEE-KELLEY, L. & BARTON, M. 2003. Technophobia, gender influences and consumer decision-making for technology-related products. *European Journal of Innovation Management,* 6**,** 28-39.

GLASCOCK, J. & RUGGIERO, T. E. 2006. The Relationship of Ethnicity and Sex to Professor Credibility at a Culturally Diverse University. *Communication Education,* 55**,** 197-207.

GODDARD, R.D. 2002. A theoretical and empirical analysis of the measurement of collective efficacy: The development of a short form. *Educational and Psychological Measurement*.

GODDARD, R.D., HOY, W.K., WOOLFOLK, A. 2000. Collective teacher efficacy: Its meaning, measure, and effect on student achievement. *American Education Research Journal,* 37(2), 479-507.

GODSELL, G. 1981. Work Value Differences in South Africa: An Introduction. *In:* CSIR (ed.) *CSIR Special Report Pers.* CSIR, NIPR.

GODSELL, G. 1982. Work Values and Work Value Conflict in South African Organisations. *IACCP Congress.* Aberdeen.

GORHAM, J. S. 1988. The relationship between verbal teacher immediacy behaviors and student learning. *Communication Education,* 37**,** 40-43.

GRANT, D. M., MALLOY, A. D. & MURPHY, M. C. 2009. A Comparison of Student Perceptions of their Computer Skills to their Actual Abilities. *Journal of Information Technology and Education,* 8**,** 141-160.

GROUT, C. M. 1991. An assessment of the relationship between teacher teaching style and student learning style with relation to academic achievement and absenteeism of seniors in a rural school in north central Massachusetts. *Dissertation Abstracts International.,* 51**,** 2619.

HALE, K. V. 2005. Gender Differences in Computer Technology Achievement. *Meridian* [Online]. Available: http://www.ncsu.edu/meridian/sum2002/gender/gender.pdf [Accessed 21/1/2012].

HANUSHEK, E. A. & RIVKIN, S. G. 2009. Harming the Best: How Schools Affect the Black-White Achievement Gap. *Journal of Policy Analysis and Management,* 28**,** 366-393.

HARGITTAI, E. & SHAFER, S. 2006. Gender differences in actual and perceived online skills: The role of gender. *Social Science Quarterly,* 87**,** 432-448.

HARMAN, H. H. 1976. *Modern Factor Analysis* (3rd Ed.), Chicago: University of Chicago Press.

HARRIS, C. W. AND KAISER, H. F. 1964. Oblique factor analytic solutions by orthogonal transformation. *Psychometrika,* 32: 363-379.

HARRIS, R. W. 1999. Attitudes towards end-user computing: a structural equation model. *Behaviour & information technology,* 18**,** 109-125.

HARRISON, A. W. & RAINER, R. K. 1997. Testing The Self-Efficacy, Performance Linkage Of Social-Cognitive Theory. *Journal Of Social Psychology,* 137**,** 79-88.

HENDRIKS, K. G. 1997. Student perceptions of verbal and nonverbal cues leading to images of Black and White professor credibility. *The Howard Journal of Communications,* 8**,** 251-273.

HERRING, C. 2009. Does diversity pay?: Race, gender, and the business case for diversity. *American Sociological Review,* 74**,** 208-224.

HOFSTEDE, G. 1986. Cultural differences in teaching and learning. *International journal of Intercultural Relations.,* 10**,** 301-320.

HOFSTEDE, G. 2012. *What about South Africa?* [Online]. Available: http://geert-hofstede.com/south-africa.html [Accessed 17/3/2012].

HOFSTEDE, G., HOFSTEDE, G. J. & MINKOV, M. 2010. *Cultures and Organizations: Software of the Mind.,* New York, McGraw-Hill USA.

HOGAN, M. 2006. Technophobia amongst older adults in Ireland. *Irish Journal of Management,* 27**,** 57-58.

HOLM, S. 1979. A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics,* 6:65-70.

HORSFORD, S. 2010. Black Superintendents on Educating Black Students in Separate and Unequal Contexts. *Urban Review,* 42**,** 58-79.

HOWIE, S., VENTER, E. & VAN STADEN, S. 2008. The effect of multilingual policies on performance and progression in reading literacy in South African primary schools. *Educational Research and Evaluation,* 14**,** 551-560.

HUBER, P. J. 1973. Robust Regression: Asymptotics, Conjectures and Monte Carlo. *Annals of Statistics*, 1, 799–821.

HUBER, P. J. 1981. *Robust Statistics*. New York: John Wiley & Sons.

HUMAN, L. 1996. Managing workforce diversity: a critique and example from South Africa. *International Journal of Manpower.,* 17**,** 46-64.

ILIAS, A. 2006. Gender differences and achievement in computer science and engineering. *SIGCSE Bulletin,* 38**,** 81-85.

ISETT SETA. 2010. *Sector skills plan 2011–2016*. [Online]. Available: http://www.isett.org.za/isett/downloads/Isett_Seta_Sector_Skills_Plan_2011_2016_Sept_2010_Version_v1p1.zip [Accessed 23/11/2011].

JAGACINSKI, C. M., LEBOLD, W. K. & SALVENDY, G. 1988. Gender differences in persistence in computer-related fields. *Journal of Educational Computing Research,* 4**,** 185-202.

JANSEN, J. D. (ed.) 2002. *Mergers in Higher Education: theorising change in transitional context*, Pretoria: Unisa Press.

JOHNSON, R. D., STONE, D. L. & PHILLIPS, T. N. 2008. Relations Among Ethnicity, Gender, Beliefs, Attitudes, and Intention to Pursue a Career in Information Technology. *Journal of Applied Social Psychology,* 38**,** 999–1022.

JUSSIM, L., ECCLES, J. & MADON, S. 1996. Social Perception, Social Stereotypes, and Teacher Expectations: Accuracy and the Quest for the Powerful Self-Fulifilling Prophecy. *Advances in Experimental Social Psychology,* 28**,** 281-387.

KAFAI, Y. B. 1998. Video game designs by children: Consistency and variability of gender differences. *In:* CASSELL, J. & JENKINS, H. (eds.) *From Barbie to Mortal Kombat: Gender and Computer Games*. Boston, MA.: M.I.T. Press.

KAGAN, D. 1988. Learning how to program or use computers: A review of six applied studies. *Educational Technology,* 28**,** 49-51.

KAO, G. & THOMPSON, J. S. 2003. Racial and Ethnic Stratification in Educational Achievement and Attainment. *Annual Review of Sociology,* 29**,** 417-442.

KATZ, S., ARONIS, J., ALLBRITTON, D., WILSON, C. & SOFFA, M. L. 2003. Gender and Race in Predicting Achievement in Computer Science. *IEEE Technology and Society Magazine***,** 20-27.

KAUFFMAN, J. M., CONROY, M., GARDNER, R., III & OSWALD, D. 2008. Cultural sensitivity in the application of behavior principles to education. *Education & Treatment of Children*, 31**,** 239-262.

KAUFMAN, A. S., MCLEAN, J. E. & KAUFMAN, J. C. 1995. The fluid and crystallized abilities of white, black, and hispanic adolescents and adults, both with and without an education covariate. *Journal of Clinical Psychology,* 51**,** 636-647.

KEARNEY, P. & MCCROSKEY, J. C. 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.

KELLEY, D. H. & GORHAM, J. S. 1988. Effects of immediacy on recall of information. *Communication Education,* 37**,** 198-207.

KING, K., SHUMOW, L. & LIETZ, S. 2001. Science education in an urban elementary school: Case studies of teacher beliefs and classroom practices. *Science Education,* 85**,** 89-110.

KIRKPATRICK, D. L. 1998. *Evaluating Training Programs: The Four Levels,* San Francisco, Berret-Koehler Publishers.

KIRKPATRICK, H. & CUBAN, L. 1998. Should We Be Worried? What the Research Says About Gender Differences in Access, Use, Attitudes, and Achievement with Computers. *Educational Technology,* 38**,** 56-61.

KIRKUP, G., ZALEVSKI, A., MARUYAMA, T. & BATOOL, I. 2010. Women and men in science, engineering and technology: the UK statistics guide 2010. Bradford: UKRC.

KLASSEN, R. M., USHER, E. L. & BONG, M. 2010. Teachers' Collective Efficacy, Job Satisfaction, and Job Stress in Cross-Cultural Context. *Journal of Experimental Education,* 78**,** 464-486.

KLINE, R. B. 2010. *Principles and practice of structural equation modeling* (3rd Ed.), New York: Guilford.

KOOHANG, A. A. & BYRD, D. M. 1987. A study of selected variables and future study. *Library and Information Science Research,* 9**,** 214-288.

KOUL, R. & RUBBA, P. 1999. *An analysis of the reliability and validity of personal internet teaching efficacy beliefs scale.* [Online]. Electronic journal of science education. Available: http://ejse.southwestern.edu/article/viewArticle/7621/5388 [Accessed 21/02/2012].

KURBANOGLU, S. 2003. Self-efficacy: a concept closely linked to information literacy and lifelong learning. *Journal of Documentation,* 59**,** 635-646.

LEMMER, E. & SQUELCH, J. 1993. *Multicultural Education. A teacher's manual.,* Pretoria, Sigma Press.

LEMON, A. 2008. Indian identities in the 'rainbow nation': Responses to transformation in South African schools. *National Identities,* 10**,** 295-312.

LEMONE, K. Year. Analyzing Cultural Influences on ELearning Transactional Issues. *In:* RICHARDS, G., ed. World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education, 2005 Chesapeake, VA. AACE.

LEROUX, J. 2000. Multicultural education: a new approach for a new South African dispensation. *Intercultural Education,* 11**,** 19-29.

LESLIE, D. 2005. Why People from the UK's Minority Ethnic Communities Achieve Weaker Degree Results than Whites. *Applied Economics,* 37**,** 619-632.

LETSEKA, M. 2009. Chapter 7: University drop-out and researching work and (lifelong) learning. *In:* COOPER, L. & WALTERS, S. (eds.) *Learning / Work Turning work and lifelong learning inside out.* Cape Town: HSRC Press.

LETSEKA, M. & MAILE, S. 2008. *High university drop-out rates: a threat to South Africa's future* [Online]. Human Sciences Research Council. Available: http://www.hsrc.ac.za/Document-2717.phtml [Accessed 11/11/2011].

LIGHT, J. 2001. Rethinking the digital divide. *Harvard Educational Review,* 71**,** 709-733.

MAKOE, M. Q. 2006. South African distance students' accounts of learning in socio-cultural context: a habitus analysis. *Race, Ethnicity & Education,* 9**,** 361-380.

MAKRAKIS, V. 1992. Cross-cultural comparison of gender differences in attitude towards computers in Japan and Sweden. *Scandinavian Journal of Educational Research and Evaluation,* 36**,** 275-287.

MARAKAS, G. M., YI, M. Y. & JOHNSON, R. D. 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.

MARGOLIS, J. 2001. *Unlocking the Clubhouse: Women in Computing.,* Boston, MA., M.I.T. Press.

MARKUS, H. R. 2008. Pride, prejudice, and ambivalence: Toward a unified theory of race and ethnicity. *American Psychologist,* 63**,** 651-670.

MATTHEWS, D. B. 1991. Learning styles research: Implications for increasing students in teacher education programs. *Journal of Instructional Psychology*, 18**,** 228.

MCCROSKEY, J. C. & RICHMOND, V. P. 1992. Increasing teacher influence through immediacy. In V. P. Richmond, & J. C. McCroskey (Eds.), (pp. 101-119). Hillsdale, NJ: Erlbaum Associates, Inc. *Power in the classroom: Communication, control, and concern***,** 101-119.

MCCROSKEY, J. C. & YOUNG, T. J. 1981. Ethos and credibility: The construct and its measurement after three decades. *Central States Speech Journal,* 32**,** 24-34.

MCCROSKEY, L. L. 2002. Domestic and international college instructors: An examination of perceived differences and their correlates. *Journal of Intercultural Communication Research,* 31**,** 63-83.

MCCROSKEY, L. L. 2003. Relationships of instructional communication styles of domestic and foreign instructors with instructional outcomes. *Journal of Intercultural Communication Research,* 32.

MCILROY, D., BUNTING, B., TIERNEY, K. & GORDON, M. 2001. The relation of gender and background experience to self-reported computing anxieties and cognitions. *Computers in Human Behavior,* 17**,** 21-33.

MCSWEENEY, B. 2002. Hofstede's Identification of National Cultural Differences - A Triumph of Faith a Failure of Analysis. *Human Relations,* 55**,** 89-118.

MEAD, S. 2006. *The Truth About Girls and Boys*. [Online]. Washington, DC. Available: http://www.educationsector.org/usr_doc/ESO_BoysAndGirls.pdf [Accessed 21/1/2012].

MEYER, M., OPPERMAN, C. & DYRBYE, C. 2003. *Measuring ROI in Training: A Practical Implementation Guide*, Knowres Publishing (Pty) Ltd.

MILNER, H. R. 2003. Reflection, Racial Competence, and Critical Pedagogy: how do we prepare pre-service teachers to pose tough questions? *Race, Ethnicity and Education,* 6**,** 193-208.

MOORMAN, P. & JOHNSON, E. 2003. Still a stranger here: Attitudes among secondary school students towards computer science. *ITiCSE 2003 Conference*. Thessaloniki, Greece.

MOSELEY, C. & TAYLOR, B. 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.

MURPHY, C. A., COOVER, D. & OWEN, S. V. 1989. Development and validation of the computer self-efficacy scale. *Educational and Psychological Measurement,* 49**,** 893-899.

NATIONAL PLANNING COMMISSION. 2011. *Diagnostic Overview* [Online]. Available: http://www.npconline.co.za/MediaLib/Downloads/Home/Tabs/Diagnostic/Diagnostic%20Overview.pdf [Accessed 23/11/2011].

NAYLOR, R. A. & SMITH, J. 2004. Determinants of Educational Success in Higher Education. *In:* JOHNES, G. & JOHNES, J. (eds.) *International handbook on the economics of education.* Cheltenham, U.K. and Northampton, Mass.

NDLETYANA, D. 2003. The Impact of Culture on Team Learning in a South African Context. *Advances in Developing Human Resources.,* 5**,** 84-102.

NEAL, D. 2006. Why has black-white skill convergence stopped? *In:* HANUSHEK, E. A. & WELCH, F. (eds.) *Handbook of the economics of education.* Amsterdam: North Holland.

NEULIEP, J. W. 1995. A comparison of teacher immediacy in African-American and Euro-American college classrooms. *Communication Education,* 44**,** 267-277.

NKABINDE, Z. P. 1997. *An analysis of educational challenges in the New South Africa,* Lanham, MD, University Press of America.

OATES, G. L. 2003. Teacher-Student Racial Congruence, Teacher Perceptions, and Test Performance. *Social Science Quarterly (Blackwell Publishing Limited),* 84**,** 508-525.

OBIAKOR, F. E. 2004. Educating African American Urban Learners: Brown in Context. *Western Journal of Black Studies,* 28**,** 399-406.

OETTINGEN, G. 1995. Cross-cultural perspectives on self-efficacy. *In:* BANDURA, A. (ed.) *Self-efficacy in changing societies.* New York: Cambridge University Press.

PATTON, T. O. 1999. Ethnicity and gender: An examination of its impact on instructor credibility in the university classsroom. *The Howard Journal of Communications,* 10**,** 123-144.

PAYTON, F. C. 2003. Rethinking the digital divide. *Communications of the ACM,* 46**,** 89-91.

PEAK, D. & BERGE, Z. L. 2006. Evaluation and eLearning, . *Turkish Online Journal of Distance Education-TOJDE,* 7.

PHILLIPS, D. C. & ORTON, R. 1983. The new causal principle of cognitive learning theory: Perspectives on Bandura's "reciprocal determinism.". *Psychological Review,* 90**,** 158-165.

PHILLIPS, J. & PHILLIPS, P. 2001. In action: measuring return on investment: volume 3. Alexandria: American Society for Training & Development.

