# Examining the impact of the Ethnoscience Teaching Philosophy on Academic Performance in Introductory Computer Programming

Submitted in fulfilment of the requirements for the degree

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# ABSTRACT

The mastery of the core technologies of the Fourth Industrial Revolution (4IR) seems to require a set of skills that are reputed to be difficult to learn. This also includes general STEM (Science, Technology, Engineering and Mathematics) related know- how where computer programming is considered by many as the new linking glue of the 4IR despite its reputation of being difficult to learn and to master. 4IR is credited with a wide range of advantages, such as improved production, communication and participation, but it also comes with several disadvantages, such as the widening of the digital divide and higher levels of unemployment, especially for unskilled people. In fact, computer programming and other STEM related skills are crucial for the optimization of the benefits of the 4IR and for the minimization of its disadvantages. This is why this study is examining the impact of a different type of teaching approach known as the ethnoscience teaching approach, a STEM teaching philosophy, on students' academic performance in introductory computer programming. A content analysis of existing literature on academic performance factors was first undertaken, both for introductory programming and for STEM subjects, in order to design an aggregated theoretically sound model of academic performance factors for these two fields. That model was then partially empirically tested by this study first within a totally culturally neutral teaching approach, then with a quasi-experiment whose experimental group was taught and tested with the use of the ethnoscientific teaching approach and philosophy while the control group stayed with the conventional culturally neutral teaching approach. The results of this study indicate that the ethnoscience teaching approach significantly improves students' academic performance in introductory computer programming compared to the conventional teaching approach. They also indicate that students' prior language and computing subject choices affect their performance in conventional but not in culturally sensitive introductory computer programming. The participants of this study were selected from the introductory programming 2018 class of the IT Department of the Durban University of Technology. Should the findings of this study be confirmed with more programming concepts and with different samples, they will confirm the intrinsic value of culturally sensitive computing education.

Keywords: computer programming, ethnoscience, academic performance.

# DECLARATION

I, Mayowa Abiola Sofowora, hereby declare that this thesis is original and all the materials used are appropriately acknowledged and explicitly referenced. A bibliography is appended to the dissertation.

I also certify that the dissertation has not heretofore been submitted in any of its part or entirety for a degree in any other institution of higher learning locally or internationally.

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20/09/2021

Supervisor | Date

Professor Seraphim, D. Eyono Obono

# DEDICATION

This thesis is dedicated to my parents and siblings for their unwavering support, their steadfast love, and their unrelenting motivation throughout the duration of this study.

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I would like to express my sincere appreciation to the Almighty God, for infinite mercies, strength and grace throughout the duration of this study.

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# ACRONYMS

| | |
|---|---|
| **STEM** | Science, Technology, Engineering and Mathematics |
| **4IR** | Fourth Industrial Revolution |
| **IT** | Information Technology |
| **IoT** | Internet of Things |
| **VR** | Virtual Reality |
| **AR** | Augmented Reality |
| **AI** | Artificial Intelligence |
| **3D** | Three-Dimensional |
| **ACM** | Association for Computing Machinery |
| **IEEE** | Institute of Electrical and Electronics Engineers |
| **PBL** | Problem Based Learning |
| **UNESCO** | United Nations Educational, Scientific and Cultural Organization |
| **CSDT** | Culturally Situated Design Tools |
| **pCSDT** | programmable Culturally Situated Design Tools |
| **CRC** | Culturally responsive computing |
| **ISI** | International science index |
| **CN** | Culturally Neutral |
| **CS** | Culturally Sensitive |
| **ANOVA** | Analysis of Variance |
| **IPO** | Input Processing Output |
| **CAT** | Computer Application Technology |
| **CONV.** | Conventional |
| **EXP.** | Experimental |

# CHAPTER ONE

# GENERAL INTRODUCTION

This chapter starts with a discussion on the importance of Science, Technology, Engineering and Mathematics (STEM), in general, in this emerging 4IR (Fourth Industrial Revolution) era; and of computer programming, in particular. It also describes the excitement that computer programmers experience during their programming activities. This chapter will then contrast that excitement against the generally reported high failure rates in introductory computer programming courses. A brief presentation of ethnoscience is also presented in this chapter in support of the following main hypothesis of this thesis: Ethnoscience has the ability to reduce students' high failure rates in introductory computer programming courses in higher education, based on claims from existing research that it has contributed to the reduction of such failures for STEM subjects in primary and in secondary education.