PHILLIPS, J. J. 1997. *Handbook of Training Evaluation and Measurement Methods.,* Houston, Gulf Publishing.

PHILLIPS, J. J. & STONE, R. D. 2002. *How to Measure Training Results: A Practical Guide to Tracking the Six Key Indicators.,* McGraw-Hill.

PICOWER, B. 2009. The unexamined Whiteness of teaching: how White teachers maintain and enact dominant racial ideologies. *Race, Ethnicity & Education,* 12**,** 197-215.

PIGOTT, R. L. & COWEN, E. L. 2000. Teacher race, child race, racial congruence, and teacher ratings of children's school adjustment. *Journal of School Psychology.,* 38**,** 177.

POWELL, R. G. & HARVILLE, B. 1990. The effects of teacher immediacy and clarity on instructional outcomes: An intercultural assessment. *Communication Education,* 39**,** 369-379.

RAINER, R. K., LAOSETHAKUL, K. & ASTONE, M. K. 2003. Are gender perceptions of computing changing over time? . *The Journal of Computer Information Systems,* 43**,** 108-114.

REDDY, V., PRINSLOO, C. H., NETSHITANGANI, T., MOLETSANE, R., JUAN, A. & JANSE VAN RENSBURG, D. 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.

REID, K. W. 2007. *Black Gold: Understanding the Relationships Between Racial Identity, Self-Efficacy, Institutional Integration and Academic Achievement of Black Males in Research Universities.* Doctor of Education, Harvard University.

REID, L. D. 2010. The role of perceived race and gender in the evaluation of college teaching on RateMyProfessors.Com. *Journal of Diversity in Higher Education,* 3**,** 137-152.

REPUBLIC OF SOUTH AFRICA 1996. Constitution of the Republic of South Africa, Act 108 of 1996. Republic of South Africa: Government Gazette.

RICHARDSON, J. T. E. 2008. The attainment of ethnic minority students in UK higher education. *Studies in Higher Education,* 33**,** 33-48.

RICHARDSON, J. T. E. 2009. The role of ethnicity in the attainment and experiences of graduates in distance education. *Higher Education,* 58**,** 321-338.

RICHMOND, V. P. 1990. Communication in the classroom: Power and motivation. *Communication Education,* 39**,** 181-195.

RICHMOND, V. P., GORHAM, J. S. & MCCROSKEY, J. C. 1987. The relationship between selected immediacy behaviors and cognitive learning. *In:* MCLAUGHLIN, M. L. (ed.) *Communication yearbook 10.* Newbury Park, C.A.: Sage.

RICHMOND, V. P., MCCROSKEY, J. C., PLAX, T. G. & KEARNEY, P. 1986 Teacher nonverbal immediacy training and student affect. *World Communication,* 15**,** 181-194.

RIEGLE-CRUMB, C. & KING, B. 2010. Questioning a White Male Advantage in STEM: Examining Disparities in College Major by Gender and Race/Ethnicity. *Educational Researcher,* 39**,** 656-664.

RIJKSCHROEFF, R., TEN DAM, G., DUYVENDAK, J. W., DE GRUIJTER, M. & PELS, T. 2005. Educational policies on migrants and minorities in the Netherlands: success or failure? *Journal of Education Policy,* 20**,** 417-435.

ROBERTS, T. S. 2006. The Use of Multiple Choice Tests for Formative and Summative Assessment. *In:* TOLHURST, D. & MANN, S. (eds.) *Eighth Australasian Computing Education Conference (ACE2006).* Hobart, Tasmania, Australia.

RODRIGUEZ, J. I., PLAX, T. G. & KEARNEY, P. 1996. Clarifying the relationship between teacher nonverbal immediacyand student cognitive learning: Affective learning as the central causal mediator. *Communication Education,* 45**,** 293-305.

ROTTER, J. B. 1954. *Social Learning and Clinical Psychology,* Englewood Cliffs, NJ, Prentice-Hall.

ROUSSEEUW, P. J. & VAN DRIESSEN, K. 1990. A Fast Algorithm for the Minimum Covariance Determinant Estimator. *Technometrics*, 41, 212-223.

ROUSSEEUW, P. J. AND YOHAI, V. 1984. Robust Regression by Means of S Estimators. *In:* FRANKE, J., HÄRDLE, W. AND MARTIN, R.D. (eds.) *Robust and Nonlinear Time Series Analysis, Lecture Notes in Statistics,* 26, New York: Springer-Verlag, 256–274.

RUBIN, D. L. 1998. Help! My professor (or doctor or boss) doesn't talk English. *In:* MARTIN, J. N., NAKAYAMA, K. & FLORES, L. A. (eds.) *Readings in cultural contexts.* Mountain View, CA: Mayfield.

RUCKER, M. L. & GENDRIN, D. M. 2003. The Impact of Ethnic Identification on Student Learning in the HBCU Classroom. *Journal of Instructional Psychology,* 30**,** 207-215.

RUSHTON, J. P. & JENSEN, A. R. 2005. Thirty years of research on race differences in cognitive ability. *Psychology, Public Policy, and Law,* 11**,** 235-294.

SALEEM, H., BEAUDRY, A. & CROTEAU, A. 2011. Antecedents of computer self-efficacy: A study of the role of personality traits and gender. *Computers in Human Behavior,* 27**,** 1922~1936.

SANDERS, J. A. & WISEMAN, R. L. 1990. The effects of verbal and nonverbalteacher immediacy on perceived cognitive, affective, and behavioural learning in the multicultural classroom. *Communication Education,* 39**,** 341-353.

SANTHANAM, R., SASIDHARAN, S. & WEBSTER, J. 2008. Using Self-Regulatory Learning to Enhance E-Learning-Based Information Technology Training. *Information Systems Research,* 19**,** 26-47.

SARACHO, O. N. & DAYTON, C. M. 1980. Relationship of teachers' cognitive styles to pupils' academic achievement gains. *Journal of Educational Psychology,* 72**,** 544-549.

SCHRODT, P., WITT, P. L., TURMAN, P. D., MYERS, S. A., BARTON, M. H. & JERNBERG, K. A. 2009. Instructor Credibility as a Mediator of Instructors' Prosocial Communication Behaviors and Students' Learning Outcomes. *Communication Education,* 58**,** 350-371.

SCHUMACHER, P. & MORAHAN-MARTIN, J. 2001. Gender, Internet, and computer attitudes and experiences. *Computers in Human Behavior*, 17**,** 95-110.

SELLERS, R. M., SHELTON, J. N., COOKE, D. Y., CHAVOUS, T. M., ROWLEY, S. J. & SMITH, M. A. 1998. A multidimensional model of racial identity: Assumptions, findings, and future directions. *In:* JONES, R. L. (ed.) *African American identity development.* Hampton, V.A.: Cobb & Henry Publishers.

SHEEHAN, D. S. & MARCUS, M. 1977. The Effects of Teacher Race and Student Race on Vocabulary and Mathematics Achievement. *The Journal of Educational Research,* 70**,** 123-126.

SIGNORINI, P., WIESEMES, R. & MURPHY, R. 2009. Developing alternative frameworks for exploring intercultural learning: A critique of Hofstede's cultural difference model. *Teaching in Higher Education,* 14**,** 253-264.

SINGH, A., BHADAURIA, V. & LIAO, Q. 2010. Role of Computer Self-efficacy and Playfulness as Determinants of Academic Success in Learning Spreadsheets *Forty First Annual Conference of the Southwest Decision Sciences Institute, 2010.* Dallas.

SKAALVIK, E. M. & SKAALVIK, S. 2007. Dimensions of Teacher Self-Efficacy and Relations With Strain Factors, Perceived Collective Teacher Efficacy, and Teacher Burnout. *Journal of Educational Psychology*, 2007, 99(3), 611–625.

SLEETER, C. E. 2008. Studying diversity in teacher education: Historical trends and issues. *American Educational Research Association Conference.* New York.

SMITH, P. B. 2002a. Culture's consequences: Something old and something new. *Human Relations,* 55**,** 119-135.

SMITH, S. M. 2002b. The Role of Social Cognitive Career Theory in Information Technology based Academic Performance. *Information Technology, Learning, and Performance Journal,* 20**,** 1-10.

SPENCER-OATEY, H. 2000. *Culturally speaking.,* New York, Continuum International Publishing Group Ltd.

STATISTICS SOUTH AFRICA 2001. Census 2001. Pretoria: Statistics South Africa.

STATISTICS SOUTH AFRICA. 2011. *Quarterly Labour Force Survey Quarter 3, 2011.* [Online]. Available: http://www.statssa.gov.za/publications/P0211/P02111stQuarter2011.pdf [Accessed 11/12/2011].

STOCKLY, S. 2009. Is Race a Determinant of Student Performance in Economics? *Review of Black Political Economy,* 36**,** 181-195.

STONE, D. 1993. Social Cognitive Theory. *Learning* 6**,** 1-48.

STROTER, A. D. 2008. *The Effects of Teacher-Student Racial and Ethnic Congruence on Student Math Learning.* Doctor of Philosophy in Education, Curriculum and Instruction, Virginia Polytechnic Institute and State University.

TAKOOSHIAN, H. 2010. Rediscovering differential psychology? *American Psychologist,* 65**,** 57-58.

TAMIR, M. & MAUSS, I. B. 2011. Social Cognitive Factors in Emotion Regulation: Implications for Well-Being Emotion Regulation and Well-Being. *In:* NYKLÍČEK, I., VINGERHOETS, A. & ZEELENBERG, M. (eds.). Springer New York.

TAYLOR, H. G. & MOUNFIELD, L. C. 1994. Exploring the relationship between prior computing experience and gender on success in college computer science. *Journal of Educational Computing Research,* 11**,** 291-306.

TEMPLE, L. & LIPS, H. M. 1989. Gender differences and similarities in attitudes toward computers. *Computers in Human Behavior,* 5**,** 215-226.

TERLECKI, M. & NEWCOMBE, N. 2005. How important is the digital divide? The relation of computer and videogame usage to gender differences in metal rotation ability. *Sex Roles,* 53**,** 433-441.

THE COLLEGE BOARD. 2012. *AP report to the nation* [Online]. Available: http://media.collegeboard.com/digitalServices/public/pdf/ap/rtn/AP-Report-to-the-Nation.pdf [Accessed 21/2/2012].

THE SOUTH AFRICAN INSTITUTE OF RACE RELATIONS 2008. South African Survey 2007/2008. Johannesburg.

THE UNITED NATIONS. 2011. *Millenium Development Goals* [Online]. Available: http://www.who.int/topics/millennium_development_goals/about/en/index.html [Accessed 14 September 2011].

THOMAS, R. M. 1990. Social Learning Theory. *In:* THOMAS, R. M. (ed.) *The Encyclopedia of Human Development and Education: Theory, Research, and Studies.* New York: Pergamon Press.

TIHANYI, K. 2007. Racial integration in the USA and South Africa: lessons in a comparative perspective. *International Journal of Inclusive Education,* 11**,** 177-197.

TODMAN, J. & DAY, K. 2006. Computer anxiety: The role of psychological gender. *Computers in Human Behavior,* 22**,** 856-869.

TOLMAN, E. C. 1932. *Purposive Behavior in Animal and Men. ,* New York, Appleton-Century-Crofts.

TOMLINSON, S. 2003. Globalization, race and education:continuity and change. *Journal of Educational Change,* 4**,** 213-230.

TONG, V. M., HUANG, C. W. & MCINTYRE, T. 2006. Promoting a Positive Cross-Cultural Identity: Reaching Immigrant Students. *Reclaiming Children & Youth,* 14**,** 203-208.

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

TSCHANNEN-MORAN, M. & HOY, A. W. 2001. Teacher efficacy: Capturing an elusive construct. *Teaching and Teacher Education,* 17**,** 783-805.

TURKLE, S. 1984. *The second self: computers and the human spirit.,* New York, Simon and Schuster.

VERHOEVEN, L. T. 1990. Acquisition of reading in a second language. *Reading Research Quarterly.,* 25**,** 90-114.

VILLEGAS, A. M. 2008. Diversifying the workforce: Examining induction, retention, and development of new teachers of color. *American Educational Research Association Conference.* New York.

VOLET, S. E. & STYLES, I. M. 1992. Predictors of study management and performance on a first-year computer course: The significance of students' study goals and perceptions. *Journal of Educational Computing Research,* 8**,** 423-449.

WARNICH, P. & WOLHUTER, C. C. (eds.) 2009. *OBE Assessment in South Africa: Issues and Challenges,* Pretoria: Van Schaik.

WEBB, N. M. 1984. Microcomputer learning in small groups: Cognitive requirements and group processes. *Journal of Educational Computing Research,* 76**,** 1076-1088.

WEIL, M. M. & ROSSEN, L. D. 1995. The psychological impact of technology from a global perspective: A study of the technological sophistication in university students from twenty-three countries. *Computers in Human Behavior,* 11**,** 95-135.

WEIS, L. 1988. *Class, Race and Gender in American Education.,* Albany, NY, State University of New York Press.

WHALEN, T. & WRIGHT, D. 1999. Methodology for cost-benefit analysis of web-based tele-learning program: Case study of the bell institute. *The American Journal of Distance Education & Treatment of Children,* 13**,** 24-44.

WHITLEY, J., B. E. 1996. Gender differences in computer- related attitudes: It depends on what you ask. *Computers in Human Behavior,* 12**,** 275-289.

WIGGAN, G. 2008. From opposition to engagement: Lessons from high achieving African American students. *The Urban Review,* 40**,** 317-349.

WILSON, J. H. 2006. Predicting Student Attitudes and Grades From Perceptions of Instructors' Attitudes. *Teaching of Psychology,* 33**,** 91-95.

WILSON, J. H. & TAYLOR, K. W. 2001. Professor immediacy behaviors associated with liking students. *Teaching of Psychology,* 28**,** 136-138.

WOODROW, D. & SHAM, S. 2001. Chinese Pupils and Their Learning Preferences. *Race, Ethnicity & Education,* 4**,** 377-394.

WOODWARD, W. R. 1982. The "discovery" of social behaviorism and social learning theory, 1870-1980. *American Psychologist,* 37**,** 396-410.

XIAOJING, L., SHIJUAN, L., SEUNG-HEE, L. & MAGJUKA, R. J. 2010. Cultural Differences in Online Learning: International Student Perceptions. *Journal of Educational Technology & Society,* 13**,** 177-188.

YI, M. Y. & DAVIS, F. D. 2003. Developing and Validating an Observational Learning Model of Computer Software Training and Skill Acquisition. *Information Systems Research,* 14**,** 146-169.

ZEGER, S. L., LIANG, K. Y. & ALBERT, P. S. 1988. Models for longitudinal data: a generalized estimating equation approach. *Biometrics,* 1049-1060.

ZHANG, L. 2006. Does student-teacher thinking style match/mismatch matter in students' achievement? *Educational Psychology,* 26**,** 395-409.

Appendix A: Pre- and Post Assessment Test

ISTN100 and ISTN101 Pre- and Post Assessment Test

Number of Questions: 60

Time Allocated: 45 Minutes

Instructions to Candidate:

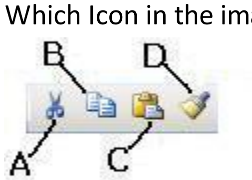
- The following questions are multiple choice.
- Each question has one right answer.
- Answer each question by filling in the correct answer in pencil on the computerized MCQ form provided. E.g.: If B was the correct answer for Question 61:

61 A B C D E

- Each question is worth one mark.
- Questions with no responses are marked incorrect.
- Negative marking does NOT apply.

Word Processing:

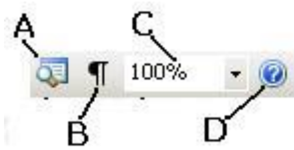
1. In Microsoft Word, which of the following are ways to save a document? (Select all that apply)
   i. Press Ctrl + S on the keyboard.
   ii. Select the Save Feature from the Windows Start Menu.
   iii. Select the Save option from the File Menu.
   iv. Click the Save button on the Standard toolbar.
   A. i, ii and iii
   B. i, iii and iv
   C. ii, iii and iv
   D. i, ii and iv
2. Why would you use the Save As option in the File menu instead of the Save option?
   A. To change how frequently Word saves AutoRecovery information about a file.
   B. To send someone an e-mail of a file.
   C. To specify if Word should always create a backup copy of a file.
   D. To save a file under a new name or location.
3. Which key combination moves your cursor to the beginning of the current line?
   A. Home
   B. There isn't such a key combination.
   C. Ctrl + Home.
   D. Ctrl + Page Up
4. To move to the end of a document, the key combination used is…
   A. Ctrl + Page Down
   B. Page Down
   C. Ctrl + End
   D. End
5. Which of the following will not allow you to select/highlight text in Microsoft Word?
   A. While holding down the Shift Key, press any directional arrow to select text in that direction
   B. Click the "Select Word Wizard" button on the toolbar and follow the on-screen instructions.
   C. Click & Drag the pointer across the text to be selected.
   D. Double-click any single word to select it.
6. Which Icon in the image is the button used to Cut Selected Text?



   A. A
   B. B

C. C
D. D

7. You want to see where the spaces, paragraphs, and tabs are in your document. Which Icon in the image allows you to do this?



A. A
B. B
C. C
D. D

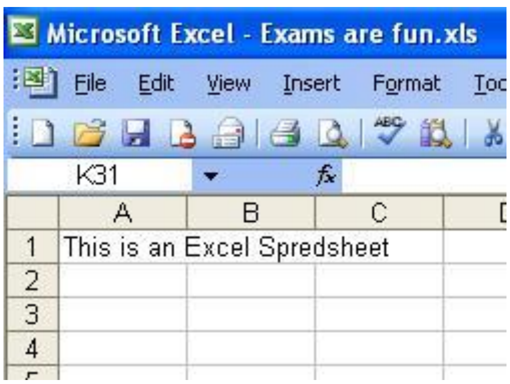
8. How do you center a paragraph?
   A. Click the Alignment arrow on the toolbar and select Center.
   B. Select Center from the Edit Menu.
   C. Click the Center button on the Formatting toolbar.
   D. Press Ctrl + C.
9. To copy character and paragraph formatting from one area in a document and apply it to another area you would use:
   A. The Format Painter button on the Standard toolbar
   B. The Edit > Copy Format and Edit > Paste Format commands from the menu
   C. There isn't a way to copy and apply formatting in Word
   D. Open the Copy and Apply Formatting dialog box by selecting Format > Copy Formatting from the menu
10. How can you print three copies of a document?
   A. Click the Print button on the Standard toolbar to print the document. Then use a photocopier to make a further 2 copies.
   B. Press Ctrl + P + 3
   C. Select Print from the File Menu. In the number of copies box enter 3. Click Print.
   D. Select Printing Properties from the Tools Menu. Enter 3 into the Print how many box.

Spreadsheets:

11. You cannot perform calculations on a cell that has been formatted to a DATE.
   A. TRUE
   B. FALSE
12. Which symbol must all formulas begin with?
   A. +
   B. (
   C. @

D. =

13. Which of the following is NOT an example of a VALUE?
    A. 350
    B. Serial Number 50671
    C. 10-May-02
    D. 57%
14. Which of the following formulae is NOT entered correctly?
    A. 60
    B. 16
    C. 10+50
    D. #VALUE!
15. Please refer to the diagram. What is the name of this workbook?



    A. Book 1.xls
    B. Exams are Fun.xls
    C. Fun.xls
    D. There is not enough information given to answer this question
16. You are the only person who has any spreadsheet knowledge in your company and have been asked to use a function that you have never used before. What do you do to solve this problem immediately?
    A. Press Ctrl-H and use help to search for that formula?
    B. Immediately book an Excel course that will cover the topic
    C. Press the F1 key and use help to search for that formula?
    D. There is not enough information given to answer this question
17. How do you select an entire column?
    A. Hold down the Shift key as you click anywhere in the column.
    B. Hold down the Ctrl key as you click anywhere in the column.
    C. Select Edit > Select > Column from the menu.
    D. Click the column heading letter.
18. What is the difference between closing and exiting in Excel?
    A. Close, closes Excel completely, while Exit closes the active window
    B. Both close Excel completely and take you to your desktop

C. Exit closes Excel completely while Close, closes the active window
D. Neither are a valid ways to exit Excel

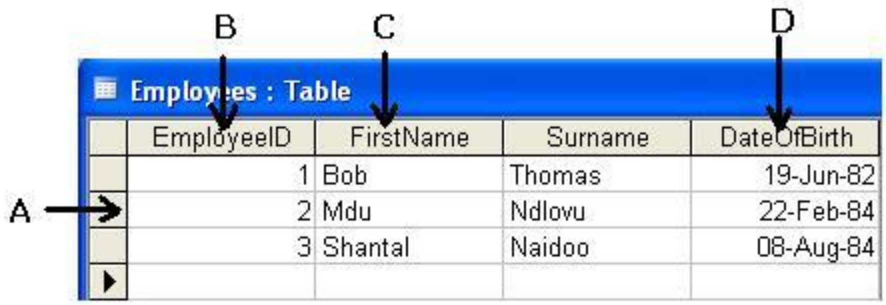
19. Which button do you click to add up a series of numbers?
    A. The Formula button.
    B. The QuickTotal button.
    C. The Total button.
    D. The AutoSum button.
20. How do you insert a row? (Select all that apply)
    i. Select the row heading where you want to insert the new row and select Edit > Insert Row from the menu
    ii. Right-click the row heading where you want to insert the new row and select Insert from the shortcut menu
    iii. Select the row heading where you want to insert the new row and click the Insert Row button on the Standard toolbar
    iv. Select the row heading where you want to insert the new row and select Insert > Row from the menu
    A. i and ii
    B. i and iii
    C. ii and iv
    D. ii and iii

Databases:

21. Which of the following shortcut keys prompts the help menu?
    A. F7
    B. F1
    C. Ctrl + H
    D. Shift + H
22. Which of the following best describes a Database?
    A. A relationship between tables
    B. A grouping of spreadsheets
    C. A batch of queries
    D. A collection of Data or information
23. Name two views used when exploring tables.
    i. Table View
    ii. Datasheet View
    iii. Design View
    iv. Column View
    A. i and ii
    B. i and iii
    C. ii and iv

D. ii and iii

24. With regards to the diagram, which of the following labels indicates fields with a datatype of NUMBER? (Select all correct answers)

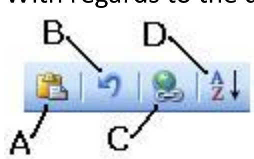


A. A
B. B
C. C
D. D

25. The Table wizard is used to…
A. Create Databases
B. Analyze Tables
C. Create Tables
D. Analyze Databases

26. What is the purpose of a primary key in a table?
A. It ensures that each record in a table is unique
B. It ensures fields can be duplicated within a table
C. It allows fields to be copied to another table
D. To enable automatic numbering within tables

27. With regards to the diagram, which label shows the icon used to sort fields in a table?



A. A
B. B
C. C
D. D

28. With regards to table creation, what is the purpose of specifying the FieldSize Property for a Field?
A. To specify the maximum amount of characters that can be entered into a field
B. To specify the dimensions of the field
C. It specifies the maximum no of records that can be entered into the table
D. It specifies the minimum no of characters that can be entered into a field

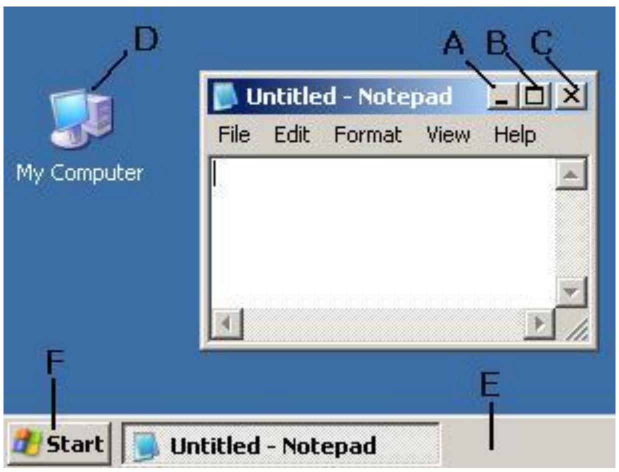
29. Which of the following best describes the purpose of a form?

A. They are utilities that allow us to design databases.
B. A graphical representation of data that allows us to view & edit information in a table.
C. They are designed to print summarized versions of information in queries.
D. A set of commands that can be executed with one instruction.

30. A query allows one to…
    A. extract macros from tables
    B. extract forms from a database
    C. extract records from tables
    D. extract tables from databases

Using a Computer and Managing Files:

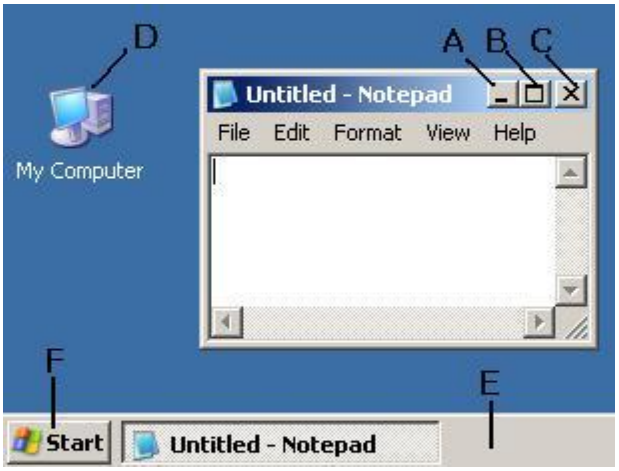
31. What is meant by the term, "Logging On"?
    A. Providing a correct username & password to access the computer.
    B. The ability to have a computer track your movements.
    C. A log file that has an entry made each time you play solitaire.
    D. Using a bootdisk to provide your computer with startup info.
32. In the diagram, which item depicts the window's taskbar?



    A. A
    B. E
    C. D
    D. F
33. Which action cannot be performed using a mouse?
    A. Right Click
    B. Click & Drag
    C. Unclick
    D. Double Click
34. Which two of the following, are not default items on the taskbar?

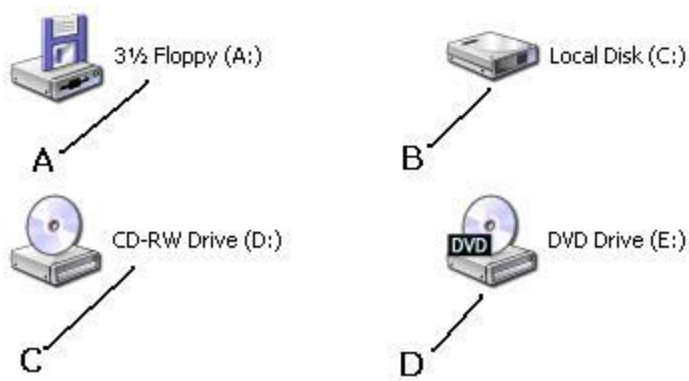
i. Start Button
ii. Solitaire
iii. Clock
iv. Calculator
  A. i and ii
  B. i and iii
  C. ii and iv
  D. ii and iii

35. In the diagram, which item is used to display a window so it takes up the entire screen space?



  A. A
  B. B
  C. C
  D. E

36. In the diagram, which label depicts the hard drive?



  A. A
  B. B
  C. C
  D. D

37. Which two of the following will correctly create a folder?
i. From Windows Explorer, click the File menu, choose New & then Folder.

ii. Double click My Computer, click the Create Menu, choose Folder.
iii. Right Click the desktop, from the Popup menu that appears, choose New & then folder.
iv. Push Shift+Ctrl+N to create a new folder.

A. i and ii
B. i and iii
C. ii and iv
D. ii and iii

38. With regards to folders, which operations cannot be performed? (Select all that apply)
    A. They may be deleted.
    B. They may be copied.
    C. They can be renamed.
    D. They may be formatted.
39. What can be used to prevent data being written to a floppy disk?
    A. The sliding cover.
    B. A write protect slider.
    C. The windows disk protector wizard.
    D. An anti-write plug.
40. When a file is deleted from your Hard Drive, what happens to it?
    A. It is moved to the Recycle Bin where it can later be permanently deleted.
    B. It is moved to the Deleted Items folder which is periodically & automatically cleared.
    C. It is always immediately removed from your computer.
    D. Nothing happens as files may never be deleted.

IT Concepts:

41. Which one of the following would be described as software?
    A. Internet browser
    B. Printer
    C. Monitor
    D. Keyboard
42. Which one of the following would be most used by someone who travels by train to work in various locations?
    A. Workstation
    B. Mainframe
    C. Laptop
    D. Desktop
43. A laptop is most likely to have which one of the following input devices fitted as standard?
    A. Touchscreen
    B. Laser pen

C. Mouse
D. Touch pad

44. What do the letters CPU stand for?
    A. Calculating Process Unit
    B. Control Program Unit
    C. Control Process Unit
    D. Central Processing Unit
45. Your computer is slow when running some applications. Which one of the following is most likely to improve the performance of the computer?
    A. Buying a zip drive
    B. Buying a bigger monitor
    C. Installing more memory
    D. Installing a faster CD-ROM drive
46. Which one of the following statements about Read Only Memory is true?
    A. Application programs can write data to ROM
    B. The contents of ROM are not deleted when the computer is switched off
    C. Internet pages are stored in ROM while they are being loaded
    D. The contents of ROM are deleted when the computer is switched off
47. What is the purpose of fully formatting a floppy disk?
    A. To scan the floppy disk for viruses
    B. To lock the floppy disk
    C. To prepare the floppy disk to store files
    D. To allow read/write access to files on the floppy disk
48. Which one of the following best describes a GUI?
    A. A method of communicating with a computer using text
    B. An international standard for rating monitors
    C. An international standard for rating input devices
    D. A method of communicating with a computer using a pointing device to manipulate icons, menus and text
49. Linux is …
    A. A database application
    B. An anti-virus scanner
    C. A backup utility
    D. An operating system
50. Which one of the following statements best describes a peripheral?
    A. A peripheral is a type of computer
    B. A peripheral is a device that can be attached to a computer
    C. A peripheral is a type of GUI
    D. A peripheral is only a type of keyboard or scanner

Information and Communication (Networks):

51. What is FTP?
    A. File Transaction Protocol
    B. Fast Transmission Protocol
    C. File Transfer Protocol
    D. Fast Transaction Protocol
52. What is a URL?
    A. User Resource Locator
    B. Uniform Refresh Locator
    C. Uniform Resource Link
    D. Uniform Resource Locator
53. Which one of the following refers to the domain name in the URL ***http://www.ecdl.com***?
    A. com
    B. http://
    C. c. //www.
    D. d. ecdl
54. Why might you bookmark a web page?
    A. To save the Web page as a text file for printing later
    B. To select the Web page as the browser home page
    C. To mark the Web page for deletion
    D. To record the URL of the Web page for future browsing
55. How do you change your Web browser's home page?
    A. Save the required home page as a bookmark
    B. Use menu options to set the current page as the home page
    C. Send an e-mail to your ISP and request the change
    D. Install a new search engine
56. A firewall is used to…
    A. protect a computer system from power failures
    B. scan for computer viruses
    C. encrypt e-mail messages
    D. protect a computer system from unauthorised access
57. Which one of the following activities is most likely to be subject to fraud?
    A. Entering your city, post code and country details on an electronic form
    B. Entering the quantity of goods to purchase on an electronic form
    C. Entering your credit card details when purchasing goods on the Internet
    D. Sending an email to ask about a product on a website
58. In the e-mail address ***dwilliams@ldce.uk*** which part of the address identifies the geographical area?
    A. @
    B. dwilliams
    C. uk
    D. ldce

59. Which one of the following statements is true?
    A. e-mail cannot transmit images as attachments
    B. e-mail is a low cost way to send and receive messages
    C. e-mail cannot be infected by computer viruses
    D. e-mail is a secure way to transmit and store confidential information
60. What is a distribution list?
    A. A list of e-mails sent
    B. A list of forwarded e-mails
    C. A list of recipients on an e-mail mailing list
    D. A list of e-mails in the outbox

Appendix B: Perception Questionnaire

Return On Investment in Training: Perceptions of the Impact of Congruence Factors

This purpose of this questionnaire is to identify student perceptions of the factors that contribute positively to their learning experience. This is part of a broader study that seeks to identify ways in which return on training investment can be maximized. Please select one option from each of the questions below by circling the appropriate response. For example:

Sample Question 1: Are you happy?

a. Yes
b. No

Consent to Participate in Research

I ____ (**Name of Participant: Optional**), _______________________________ (**Student No.: Optional**) the participant, hereby confirm that I understand the nature of the research project and I consent to participating. I understand that I am at liberty to withdraw from the project at any time. I agree that information and research data gathered for the study will be used in the analysis of the factors that influence learning and will be used in aggregate statistics. No personal details will be revealed at any time.