## 1.1 Background

Computing technologies and programming were discovered a while back, and their adoption is now widespread. However, this study was undertaken at the time when almost all world nations were only starting to witness the realities of the Fourth Industrial Revolution (4IR) that give center stage to STEM, in general, and to computer programming, in particular.

### 1.1.1 The Fourth Industrial Revolution (4IR)

Advancements in science and technology have continuously supported the development of industrialization in the world (Belvedere *et al*., 2018). In other words, industrial revolutions have always relied on the development of the new technologies of their historical periods.

The first industrial revolution is defined by Consedine *et al.* (2017: 16) as the "process of change from an agricultural and handicraft economy to one dominated by industry and machine manufacturing". That began in England in the 18th century, roughly from 1760, and lasted until the end of the 19th century, around 1830. This period was characterized by the mechanical production of goods by machines using water and steam power. This period was also characterized by a shift to a capital-intensive production, the rapid growth of productivity, increases in the living standards, the formation of large corporate hierarchies and the production of new energy sources (Chandler, 1992; Jensen, 1993).

The second industrial revolution began in the United States of America around the end of the 19th century, roughly from 1870 to 1969, with Henry Ford's invention of the assembly line. This period was characterized by the mass production of goods due to the invention of electricity, and by the birth of modern transportation and communication facilities, such as railroads, telegraphs, steamships and cable systems. It was also characterized by the invention of high-speed consumer packaging technologies, the sewing machine and of coal energy (Chandler, 1992). The overall productivity and profits of the second industrial revolution was approximately estimated to be six times higher than the ones of the first industrial revolution. This period was also characterized by the dramatic fall of production costs as well as by the reduction of the prices of basic goods, such as kerosene, tobacco, cigarette, steel rails, aluminum, chemicals, fertilizer, sugar and whisky (McCraw, 1981; Jensen, 1993).

The third industrial revolution also began in the United States of America. It started in 1969 with the invention of computers and robots. This revolution is also known as the digital revolution. It was characterized by: i) the automation of production processes due to the arrival of electronics and Information Technologies; ii) the emergence of modern markets; iii) the rise of global competition among manufacturers; iv) the rise in taxes; v) the conversion of socialist and communist economies to capitalism; and vi) the increase of the price of oil (Jensen, 1993).

The most recent industrial revolution is known as the Fourth Industrial Revolution (4IR) or the second IT revolution because it is building up from the above described digital revolution, and it is characterized by a combination of the physical, digital and biological technologies that integrate information and communication technologies with physical systems into cyber-physical systems (Schwab, 2016). This fourth industrial revolution has brought forward new technologies, such as the Internet of things (IoT), Virtual reality (VR), Augmented reality (AR), Quantum computing, Artificial intelligence (AI), 3D printing, bioengineering of genes, robotic surgery, prosthetics, social media, data science and wearable technologies (see Figure 1.1) (Schwab, 2016; Park, 2016:1).