____
____
Signature Date

1. Please select your gender:
   a. Male
   b. Female
2. Please select your race:
   a. Black
   b. White
   c. Asian
   d. Coloured
   e. Other
3. Please select your home language:

   a. English
   b. Afrikaans
   c. Zulu
   d. Xhosa
   e. Swazi
   f. Ndebele
   g. Southern Sotho
   h. Northern Sotho
   i. Tsonga
   j. Tswana
   k. Venda
   l. Other
4. Which of the following is true about your teacher's gender?
   a. I learn better from a teacher who is of the same gender as me.
   b. I learn better from a teacher who is not of the same gender as me.
   c. The teacher's gender makes no difference to how I learn.
5. Which of the following is true about your teacher's race?
   a. I learn better from a teacher who is of the same race as me.
   b. I learn better from a teacher who is not of the same race as me.
   c. The teacher's race makes no difference to how I learn.
6. Which of the following is true about your teacher's home language?
   a. I learn better from a teacher whose home language is the same as mine.
   b. I learn better from a teacher whose home language is not the same as mine.
   c. The teacher's home language makes no difference to how I learn.
7. Which of the following is true about your teacher speaking your home language while teaching you?
   a. I learn better when my teacher speaks my home language while teaching me.
   b. I learn better when my teacher does not speak my home language while teaching me.
   c. The teacher using my home language while teaching makes no difference to how I learn.

Thank you for your cooperation!

Appendix C: Student Collective Teaching Self-Efficacy Questionnaire

Student Collective Teaching Self-Efficacy Questionnaire (S-CTSE)

The purpose of this questionnaire is to identify student perceptions of collective teaching efficacy (in respect of race, home language and gender). This is part of a broader study that seeks to identify ways in which return on training investment can be maximized. Please select one option from each of the questions below by circling the appropriate response. For example:

Sample Question 1: Are you happy?

a. Yes
b. *No*

Consent to Participate in Research

I ____ (**Name of Participant**), ________________________ (**Student No.**) the participant, hereby confirm that I understand the nature of the research project and I consent to participating. I understand that I am at liberty to withdraw from the project at any time. I agree that information and research data gathered for the study will be used in the analysis of the factors that influence learning and will be used in aggregate statistics. No personal details will be revealed at any time. On that basis I agree to my academic results being used for the purposes of this research.

_____________________________ _____________________________

Signature Date

5. Please select your **gender**:
   a. Male
   b. Female

6. Please select your **race**:
   a. Black
   b. White
   c. Asian
   d. Coloured
   e. Other

7. Please select your **home language**:

a. English	d. Xhosa	g. Southern Sotho	j. Tswana
b. Afrikaans	e. Swazi	h. Northern Sotho	k. Venda
c. Zulu	f. Ndebele	i. Tsonga	l. Other

8. **Student Perception of Collective Teaching Self-Efficacy:**
(Directions: The following questions seek to identify your general perceptions of teachers of your own race, home language and gender. Please indicate your level of agreement with each of the following statements from **Strongly Disagree** to **Strongly Agree**. Your answers are strictly confidential.)

	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree
Subject Expertise						
4.1 I have confidence in the ability of teachers that are of the same **race** as me to teach computer related subjects effectively.	1	2	3	4	5	6
4.2 I am confident that teachers that are of the same **race** as me receive a high level of technical training to prepare them to effectively teach computer related subjects.	1	2	3	4	5	6
4.3 I believe that teachers that are of the same **race** as me are highly competent users of computer technology.	1	2	3	4	5	6
4.4 I have confidence in the ability of teachers that are of the same **home language** as me to teach computer related subjects effectively.	1	2	3	4	5	6
4.5 I am confident that teachers that are of the same **home language** as me receive a high level of technical training to prepare them to effectively teach computer related subjects.	1	2	3	4	5	6
4.6 I believe that teachers that are of the same **home language** as me are highly competent users of computer technology.	1	2	3	4	5	6
4.7 I have confidence in the ability of teachers that are of the same **gender** as me to teach computer related subjects effectively.	1	2	3	4	5	6
4.8 I am confident that teachers that are of the same **gender** as me receive a high level of technical training to prepare them to effectively teach computer related subjects.	1	2	3	4	5	6
4.9 I believe that teachers that are of the same **gender** as me are highly competent users of computer technology.	1	2	3	4	5	6
Instructional Strategies						
4.10 I believe that teachers that are of the same **race** as me are excellent at planning lessons.	1	2	3	4	5	6
4.11 I believe that teachers that are of the same **race** as me are highly organized in their teaching approach.	1	2	3	4	5	6
4.12 I have confidence that teachers that are of the same **race** as me produce meaningful student learning by using various innovative teaching techniques.	1	2	3	4	5	6
4.13 I believe that teachers that are of the same **home language** as me are excellent at planning lessons.	1	2	3	4	5	6
4.14 I believe that teachers that are of the same **home language** as me are highly organized in their teaching approach.	1	2	3	4	5	6
4.15 I have confidence that teachers that are of the same **home language** as me produce meaningful student learning by using various innovative teaching techniques.	1	2	3	4	5	6
4.16 I believe that teachers that are of the same **gender** as me are excellent at planning lessons.	1	2	3	4	5	6
4.17 I believe that teachers that are of the same **gender** as me are highly organized in their teaching approach.	1	2	3	4	5	6
4.18 I have confidence that teachers that are of the same **gender** as me produce meaningful student learning by using various innovative teaching techniques.	1	2	3	4	5	6

Classroom Management	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree
4.19 I believe that teachers that are of the same **race** as me are effective at dealing with disciplinary issues in the classroom.	1	2	3	4	5	6
4.20 I believe that teachers that are of the same **race** as me are effective at ensuring the classroom environment is highly conducive to learning.	1	2	3	4	5	6
4.21 I believe that teachers that are of the same **race** as me skillfully manage variety in student capability in the classroom.	1	2	3	4	5	6
4.22 I believe that teachers that are of the same **home language** as me are effective at dealing with disciplinary issues in the classroom.	1	2	3	4	5	6
4.23 I believe that teachers that are of the same **home language** as me are effective at ensuring the classroom environment is highly conducive to learning.	1	2	3	4	5	6
4.24 I believe that teachers that are of the same **home language** as me skillfully manage variety in student capability in the classroom.	1	2	3	4	5	6
4.25 I believe that teachers that are of the same **gender** as me are effective at dealing with disciplinary issues in the classroom.	1	2	3	4	5	6
4.26 I believe that teachers that are of the same **gender** as me are effective at ensuring the classroom environment is highly conducive to learning.	1	2	3	4	5	6
4.27 I believe that teachers that are of the same **gender** as me skillfully manage variety in student capability in the classroom.	1	2	3	4	5	6
Student Engagement						
4.28 I believe that teachers that are of the same **race** as me are effective at motivating students.	1	2	3	4	5	6
4.29 I believe that teachers that are of the same **race** as me do not give up easily on students who find learning difficult.	1	2	3	4	5	6
4.30 I believe that teachers that are of the same **race** as me are effective at getting through to the most difficult students.	1	2	3	4	5	6
4.31 I believe that teachers that are of the same **home language** as me are effective at motivating students.	1	2	3	4	5	6
4.32 I believe that teachers that are of the same **home language** as me do not give up easily on students who find learning difficult.	1	2	3	4	5	6
4.33 I believe that teachers that are of the same **home language** as me are effective at getting through to the most difficult students.	1	2	3	4	5	6
4.34 I believe that teachers that are of the same **gender** as me are effective at motivating students.	1	2	3	4	5	6
4.35 I believe that teachers that are of the same **gender** as me do not give up easily on students who find learning difficult.	1	2	3	4	5	6
4.36 I believe that teachers that are of the same **gender** as me are effective at getting through to the most difficult students.	1	2	3	4	5	6

Source: Adapted from Goddard, R.D., Hoy, W.K., Woolfolk, A. (2000). Collective teacher efficacy: Its meaning, measure, and effect on student achievement. American Education Research Journal, 37(2), 479-507 *and* Tschannen-Moran, M., & Woolfolk Hoy, A. (2001). Teacher efficacy: Capturing an elusive construct. *Teaching and Teacher Education, 17,* 783–805.

Appendix D: Teacher Collective Teaching Self-Efficacy Questionnaire

Teacher Collective Teaching Self-Efficacy Questionnaire (T-CTSE)

The purpose of this questionnaire is to identify teacher perceptions of collective teaching efficacy (in respect of race, home language and gender). This is part of a broader study that seeks to identify ways in which return on training investment can be maximized. Please select one option from each of the questions below by circling the appropriate response. For example:

Sample Question 1: Are you happy?

a. Yes
b. *No*

Consent to Participate in Research

I ____ (**Name of Participant**), _________________________ (**Institution**), the participant, hereby confirm that I understand the nature of the research project and I consent to participating. I understand that I am at liberty to withdraw from the project at any time. I agree that information and research data gathered for the study will be used in the analysis of the factors that influence learning and will be used in aggregate statistics. No personal details will be revealed at any time. On that basis I agree to my academic results being used for the purposes of this research.

__________________________ __________________________

Signature Date

1. Please select your **gender**:
   a. Male
   b. Female

2. Please select your **race**:
   a. Black
   b. White
   c. Asian
   d. Coloured
   e. Other

3. Please select your **home language**:

a. English
b. Afrikaans
c. Zulu
d. Xhosa
e. Swazi
f. Ndebele
g. Southern Sotho
h. Northern Sotho
i. Tsonga
j. Tswana
k. Venda
l. Other

4. **Teacher Perception of Collective Teaching Self-Efficacy:**
(Directions: The following questions seek to identify your general perceptions of teachers of your own race, home language and gender. Please indicate your level of agreement with each of the following statements from **Strongly Disagree** to **Strongly Agree**. Your answers are strictly confidential.)

	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree
Subject Expertise						
4.1 I have confidence in the ability of teachers that are of the same **race** as me to teach computer related subjects effectively.	1	2	3	4	5	6
4.2 I am confident that teachers that are of the same **race** as me receive a high level of technical training to prepare them to effectively teach computer related subjects.	1	2	3	4	5	6
4.3 I believe that teachers that are of the same **race** as me are highly competent users of computer technology.	1	2	3	4	5	6
4.4 I have confidence in the ability of teachers that are of the same **home language** as me to teach computer related subjects effectively.	1	2	3	4	5	6
4.5 I am confident that teachers that are of the same **home language** as me receive a high level of technical training to prepare them to effectively teach computer related subjects.	1	2	3	4	5	6
4.6 I believe that teachers that are of the same **home language** as me are highly competent users of computer technology.	1	2	3	4	5	6
4.7 I have confidence in the ability of teachers that are of the same **gender** as me to teach computer related subjects effectively.	1	2	3	4	5	6
4.8 I am confident that teachers that are of the same **gender** as me receive a high level of technical training to prepare them to effectively teach computer related subjects.	1	2	3	4	5	6
4.9 I believe that teachers that are of the same **gender** as me are highly competent users of computer technology.	1	2	3	4	5	6
Instructional Strategies						
4.10 I believe that teachers that are of the same **race** as me are excellent at planning lessons.	1	2	3	4	5	6
4.11 I believe that teachers that are of the same **race** as me are highly organized in their teaching approach.	1	2	3	4	5	6
4.12 I have confidence that teachers that are of the same **race** as me produce meaningful student learning by using various innovative teaching techniques.	1	2	3	4	5	6
4.13 I believe that teachers that are of the same **home language** as me are excellent at planning lessons.	1	2	3	4	5	6
4.14 I believe that teachers that are of the same **home language** as me are highly organized in their teaching approach.	1	2	3	4	5	6
4.15 I have confidence that teachers that are of the same **home language** as me produce meaningful student learning by using various innovative teaching techniques.	1	2	3	4	5	6
4.16 I believe that teachers that are of the same **gender** as me are excellent at planning lessons.	1	2	3	4	5	6
4.17 I believe that teachers that are of the same **gender** as me are highly organized in their teaching approach.	1	2	3	4	5	6
4.18 I have confidence that teachers that are of the same **gender** as me produce meaningful student learning by using various innovative teaching techniques.	1	2	3	4	5	6

Classroom Management	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree
4.19 I believe that teachers that are of the same **race** as me are effective at dealing with disciplinary issues in the classroom.	1	2	3	4	5	6
4.20 I believe that teachers that are of the same **race** as me are effective at ensuring the classroom environment is highly conducive to learning.	1	2	3	4	5	6
4.21 I believe that teachers that are of the same **race** as me skillfully manage variety in student capability in the classroom.	1	2	3	4	5	6
4.22 I believe that teachers that are of the same **home language** as me are effective at dealing with disciplinary issues in the classroom.	1	2	3	4	5	6
4.23 I believe that teachers that are of the same **home language** as me are effective at ensuring the classroom environment is highly conducive to learning.	1	2	3	4	5	6
4.24 I believe that teachers that are of the same **home language** as me skillfully manage variety in student capability in the classroom.	1	2	3	4	5	6
4.25 I believe that teachers that are of the same **gender** as me are effective at dealing with disciplinary issues in the classroom.	1	2	3	4	5	6
4.26 I believe that teachers that are of the same **gender** as me are effective at ensuring the classroom environment is highly conducive to learning.	1	2	3	4	5	6
4.27 I believe that teachers that are of the same **gender** as me skillfully manage variety in student capability in the classroom.	1	2	3	4	5	6
Student Engagement						
4.28 I believe that teachers that are of the same **race** as me are effective at motivating students.	1	2	3	4	5	6
4.29 I believe that teachers that are of the same **race** as me do not give up easily on students who find learning difficult.	1	2	3	4	5	6
4.30 I believe that teachers that are of the same **race** as me are effective at getting through to the most difficult students.	1	2	3	4	5	6
4.31 I believe that teachers that are of the same **home language** as me are effective at motivating students.	1	2	3	4	5	6
4.32 I believe that teachers that are of the same **home language** as me do not give up easily on students who find learning difficult.	1	2	3	4	5	6
4.33 I believe that teachers that are of the same **home language** as me are effective at getting through to the most difficult students.	1	2	3	4	5	6
4.34 I believe that teachers that are of the same **gender** as me are effective at motivating students.	1	2	3	4	5	6
4.35 I believe that teachers that are of the same **gender** as me do not give up easily on students who find learning difficult.	1	2	3	4	5	6
4.36 I believe that teachers that are of the same **gender** as me are effective at getting through to the most difficult students.	1	2	3	4	5	6

Source: Adapted from Goddard, R.D., Hoy, W.K., Woolfolk, A. (2000). Collective teacher efficacy: Its meaning, measure, and effect on student achievement. American Education Research Journal, 37(2), 479-507 *and* Tschannen-Moran, M., & Woolfolk Hoy, A. (2001). Teacher efficacy: Capturing an elusive construct. *Teaching and Teacher Education, 17,* 783–805.

Appendix E: Student CFA output (SAS)

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Fit Summary		
Absolute Index	**Chi-Square**	539.6384
	Chi-Square DF	46
	Pr > Chi-Square	<.0001
	Standardized RMSR (SRMSR)	0.0333
Parsimony Index	**RMSEA Estimate**	0.0885
	RMSEA Lower 90% Confidence Limit	0.0819
	RMSEA Upper 90% Confidence Limit	0.0953
	Akaike Information Criterion	603.6384
	Bozdogan CAIC	802.7839
	Schwarz Bayesian Criterion	770.7839
Incremental Index	**Bentler Comparative Fit Index**	0.9725
	Bentler-Bonett Non-normed Index	0.9605

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Raw Residual Matrix

	SEX_R	**SEX_L**	**SEX_G**	**IS_R**	**IS_L**	**IS_G**	**CM_R**	**CM_L**	**CM_G**	**SEN_R**	**SEN_L**	**SEN_G**
SEX_R	0.00000	0.02653	-0.01836	-0.00219	-0.04550	-0.03553	-0.04482	-0.02942	-0.02112	-0.00656	-0.03797	-0.03309
SEX_L	0.02653	0.00000	-0.04649	-0.03987	0.01909	-0.02945	-0.02174	0.02252	-0.01902	-0.03578	0.01080	-0.04057
SEX_G	-0.01836	-0.04649	-0.00114	0.10805	0.04259	0.10028	0.08181	0.07126	0.25585	0.11844	0.07012	0.22010
IS_R	-0.00219	-0.03987	0.10805	0.00000	0.01658	0.01467	0.00106	-0.01270	-0.02222	0.02287	-0.03568	0.02049
IS_L	-0.04550	0.01909	0.04259	0.01658	0.00000	0.01474	-0.02291	-0.01487	-0.02121	-0.01979	-0.01513	0.00689
IS_G	-0.03553	-0.02945	0.10028	0.01467	0.01474	0.07272	0.05178	0.06608	0.22730	0.07125	0.03850	0.11216
CM_R	-0.04482	-0.02174	0.08181	0.00106	-0.02291	0.05178	0.00000	0.01266	-0.00886	0.02070	-0.02853	-0.01225
CM_L	-0.02942	0.02252	0.07126	-0.01270	-0.01487	0.06608	0.01266	0.00000	-0.01374	-0.02111	0.00613	-0.00487
CM_G	-0.02112	-0.01902	0.25585	-0.02222	-0.02121	0.22730	-0.00886	-0.01374	0.00000	0.02413	0.02090	0.13359
SEN_R	-0.00656	-0.03578	0.11844	0.02287	-0.01979	0.07125	0.02070	-0.02111	0.02413	0.00000	0.00273	0.00115

Raw Residual Matrix												
	SEX_R	**SEX_L**	**SEX_G**	**IS_R**	**IS_L**	**IS_G**	**CM_R**	**CM_L**	**CM_G**	**SEN_R**	**SEN_L**	**SEN_G**
SEN_L	-0.03797	0.01080	0.07012	-0.03568	-0.01513	0.03850	-0.02853	0.00613	0.02090	0.00273	0.00000	0.01305
SEN_G	-0.03309	-0.04057	0.22010	0.02049	0.00689	0.11216	-0.01225	-0.00487	0.13359	0.00115	0.01305	0.02125

Average Absolute Residual	0.037221
Average Off-diagonal Absolute Residual	0.042548

Rank Order of the 10 Largest Raw Residuals		
Var1	**Var2**	**Residual**
CM_G	**SEX_G**	0.25585
CM_G	**IS_G**	0.22730
SEN_G	**SEX_G**	0.22010
SEN_G	**CM_G**	0.13359
SEN_R	**SEX_G**	0.11844
SEN_G	**IS_G**	0.11216
IS_R	**SEX_G**	0.10805
IS_G	**SEX_G**	0.10028
CM_R	**SEX_G**	0.08181
IS_G	**IS_G**	0.07272

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Normalized Residual Matrix												
	SEX_R	**SEX_L**	**SEX_G**	**IS_R**	**IS_L**	**IS_G**	**CM_R**	**CM_L**	**CM_G**	**SEN_R**	**SEN_L**	**SEN_G**
SEX_R	0.00000	0.43373	-0.27984	-0.03681	-0.77932	-0.59459	-0.79270	-0.53483	-0.37545	-0.11271	-0.68271	-0.58458
SEX_L	0.43373	0.00000	-0.74684	-0.70755	0.34432	-0.51963	-0.40548	0.43172	-0.35675	-0.64834	0.20485	-0.75696
SEX_G	-0.27984	-0.74684	-0.01389	1.77487	0.71262	1.53250	1.40465	1.25826	4.40326	1.96727	1.22086	3.75219
IS_R	-0.03681	-0.70755	1.77487	0.00000	0.27906	0.24326	0.01869	-0.22991	-0.39496	0.39493	-0.64444	0.36512
IS_L	-0.77932	0.34432	0.71262	0.27906	0.00000	0.24823	-0.41039	-0.27355	-0.38347	-0.34777	-0.27796	0.12502
IS_G	-0.59459	-0.51963	1.53250	0.24326	0.24823	1.03836	0.90880	1.19196	4.01622	1.22177	0.69092	1.90065
CM_R	-0.79270	-0.40548	1.40465	0.01869	-0.41039	0.90880	0.00000	0.22190	-0.15298	0.35310	-0.50846	-0.21617
CM_L	-0.53483	0.43172	1.25826	-0.22991	-0.27355	1.19196	0.22190	0.00000	-0.24374	-0.37002	0.11231	-0.08828
CM_G	-0.37545	-0.35675	4.40326	-0.39496	-0.38347	4.01622	-0.15298	-0.24374	0.00000	0.41543	0.37598	2.37569
SEN_R	-0.11271	-0.64834	1.96727	0.39493	-0.34777	1.22177	0.35310	-0.37002	0.41543	0.00000	0.04483	0.01878

Normalized Residual Matrix												
	SEX_R	SEX_L	SEX_G	IS_R	IS_L	IS_G	CM_R	CM_L	CM_G	SEN_R	SEN_L	SEN_G
SEN_L	-0.68271	0.20485	1.22086	-0.64444	-0.27796	0.69092	-0.50846	0.11231	0.37598	0.04483	0.00000	0.22216
SEN_G	-0.58458	-0.75696	3.75219	0.36512	0.12502	1.90065	-0.21617	-0.08828	2.37569	0.01878	0.22216	0.31468

Average Normalized Residual	0.641155
Average Off-diagonal Normalized Residual	0.737017

Rank Order of the 10 Largest Normalized Residuals		
Var1	**Var2**	**Residual**
CM_G	SEX_G	4.40326
CM_G	IS_G	4.01622
SEN_G	SEX_G	3.75219
SEN_G	CM_G	2.37569
SEN_R	SEX_G	1.96727
SEN_G	IS_G	1.90065
IS_R	SEX_G	1.77487
IS_G	SEX_G	1.53250
CM_R	SEX_G	1.40465
CM_L	SEX_G	1.25826

CMB

The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Distribution of Normalized Residuals				
Each * Represents 1 Residuals				
Range		**Freq**	**Percent**	
-1.00000	**-0.75000**	3	3.85	***
-0.75000	**-0.50000**	10	12.82	**********
-0.50000	**-0.25000**	11	14.10	***********
-0.25000	**0**	8	10.26	********
0	**0.25000**	19	24.36	*******************
0.25000	**0.50000**	10	12.82	**********
0.50000	**0.75000**	2	2.56	**
0.75000	**1.00000**	1	1.28	*
1.00000	**1.25000**	4	5.13	****
1.25000	**1.50000**	2	2.56	**
1.50000	**1.75000**	1	1.28	*
1.75000	**2.00000**	3	3.85	***
2.00000	**2.25000**	0	0.00	
2.25000	**2.50000**	1	1.28	*
2.50000	**2.75000**	0	0.00	
2.75000	**3.00000**	0	0.00	
3.00000	**3.25000**	0	0.00	
3.25000	**3.50000**	0	0.00	
3.50000	**3.75000**	0	0.00	
3.75000	**4.00000**	1	1.28	*
4.00000	**4.25000**	1	1.28	*

Distribution of Normalized Residuals				
Each * Represents 1 Residuals				
Range		Freq	Percent	
4.25000	**4.50000**	1	1.28	*

CMB

The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

PATH List						
Path			Parameter	Estimate	Standard Error	t Value
SEX	--->	**SEX_R**	_Parm01	1.20619	0.02996	40.25412
SEX	--->	**SEX_L**	_Parm02	1.16365	0.02778	41.88154
SEX	--->	**SEX_G**	_Parm03	1.12657	0.03405	33.08926
IS	--->	**IS_R**	_Parm04	1.18942	0.02761	43.07641
IS	--->	**IS_L**	_Parm05	1.19364	0.02628	45.42180
IS	--->	**IS_G**	_Parm06	1.13455	0.02966	38.25005
CM	--->	**CM_R**	_Parm07	1.18617	0.02658	44.62677
CM	--->	**CM_L**	_Parm08	1.16043	0.02565	45.24626
CM	--->	**CM_G**	_Parm09	1.13515	0.02788	40.71563
SEN	--->	**SEN_R**	_Parm10	1.22157	0.02845	42.94188
SEN	--->	**SEN_L**	_Parm11	1.18612	0.02657	44.64176
SEN	--->	**SEN_G**	_Parm12	1.14019	0.02890	39.45523

Variance Parameters					
Variance Type	Variable	Parameter	Estimate	Standard Error	t Value
Exogenous	**SEX**		1.00000		
	IS		1.00000		
	CM		1.00000		
	SEN		1.00000		
Error	**SEX_R**	_Add01	0.43235	0.02390	18.08687
	SEX_L	_Add02	0.31837	0.01985	16.04248

Variance Parameters					
Variance Type	**Variable**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
	SEX_G	_Add03	0.87819	0.03845	22.83835
	IS_R	_Add04	0.30983	0.01590	19.48024
	IS_L	_Add05	0.20907	0.01290	16.20915
	IS_G	_Add06	0.54578	0.02367	23.05476
	CM_R	_Add07	0.24311	0.01318	18.44701
	CM_L	_Add08	0.20809	0.01187	17.53324
	CM_G	_Add09	0.39483	0.01802	21.91659
	SEN_R	_Add10	0.32867	0.01747	18.81201
	SEN_L	_Add11	0.23403	0.01421	16.47049
	SEN_G	_Add12	0.46696	0.02152	21.70205

Covariances Among Exogenous Variables					
Var1	**Var2**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
IS	**SEX**	_Add13	0.87491	0.00895	97.77528
CM	**SEX**	_Add14	0.78607	0.01287	61.08411
CM	**IS**	_Add15	0.88616	0.00789	112.36500
SEN	**SEX**	_Add16	0.74651	0.01466	50.90984
SEN	**IS**	_Add17	0.82957	0.01043	79.56657
SEN	**CM**	_Add18	0.90027	0.00730	123.34699

Covariances Among Errors					
Error of	**Error of**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEX_G	**IS_G**	_Parm13	0.27111	0.02182	12.42576
SEN_G	**IS_G**	_Parm14	0.16471	0.01541	10.68494

Squared Multiple Correlations			
Variable	**Error Variance**	**Total Variance**	**R-Square**
CM_G	0.39483	1.68339	0.7655
CM_L	0.20809	1.55469	0.8662
CM_R	0.24311	1.65012	0.8527
IS_G	0.54578	1.83300	0.7022
IS_L	0.20907	1.63385	0.8720
IS_R	0.30983	1.72455	0.8203
SEN_G	0.46696	1.76700	0.7357
SEN_L	0.23403	1.64091	0.8574
SEN_R	0.32867	1.82090	0.8195
SEX_G	0.87819	2.14735	0.5910
SEX_L	0.31837	1.67244	0.8096
SEX_R	0.43235	1.88724	0.7709

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Stability Coefficient of Reciprocal Causation = 0
Stability Coefficient < 1
Total and Indirect Effects Converge

Note: All effects are direct effects. There are no indirect effects.

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Standardized Results for PATH List						
Path			**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEX	**--->**	**SEX_R**	_Parm01	0.87801	0.00809	108.49689
SEX	**--->**	**SEX_L**	_Parm02	0.89980	0.00732	122.91223
SEX	**--->**	**SEX_G**	_Parm03	0.76879	0.01237	62.15890
IS	**--->**	**IS_R**	_Parm04	0.90573	0.00593	152.83007
IS	**--->**	**IS_L**	_Parm05	0.93383	0.00479	194.86768
IS	**--->**	**IS_G**	_Parm06	0.83800	0.00882	95.04297
CM	**--->**	**CM_R**	_Parm07	0.92340	0.00503	183.74568
CM	**--->**	**CM_L**	_Parm08	0.93067	0.00473	196.86406
CM	**--->**	**CM_G**	_Parm09	0.87490	0.00716	122.11630
SEN	**--->**	**SEN_R**	_Parm10	0.90526	0.00611	148.11366
SEN	**--->**	**SEN_L**	_Parm11	0.92595	0.00530	174.82483
SEN	**--->**	**SEN_G**	_Parm12	0.85775	0.00814	105.34702

Standardized Results for Variance Parameters					
Variance Type	**Variable**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
Exogenous	**SEX**		1.00000		
	IS		1.00000		
	CM		1.00000		
	SEN		1.00000		
Error	**SEX_R**	_Add01	0.22909	0.01421	16.12103
	SEX_L	_Add02	0.19036	0.01317	14.44934
	SEX_G	_Add03	0.40896	0.01902	21.50532
	IS_R	_Add04	0.17966	0.01074	16.73541
	IS_L	_Add05	0.12796	0.00895	14.29688
	IS_G	_Add06	0.29775	0.01478	20.14929
	CM_R	_Add07	0.14733	0.00928	15.87433
	CM_L	_Add08	0.13385	0.00880	15.21101
	CM_G	_Add09	0.23455	0.01254	18.70901
	SEN_R	_Add10	0.18050	0.01107	16.31129
	SEN_L	_Add11	0.14262	0.00981	14.54061
	SEN_G	_Add12	0.26427	0.01397	18.91971

Standardized Results for Covariances Among Exogenous Variables					
Var1	**Var2**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
IS	**SEX**	_Add13	0.87491	0.00895	97.77528
CM	**SEX**	_Add14	0.78607	0.01287	61.08411
CM	**IS**	_Add15	0.88616	0.00789	112.36500
SEN	**SEX**	_Add16	0.74651	0.01466	50.90984
SEN	**IS**	_Add17	0.82957	0.01043	79.56657

Standardized Results for Covariances Among Exogenous Variables					
Var1	**Var2**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEN	**CM**	_Add18	0.90027	0.00730	123.34699

Standardized Results for Covariances Among Errors					
Error of	**Error of**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEX_G	**IS_G**	_Parm13	0.13665	0.01100	12.42612
SEN_G	**IS_G**	_Parm14	0.09152	0.00867	10.56136

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Note: All standardized effects are direct effects. There are no indirect effects.

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Note: All parameters in the model are significant. No parameter can be dropped in the Wald tests.

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Rank Order of the 10 Largest LM Stat for Path Relations

To	From	LM Stat	Pr > ChiSq	Parm Change
CM_G	**IS_G**	128.58546	<.0001	0.24598
CM_G	**SEN_G**	88.28537	<.0001	0.22157
SEX_G	**IS_G**	84.03444	<.0001	0.54328
IS_G	**CM_G**	81.35767	<.0001	0.22717
CM_G	**SEX_G**	76.32271	<.0001	0.14323
SEX_G	**SEN_G**	70.46285	<.0001	0.22986
SEX_G	**CM_G**	60.74373	<.0001	0.22500
SEX_G	**IS_R**	51.48072	<.0001	0.26368
SEX	**SEX_G**	48.66387	<.0001	-0.16345
SEX_L	**SEX_R**	44.71405	<.0001	0.39164

Note:* *No LM statistic in the default test set for the covariances of exogenous variables is nonsingular. Ranking is not displayed.