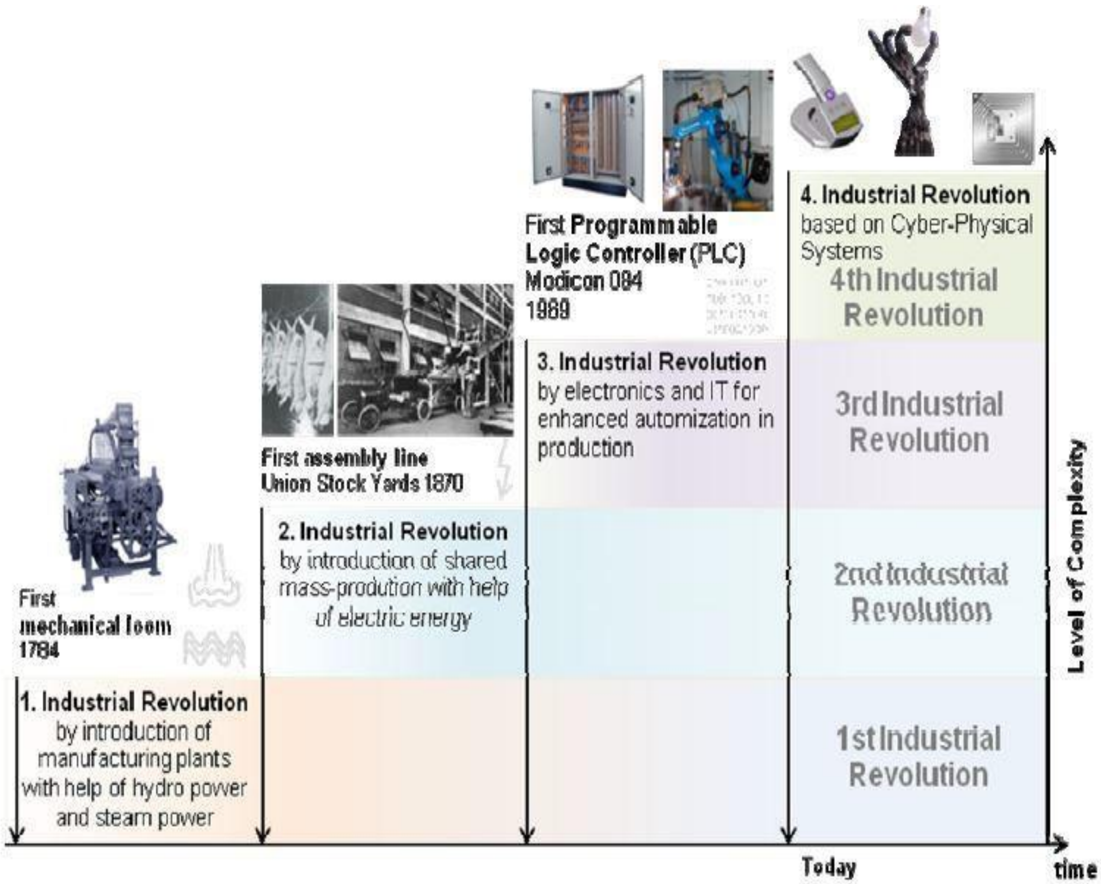


Figure 1.1: The industrial revolutions (adapted from Anderl, 2014)

### 1.1.2 Science, Technology, Engineering and Mathematics (STEM) and 4IR

STEM stands for Science, Technology, Engineering and Mathematics; and, even though the core of the Fourth Industrial Revolution revolves around Information Technologies, it is important to note that it also grows from the advances made by other STEM disciplines. For example, Karacay (2018:128) asserts that "Industry 4.0 work systems evidently necessitate employees [that are] having degrees in fields related to science, technology, engineering, and mathematics (STEM) so that these employees would have core skills built on these basic sciences required for technology based innovations".

A brief description of these four STEM disciplines seems appropriate. According to White (2014), science is the systematic formulation of scientific laws to describe the physical universe based on observations, experiments, measurements, collaborations, research, critical enquiry, explorations and discoveries, for a better understanding of the world. As for technology, it is defined by White (2014) as the branch of knowledge that deals with the use of scientifically engineered products by society for a better life within its environment. Similarly, White (2014) defines engineering as the conversion of pure scientific knowledge into the creation of useful systems and products including, but not limited to, vehicles, bridges, buildings and electronic systems. It is common knowledge that the purpose of mathematics is to equip one with the necessary skills and approaches to interpret and analyze information, and to simplify and solve problems; and mathematics is the foundation of STEM. In addition to serving as a foundation for STEM, the field of mathematics has become so vast that its full description is beyond the scope of the current study. However, it is worth mentioning that some of the sub-fields of mathematics include algebra, geometry and calculus, just to name a few, which are all concerned with the study of numbers, quantities, shapes and their interrelationships by using specialized notations (White, 2014). In the currently emerging Fourth Industrial Revolution, the computing field is also starting to emerge as the linking glue between the above described four STEM fields.