Rank Order of the 10 Largest LM Stat for Error Variances and Covariances				
Error of	**Error of**	**LM Stat**	**Pr > ChiSq**	**Parm Change**
IS_G	**CM_G**	54.97296	<.0001	0.09531
SEX_G	**SEN_G**	52.55993	<.0001	0.14524
SEX_R	**SEX_L**	44.71198	<.0001	0.16932
SEX_G	**CM_G**	41.82688	<.0001	0.10961
SEX_L	**IS_R**	39.57811	<.0001	-0.07803
SEN_G	**CM_G**	36.09587	<.0001	0.07873
SEX_L	**IS_L**	29.52617	<.0001	0.06145
SEX_L	**SEN_L**	28.00785	<.0001	0.05948
IS_R	**IS_L**	27.71584	<.0001	0.07906
SEX_G	**IS_R**	25.46460	<.0001	0.08255

Appendix F: Teacher CFA output (SAS)

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The CALIS Procedure
Covariance Structure Analysis: Descriptive Statistics

Simple Statistics				
Variable	**Mean**	**Std Dev**	**Skewness**	**Kurtosis**
SEX_R	4.46154	1.29378	-1.00422	0.54702
SEX_L	4.35256	1.28578	-0.74058	0.27759
SEX_G	4.35897	1.40625	-0.96671	0.33895
IS_R	4.27564	1.33288	-0.71552	0.34292
IS_L	4.20513	1.25272	-0.44793	0.03650
IS_G	4.12179	1.41117	-0.45836	-0.34268
CM_R	4.08333	1.30338	-0.61283	0.15825
CM_L	4.11538	1.27124	-0.42956	0.04026
CM_G	4.08974	1.33515	-0.48928	0.14900
SEN_R	4.23077	1.19829	-0.56102	0.37631
SEN_L	4.25641	1.18380	-0.47168	0.29601
SEN_G	4.34615	1.34142	-0.87779	0.65234

Mardia's Multivariate Kurtosis	58.0014
Relative Multivariate Kurtosis	1.3452
Normalized Multivariate Kurtosis	11.4088
Mardia Based Kappa (Browne, 1982)	0.3452
Mean Scaled Univariate Kurtosis	0.0798
Adjusted Mean Scaled Univariate Kurtosis	0.0798
Multivariate Mean Kappa (Bentler, 1985)	0.1069
Multivariate LS Kappa (Bentler, 1983)	0.0887

Observation Numbers with Largest Contribution to Normalized Multivariate Kurtosis				
32	**47**	**44**	**43**	**26**
204.5222	202.9820	133.5024	133.4584	117.3734

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Fit Summary		
Absolute Index	**Chi-Square**	96.6004
	Chi-Square DF	43
	Pr > Chi-Square	<.0001
	Standardized RMSR (SRMSR)	0.0401
Parsimony Index	**RMSEA Estimate**	0.1563
	RMSEA Lower 90% Confidence Limit	0.1147
	RMSEA Upper 90% Confidence Limit	0.1981
	Akaike Information Criterion	166.6004
	Bozdogan CAIC	269.8939
	Schwarz Bayesian Criterion	234.8939
Incremental Index	**Bentler Comparative Fit Index**	0.9516
	Bentler-Bonett Non-normed Index	0.9258

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Raw Residual Matrix

	SEX_R	SEX_L	SEX_G	IS_R	IS_L	IS_G	CM_R	CM_L	CM_G	SEN_R	SEN_L	SEN_G
SEX_R	0.00000	0.01407	0.07279	-0.03964	-0.03604	0.07764	-0.07459	-0.07189	0.06107	0.00142	0.05228	-0.11765
SEX_L	0.01407	0.00000	-0.02825	-0.02748	0.01096	-0.01894	0.01986	-0.03518	0.07465	-0.02483	0.01267	-0.07617
SEX_G	0.07279	-0.02825	0.01242	0.05218	0.03864	0.04899	0.10244	0.07543	0.23992	0.09590	0.07644	0.17886
IS_R	-0.03964	-0.02748	0.05218	0.00000	0.00280	0.04400	-0.00561	-0.05924	0.07060	0.00320	0.02241	-0.00933
IS_L	-0.03604	0.01096	0.03864	0.00280	0.00000	0.00745	-0.00225	-0.03408	0.05770	-0.00520	0.02702	-0.06872
IS_G	0.07764	-0.01894	0.04899	0.04400	0.00745	0.04410	0.12126	0.08657	0.30219	0.09369	0.03516	0.15035
CM_R	-0.07459	0.01986	0.10244	-0.00561	-0.00225	0.12126	0.00000	0.00536	0.00205	-0.01072	-0.06647	0.09821
CM_L	-0.07189	-0.03518	0.07543	-0.05924	-0.03408	0.08657	0.00536	0.00000	-0.01771	0.00433	-0.06120	0.05703
CM_G	0.06107	0.07465	0.23992	0.07060	0.05770	0.30219	0.00205	-0.01771	0.00000	0.05328	0.03799	0.14252
SEN_R	0.00142	-0.02483	0.09590	0.00320	-0.00520	0.09369	-0.01072	0.00433	0.05328	0.01384	-0.01320	0.04794

Raw Residual Matrix												
	SEX_R	**SEX_L**	**SEX_G**	**IS_R**	**IS_L**	**IS_G**	**CM_R**	**CM_L**	**CM_G**	**SEN_R**	**SEN_L**	**SEN_G**
SEN_L	0.05228	0.01267	0.07644	0.02241	0.02702	0.03516	-0.06647	-0.06120	0.03799	-0.01320	0.00000	0.00000
SEN_G	-0.11765	-0.07617	0.17886	-0.00933	-0.06872	0.15035	0.09821	0.05703	0.14252	0.04794	0.00000	0.00000

Average Absolute Residual	0.048128
Average Off-diagonal Absolute Residual	0.055813

Rank Order of the 10 Largest Raw Residuals		
Var1	**Var2**	**Residual**
CM_G	**IS_G**	0.30219
CM_G	**SEX_G**	0.23992
SEN_G	**SEX_G**	0.17886
SEN_G	**IS_G**	0.15035
SEN_G	**CM_G**	0.14252
CM_R	**IS_G**	0.12126
SEN_G	**SEX_R**	-0.11765
CM_R	**SEX_G**	0.10244
SEN_G	**CM_R**	0.09821
SEN_R	**SEX_G**	0.09590

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The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Normalized Residual Matrix

	SEX_R	SEX_L	SEX_G	IS_R	IS_L	IS_G	CM_R	CM_L	CM_G	SEN_R	SEN_L	SEN_G
SEX_R	0.00000	0.04482	0.22092	-0.12423	-0.11957	0.23967	-0.25494	-0.25259	0.20689	0.00521	0.19722	-0.40089
SEX_L	0.04482	0.00000	-0.08439	-0.08467	0.03573	-0.05760	0.06702	-0.12206	0.24995	-0.08992	0.04720	-0.25673
SEX_G	0.22092	-0.08439	0.03191	0.15321	0.12013	0.13382	0.32710	0.24758	0.75879	0.32922	0.26938	0.56871
IS_R	-0.12423	-0.08467	0.15321	0.00000	0.00858	0.12611	-0.01764	-0.19166	0.22075	0.01067	0.07774	-0.02938
IS_L	-0.11957	0.03573	0.12013	0.00858	0.00000	0.02261	-0.00748	-0.11674	0.19106	-0.01854	0.09925	-0.22917
IS_G	0.23967	-0.05760	0.13382	0.12611	0.02261	0.11437	0.37534	0.27551	0.92828	0.30800	0.12003	0.46455
CM_R	-0.25494	0.06702	0.32710	-0.01764	-0.00748	0.37534	0.00000	0.01681	0.00623	-0.03678	-0.23976	0.32101
CM_L	-0.25259	-0.12206	0.24758	-0.19166	-0.11674	0.27551	0.01681	0.00000	-0.05536	0.01528	-0.22699	0.19165
CM_G	0.20689	0.24995	0.75879	0.22075	0.19106	0.92828	0.00623	-0.05536	0.00000	0.18200	0.13609	0.46194
SEN_R	0.00521	-0.08992	0.32922	0.01067	-0.01854	0.30800	-0.03678	0.01528	0.18200	0.04913	-0.04925	0.16278

Normalized Residual Matrix												
	SEX_R	**SEX_L**	**SEX_G**	**IS_R**	**IS_L**	**IS_G**	**CM_R**	**CM_L**	**CM_G**	**SEN_R**	**SEN_L**	**SEN_G**
SEN_L	0.19722	0.04720	0.26938	0.07774	0.09925	0.12003	-0.23976	-0.22699	0.13609	-0.04925	0.00000	0.00000
SEN_G	-0.40089	-0.25673	0.56871	-0.02938	-0.22917	0.46455	0.32101	0.19165	0.46194	0.16278	0.00000	0.00000

Average Normalized Residual	0.156495
Average Off-diagonal Normalized Residual	0.181988

Rank Order of the 10 Largest Normalized Residuals		
Var1	**Var2**	**Residual**
CM_G	**IS_G**	0.92828
CM_G	**SEX_G**	0.75879
SEN_G	**SEX_G**	0.56871
SEN_G	**IS_G**	0.46455
SEN_G	**CM_G**	0.46194
SEN_G	**SEX_R**	-0.40089
CM_R	**IS_G**	0.37534
SEN_R	**SEX_G**	0.32922
CM_R	**SEX_G**	0.32710
SEN_G	**CM_R**	0.32101

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The CALIS Procedure

Covariance Structure Analysis: Maximum Likelihood Estimation

Distribution of Normalized Residuals				
Each * Represents 2 Residuals				
Range		**Freq**	**Percent**	
-0.50000	**-0.25000**	4	5.13	**
-0.25000	**0**	19	24.36	*********
0	**0.25000**	43	55.13	*********************
0.25000	**0.50000**	9	11.54	****
0.50000	**0.75000**	1	1.28	
0.75000	**1.00000**	2	2.56	*

CMB

The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

PATH List						
Path			Parameter	Estimate	Standard Error	t Value
SEX	**--->**	**SEX_R**	_Parm01	1.19743	0.13760	8.70248
SEX	**--->**	**SEX_L**	_Parm02	1.25431	0.13087	9.58416
SEX	**--->**	**SEX_G**	_Parm03	1.25187	0.15227	8.22137
IS	**--->**	**IS_R**	_Parm04	1.30656	0.13461	9.70592
IS	**--->**	**IS_L**	_Parm05	1.24269	0.12512	9.93212
IS	**--->**	**IS_G**	_Parm06	1.26910	0.14924	8.50391
CM	**--->**	**CM_R**	_Parm07	1.27041	0.13261	9.57993
CM	**--->**	**CM_L**	_Parm08	1.22966	0.13023	9.44231
CM	**--->**	**CM_G**	_Parm09	1.24427	0.14110	8.81862
SEN	**--->**	**SEN_L**	_Parm10	1.06759	0.12912	8.26792
SEN	**--->**	**SEN_G**	_Parm11	1.12741	0.15242	7.39659

Variance Parameters					
Variance Type	Variable	Parameter	Estimate	Standard Error	t Value
Exogenous	**SEX**		1.00000		
	IS		1.00000		
	CM		1.00000		
	SEN		1.00000		
	SEN_R	_Add01	1.42206	0.28135	5.05451
Error	**SEX_R**	_Add02	0.24005	0.05681	4.22538
	SEX_L	_Add03	0.07993	0.03327	2.40251

Variance Parameters					
Variance Type	**Variable**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
	SEX_G	_Add04	0.39795	0.08839	4.50220
	IS_R	_Add05	0.06946	0.01857	3.74001
	IS_L	_Add06	0.02502	0.01315	1.90312
	IS_G	_Add07	0.33670	0.06835	4.92593
	CM_R	_Add08	0.08485	0.03037	2.79419
	CM_L	_Add09	0.10399	0.03174	3.27620
	CM_G	_Add10	0.23443	0.05457	4.29583
	SEN_L	_Add11	0.26162	0.06609	3.95832
	SEN_G	_Add12	0.52834	0.11420	4.62648

Covariances Among Exogenous Variables					
Var1	**Var2**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEN_R	**SEX**	_Add13	0.98887	0.13635	7.25257
SEN_R	**IS**	_Add14	1.10013	0.12692	8.66777
IS	**SEX**	_Add15	0.95202	0.01655	57.53090
SEN_R	**CM**	_Add16	1.08883	0.12777	8.52154
CM	**SEX**	_Add17	0.81094	0.05213	15.55603
CM	**IS**	_Add18	0.88048	0.03412	25.80709
SEN_R	**SEN**	_Add19	1.21089	0.11827	10.23826
SEN	**SEX**	_Add20	0.87022	0.04966	17.52299
SEN	**IS**	_Add21	0.94751	0.03109	30.47256
SEN	**CM**	_Add22	0.91483	0.03920	23.33799

Covariances Among Errors					
Error of	**Error of**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEX_G	**IS_G**	_Parm12	0.22180	0.06323	3.50760

Covariances Between Variables and Errors					
Variable	**Error of**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEN_R	**IS_L**	_Parm13	-0.03328	0.01156	-2.87955

Squared Multiple Correlations			
Variable	**Error Variance**	**Total Variance**	**R-Square**
CM_G	0.23443	1.78264	0.8685
CM_L	0.10399	1.61605	0.9357
CM_R	0.08485	1.69880	0.9501
IS_G	0.33670	1.94731	0.8271
IS_L	0.02502	1.56930	0.9841
IS_R	0.06946	1.77656	0.9609
SEN_G	0.52834	1.79940	0.7064
SEN_L	0.26162	1.40137	0.8133
SEX_G	0.39795	1.96513	0.7975
SEX_L	0.07993	1.65322	0.9517
SEX_R	0.24005	1.67387	0.8566

CMB

The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Stability Coefficient of Reciprocal Causation = 0
Stability Coefficient < 1
Total and Indirect Effects Converge

Note: All effects are direct effects. There are no indirect effects.

CMB

The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Standardized Results for PATH List						
Path			**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEX	--->	**SEX_R**	_Parm01	0.92552	0.02245	41.22388
SEX	--->	**SEX_L**	_Parm02	0.97553	0.01132	86.17651
SEX	--->	**SEX_G**	_Parm03	0.89303	0.03049	29.29374
IS	--->	**IS_R**	_Parm04	0.98025	0.00654	149.80953
IS	--->	**IS_L**	_Parm05	0.99200	0.00450	220.26309
IS	--->	**IS_G**	_Parm06	0.90945	0.02455	37.04695
CM	--->	**CM_R**	_Parm07	0.97471	0.01036	94.11428
CM	--->	**CM_L**	_Parm08	0.96729	0.01187	81.49968
CM	--->	**CM_G**	_Parm09	0.93193	0.02034	45.82193
SEN	--->	**SEN_L**	_Parm10	0.90184	0.03077	29.30625
SEN	--->	**SEN_G**	_Parm11	0.84046	0.04381	19.18396

Standardized Results for Variance Parameters					
Variance Type	**Variable**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
Exogenous	**SEX**		1.00000		
	IS		1.00000		
	CM		1.00000		
	SEN		1.00000		
	SEN_R	_Add01	1.00000		
Error	**SEX_R**	_Add02	0.14341	0.04156	3.45077
	SEX_L	_Add03	0.04835	0.02209	2.18911

Standardized Results for Variance Parameters					
Variance Type	**Variable**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
	SEX_G	_Add04	0.20250	0.05445	3.71920
	IS_R	_Add05	0.03910	0.01283	3.04798
	IS_L	_Add06	0.01594	0.00894	1.78439
	IS_G	_Add07	0.17290	0.04465	3.87235
	CM_R	_Add08	0.04995	0.02019	2.47401
	CM_L	_Add09	0.06434	0.02296	2.80237
	CM_G	_Add10	0.13151	0.03791	3.46918
	SEN_L	_Add11	0.18669	0.05550	3.36342
	SEN_G	_Add12	0.29362	0.07364	3.98706

Standardized Results for Covariances Among Exogenous Variables					
Var1	**Var2**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEN_R	**SEX**	_Add13	0.82924	0.04576	18.12053
SEN_R	**IS**	_Add14	0.92254	0.02317	39.81357
IS	**SEX**	_Add15	0.95202	0.01655	57.53090
SEN_R	**CM**	_Add16	0.91306	0.02457	37.15616
CM	**SEX**	_Add17	0.81094	0.05213	15.55603
CM	**IS**	_Add18	0.88048	0.03412	25.80709
SEN_R	**SEN**	_Add19	1.01542	0.01969	51.58068
SEN	**SEX**	_Add20	0.87022	0.04966	17.52299
SEN	**IS**	_Add21	0.94751	0.03109	30.47256
SEN	**CM**	_Add22	0.91483	0.03920	23.33799

Standardized Results for Covariances Among Errors					
Error of	**Error of**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEX_G	**IS_G**	_Parm12	0.11338	0.03599	3.15033

Standardized Results for Covariances Between Variables and Errors					
Variable	**Error of**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
SEN_R	**IS_L**	_Parm13	-0.02228	0.00873	-2.55187

CMB

The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Note: All standardized effects are direct effects. There are no indirect effects.

CMB

The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Stepwise Multivariate Wald Test					
Parm	**Cumulative Statistics**			**Univariate Increment**	
	Chi-Square	**DF**	**Pr > ChiSq**	**Chi-Square**	**Pr > ChiSq**
_Add06	3.62188	1	0.0570	3.62188	0.0570

CMB

The CALIS Procedure
Covariance Structure Analysis: Maximum Likelihood Estimation

Rank Order of the 10 Largest LM Stat for Path Relations				
To	**From**	**LM Stat**	**Pr > ChiSq**	**Parm Change**
CM_G	**IS_G**	12.15965	0.0005	0.31766
SEN_G	**SEN_R**	10.39586	0.0013	2.48451
IS_G	**CM_G**	9.81245	0.0017	0.28429
SEX_L	**SEX_G**	6.83920	0.0089	-0.31098
IS_L	**SEN_G**	6.70240	0.0096	-0.12051
SEN_R	**CM_L**	6.34760	0.0118	0.38749
IS_L	**IS_G**	5.19756	0.0226	-0.16011
SEN_L	**CM_L**	5.08557	0.0241	-0.35483
CM_G	**SEX_G**	5.01564	0.0251	0.17433
CM_L	**IS_R**	5.00413	0.0253	-0.20938

Note: No LM statistic in the default test set for the covariances of exogenous variables is nonsingular. Ranking is not displayed.

Rank Order of the 10 Largest LM Stat for Error Variances and Covariances				
Error of	**Error of**	**LM Stat**	**Pr > ChiSq**	**Parm Change**
IS_G	**CM_G**	7.64609	0.0057	0.09603
SEN_G	**IS_L**	6.66747	0.0098	-0.07250
SEX_L	**IS_L**	6.30106	0.0121	0.03990
IS_R	**CM_L**	5.44166	0.0197	-0.03551
SEX_R	**CM_R**	4.76699	0.0290	-0.06128
SEX_R	**IS_G**	3.59655	0.0579	0.06911

Rank Order of the 10 Largest LM Stat for Error Variances and Covariances				
Error of	**Error of**	**LM Stat**	**Pr > ChiSq**	**Parm Change**
IS_L	**IS_G**	3.47180	0.0624	-0.03758
SEX_L	**SEX_G**	3.42543	0.0642	-0.08128
SEX_R	**IS_L**	3.34929	0.0672	-0.03381
SEX_L	**IS_R**	3.25610	0.0712	-0.03142

Appendix G: Race TCTSE Moderation (Institution 2) output (SAS)

&IV &MOD

The REG Procedure
Model: MODEL1
Dependent Variable: DIFF

Number of Observations Read	740
Number of Observations Used	394
Number of Observations with Missing Values	346

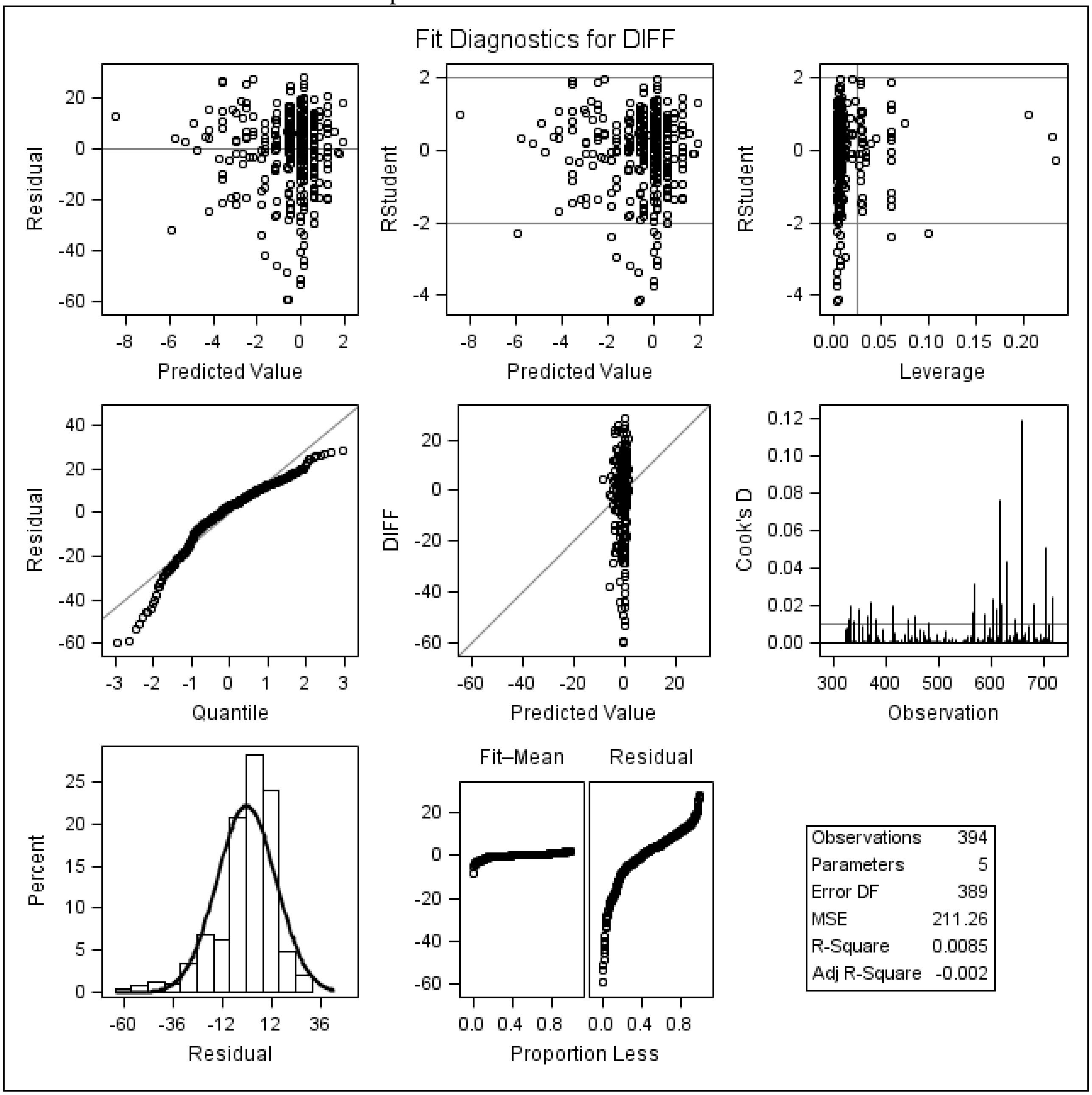
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	700.56118	175.14030	0.83	0.5073
Error	389	82179	211.25696		
Corrected Total	393	82880			

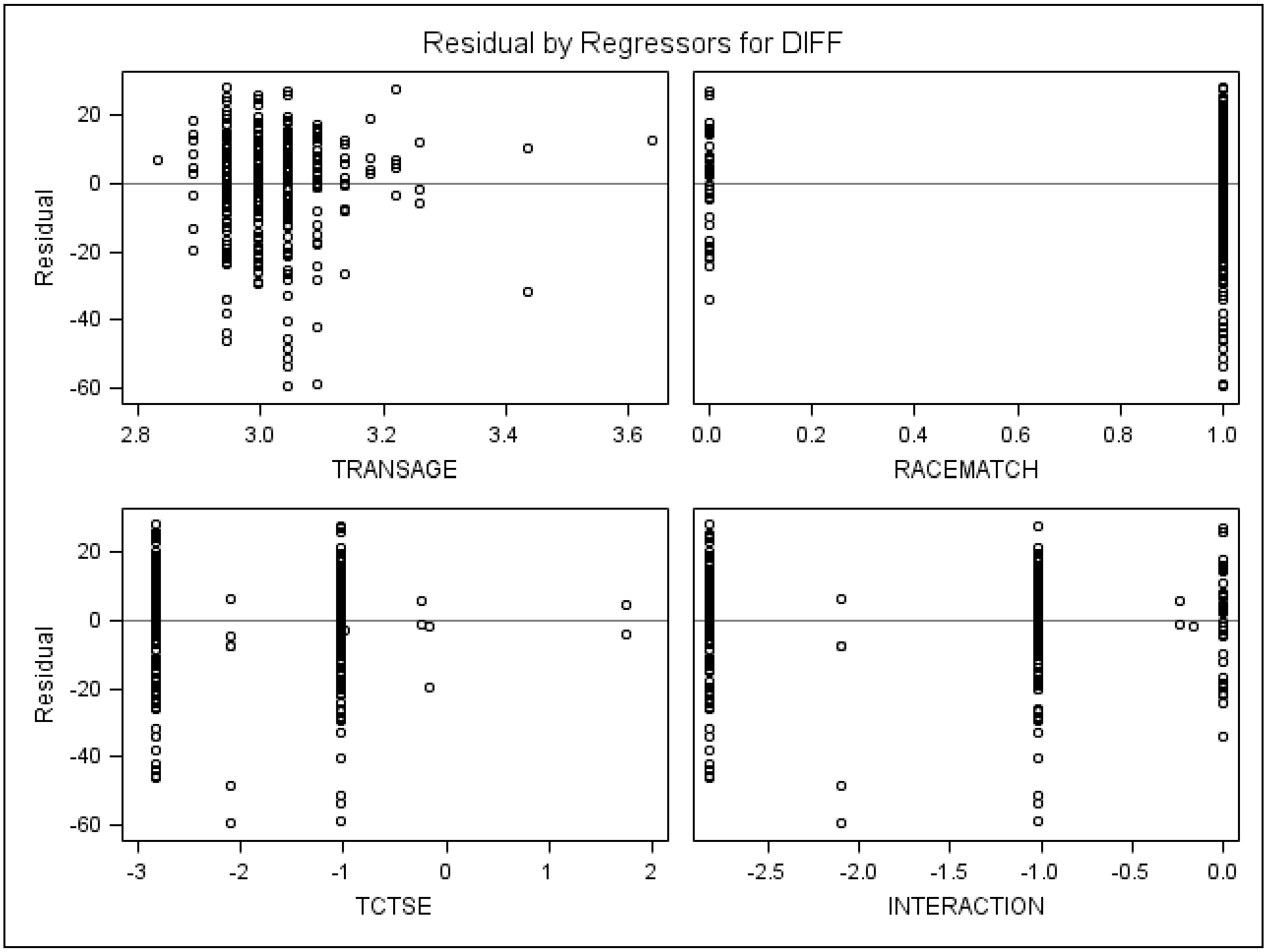
Root MSE	14.53468	**R-Square**	0.0085
Dependent Mean	-0.40546	**Adj R-Sq**	-0.0017
Coeff Var	-3584.72236		

Parameter Estimates						
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Standardized Estimate**
Intercept	**1**	34.11642	30.35828	1.12	0.2618	0
TRANSAGE	**1**	-12.47388	9.86192	-1.26	0.2067	-0.06866
RACEMATCH	**1**	4.45919	4.17967	1.07	0.2867	0.09182
TCTSE	**1**	-0.27898	2.03790	-0.14	0.8912	-0.01784
INTERACTION	**1**	0.87105	2.20862	0.39	0.6935	0.06021

&IV &MOD

The REG Procedure
Model: MODEL1
Dependent Variable: DIFF




Residual by Regressors for DIFF
Residual
20
0
-20
-40
-60
2.8
3.0
3.2
3.4
3.6
TRANSAGE
0.0
0.2
0.4
0.6
0.8
1.0
RACEMATCH
-3
-2
-1
0
1
2
TCTSE
-2.5
-2.0
-1.5
-1.0
-0.5
0.0
INTERACTION

Appendix H: Home Language TCTSE Moderation (Institution 2) output (SAS)

&IV &MOD

The REG Procedure
Model: MODEL1
Dependent Variable: DIFF

Number of Observations Read	740
Number of Observations Used	394
Number of Observations with Missing Values	346

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	593.32326	148.33082	0.70	0.5915
Error	389	82286	211.53264		
Corrected Total	393	82880			

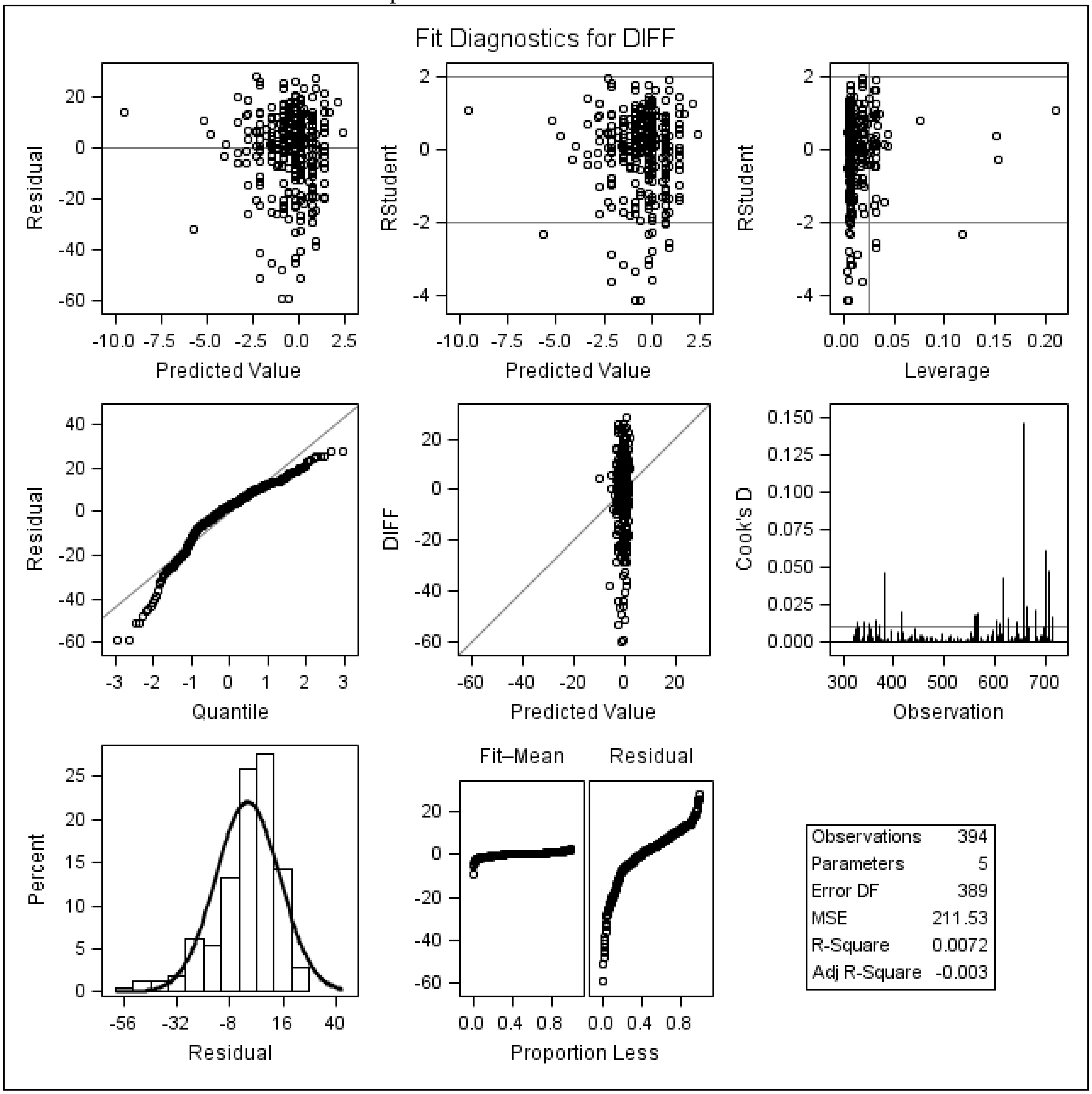
Root MSE	14.54416	**R-Square**	0.0072
Dependent Mean	-0.40546	**Adj R-Sq**	-0.0031
Coeff Var	-3587.06051		

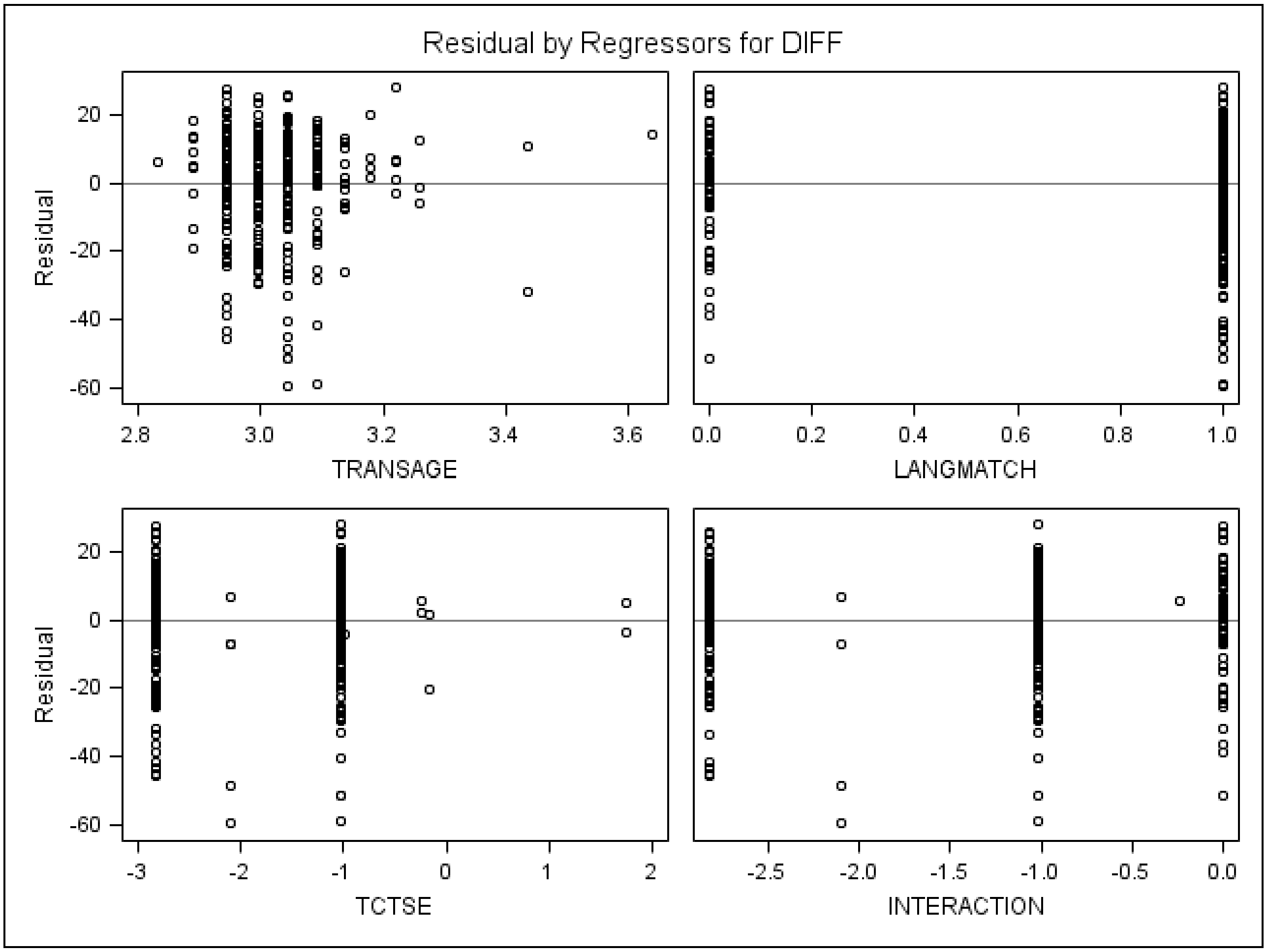
Parameter Estimates						
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Standardized Estimate**
Intercept	**1**	38.01235	30.33855	1.25	0.2110	0
TRANSAGE	**1**	-13.50351	9.92204	-1.36	0.1743	-0.07433
LANGMATCH	**1**	4.04814	3.61392	1.12	0.2633	0.10844
TCTSE	**1**	-0.94680	1.59482	-0.59	0.5531	-0.06056

Parameter Estimates						
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Standardized Estimate**
INTERACTION	**1**	1.81985	1.84525	0.99	0.3246	0.13290

&IV &MOD

The REG Procedure
Model: MODEL1
Dependent Variable: DIFF




Residual by Regressors for DIFF
Residual
20
0
-20
-40
-60
2.8
3.0
3.2
3.4
3.6
TRANSAGE
0.0
0.2
0.4
0.6
0.8
1.0
LANGMATCH
-3
-2
-1
0
1
2
TCTSE
-2.5
-2.0
-1.5
-1.0
-0.5
0.0
INTERACTION

Appendix I: Gender TCTSE Moderation (Institution 2) output (SAS)

&IV &MOD

The REG Procedure
Model: MODEL1
Dependent Variable: DIFF

Number of Observations Read	740
Number of Observations Used	394
Number of Observations with Missing Values	346

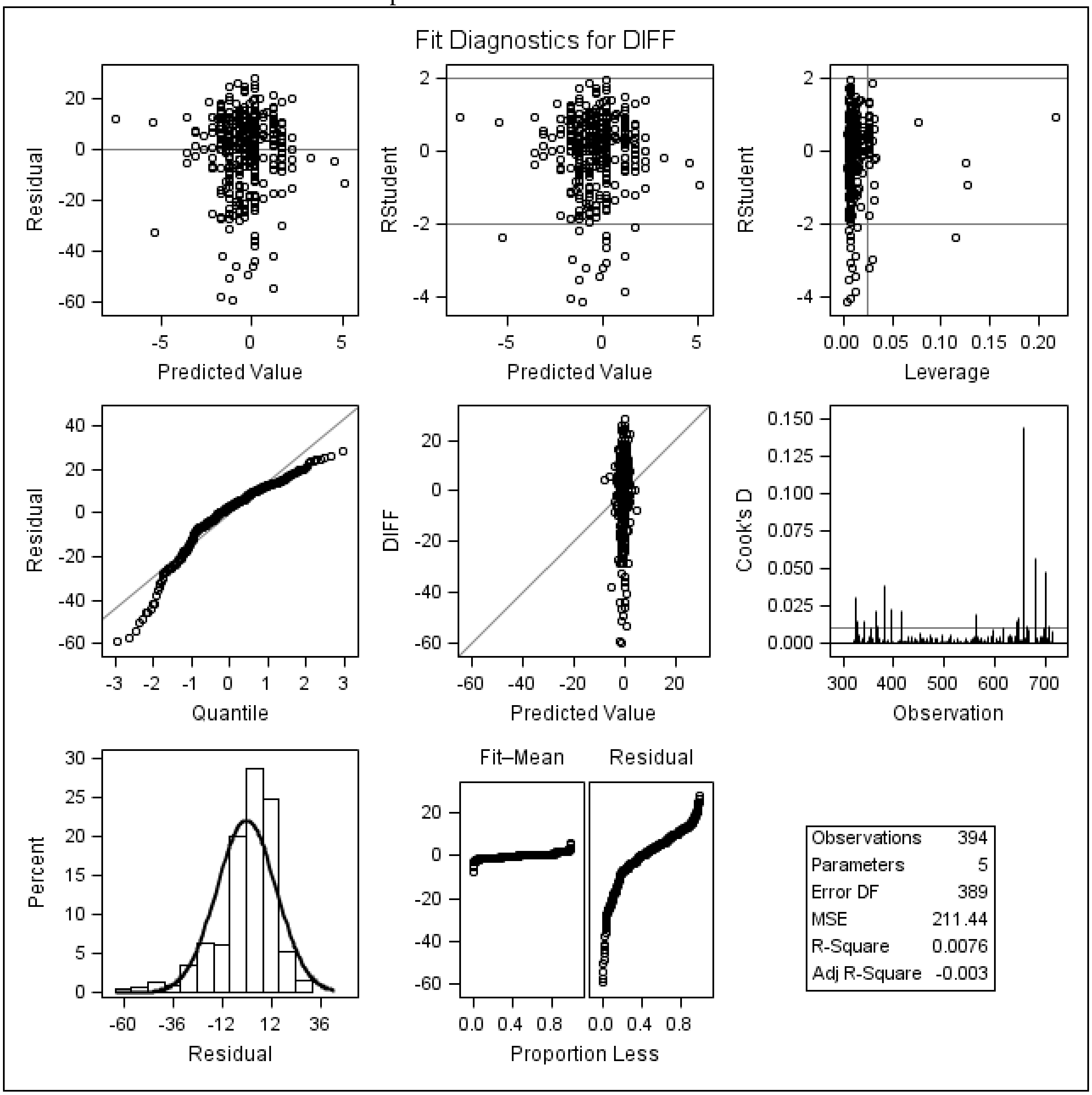
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	4	628.08277	157.02069	0.74	0.5634
Error	389	82251	211.44328		
Corrected Total	393	82880			

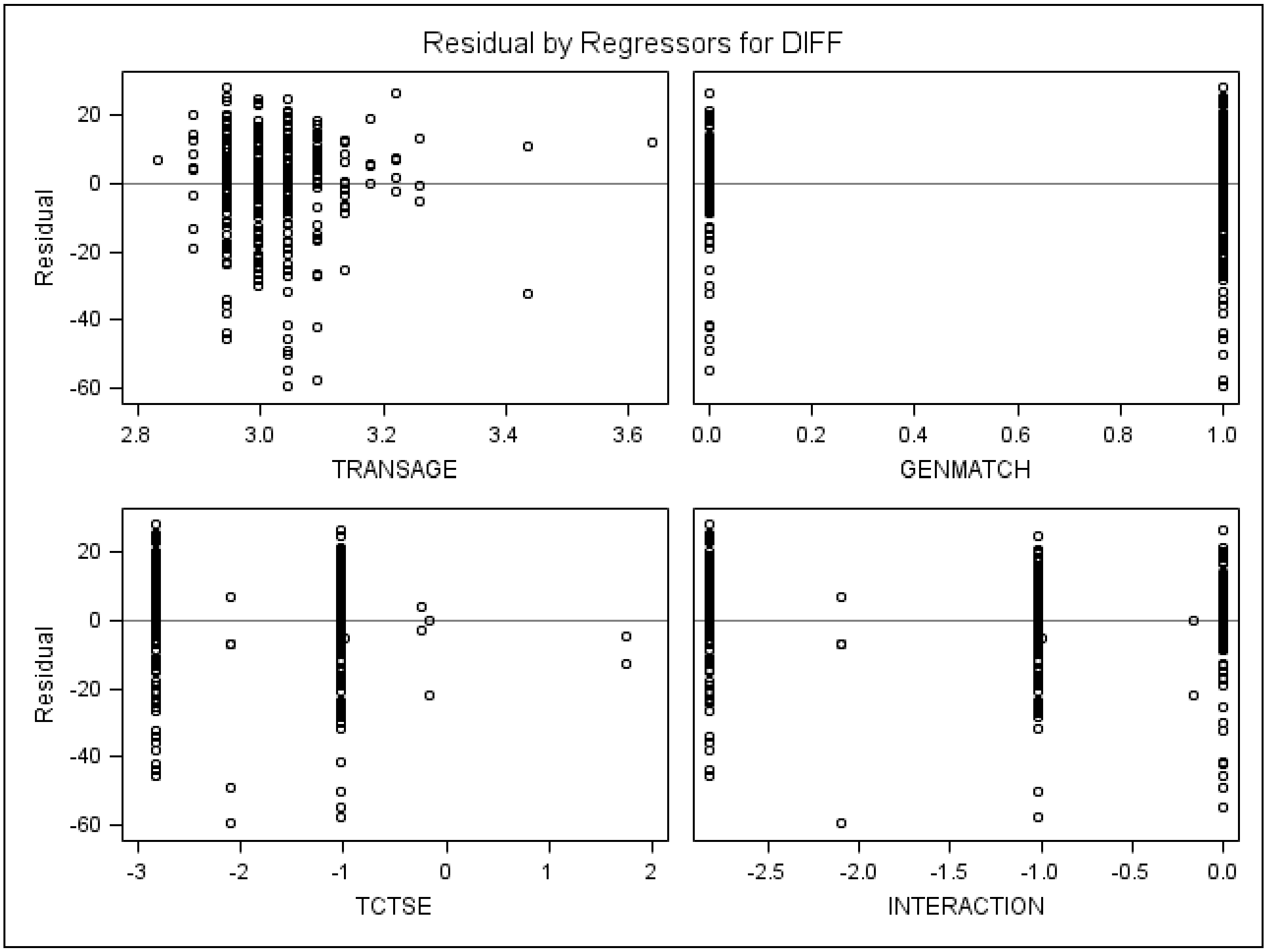
Root MSE	14.54109	**R-Square**	0.0076
Dependent Mean	-0.40546	**Adj R-Sq**	-0.0026
Coeff Var	-3586.30280		

Parameter Estimates						
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**	**Pr > |t|**	**Standardized Estimate**
Intercept	**1**	35.78585	30.33751	1.18	0.2389	0
TRANSAGE	**1**	-10.96023	9.92864	-1.10	0.2703	-0.06033
GENMATCH	**1**	-3.83072	3.36648	-1.14	0.2559	-0.11456
TCTSE	**1**	1.23922	1.47972	0.84	0.4028	0.07926
INTERACTION	**1**	-1.41116	1.76128	-0.80	0.4235	-0.10739

&IV &MOD

The REG Procedure
Model: MODEL1
Dependent Variable: DIFF





Residual by Regressors for DIFF
Residual
TRANSAGE
GENMATCH
TCTSE
INTERACTION

Appendix J: Ethical Clearance Letter

UNIVERSITY OF
KWAZULU-NATAL
INYUVESI
YAKWAZULU-NATALI

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ximbap@ukzn.ac.za

30 November 2011

Mr P Denny (871871977)
School of Information & Systems & Technology

Dear Mr Denny

PROTOCOL REFERENCE NUMBER: HSS/0022/07D
PROJECT TITLE: ***Maximising Return On Investment in I.T. Training: A South African Perspective.***

In response to your application dated 14 December 2006, the Humanities & Social Sciences Research Ethics Committee considered the abovementioned application and the protocol was granted **FULL APPROVAL.**

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment /modification prior to its implementation. In case you have further queries, please quote the above reference number.
PLEASE NOTE: Research data should be securely stored in the school/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours faithfully

....

Professor Steven Collings (Chair)
Humanities & Social Science Research Ethics Committee

cc Supervisor – Professor Manoj Maharaj
cc Mrs Christel Haddon