### 1.1.3 Central Role of Computer Programming or Coding in 4IR

The curriculum guidelines for the undergraduate degree programs in Information Technology published by the Association for Computing Machinery (ACM) and the Institute of Electrical and Electronics Engineers (IEEE) Computer Society (2008: 32) point out that the undertaking of an introductory programming course is essential for IT students because programming concepts are used in nearly all other core IT courses. The ACM computing curriculum also acknowledges the role of programming in the following five pillars or sub-disciplines of the IT curriculum: programming itself; networking; web systems; information management; and human-computer interaction. The same curriculum recommends that the remaining four pillars are best studied after students have learned the basics of programming in an appropriate high-level language (Bills and Biles, 2005).

It is also widely accepted that computer programming or coding plays an essential role in the currently emerging fourth industrial revolution (4IR). In fact, according to Benioff (2016), cited by Kwon and Schroderus (2017: 3), "coding is one of the most important skills that you can acquire today, and [it is] a critical skill for the fourth Industrial Revolution". Murai (2016) also believes that computer programming is seen as key to Japan's place in the fourth industrial revolution. A similar viewpoint is supported by Marion (2000) who states that employment adverts posted for digital librarians during the year 2000 all require computer programming skills. This central role of computer programming in the fourth industrial revolution is also highlighted by Bialon and Werner (2018: 102), who recommend that new curricula for the education of innovation marketing specialists should include introductory modules on programming languages. Hariharasudan and Kot (2018: 6) also provide the following list of the top six programming languages for the Internet of Things, also known as IoT, which is one of the main technologies of the fourth industrial revolution: C; Java, Python; JavaScript; Swift; and PHP.

### 1.1.4 Excitement of Programming

Apart from its central role in 4IR, one of the most exciting aspects of programming is that it gives to the programmer the ability to solve apparently difficult problems. In fact, the following extract from Brooks (1975: 7) eloquently portrays the different excitement facets of computer programming as well as the delights that its practitioners expect as a reward:

*"First is the sheer joy of making things. As the child delights in his mud pie, so the adult enjoys building things, especially things of his own design. I think this delight must be an image of God's delight in making things, a delight shown in the distinctness and newness of each leaf and each snowflake.*

*Second is the pleasure of making things that are useful to other people. Deep within, we want others to use our work and to find it helpful. In this respect the programming system is not essentially different from the child's first clay pencil holder "for Daddy's office.*

*Third is the fascination of fashioning complex puzzle-like objects of interlocking moving parts and watching them work in subtle cycles, playing out the consequences of principles built in from the beginning. The programmed computer has all the fascination of the pinball machine or the jukebox mechanism, carried to the ultimate.*

*Fourth is the joy of always learning, which springs from the nonrepeating nature of the task. In one way or another the problem is ever new, and its solver learns something: sometimes practical, sometimes theoretical, and sometimes both.*

*Finally, there is the delight of working in such a tractable medium. The programmer, like the poet, works only slightly removed from pure thoughtstuff. He builds his castles in the air, from air, creating by exertion of the imagination. Few media of creation are so flexible, so easy to polish and rework, so readily capable of realizing grand conceptual structures. Yet the program construct, unlike the* *poet's words, is real in the sense that it moves and works, producing visible outputs separate from the construct itself.*

*It prints results, draws pictures, produces sounds, moves arms. The magic of myth and legend has come true in our time. One types the correct incantation on a keyboard, and a display screen comes to life, showing things that never were nor could be. Programming then is fun because it gratifies creative longings built deep within us and delights sensibilities we have in common with all men"* (Brooks, 1975: 7).

### 1.1.5 High Demand for Programming Jobs

According to Forte (2003), computer programming is the "glue" that joins the different technologies that are used for the creation of solutions in the field of Information Technology. It attracts numerous job opportunities, as illustrated by Figure 1.2, Figure 1.3, Figure 1.4, Figure 1.5 and Figure 1.6. In fact, Figure 1.2 and Figure 1.3, indicate that programming jobs accounted for 44% and for 52% of the computing jobs in the United States of America in 2010 and 2014, respectively. Similarly, Figure 1.4 predicts that, for the European continent, computer programming jobs will be the mostly advertised jobs amongst the surveyed science and engineering jobs for the time period between 2014 and 2020. Figure 1.5 and Figure 1.6 alsoindicate that, in the USA, computer programming jobs accounted for the largest share of employment in 2015, and for the second highest annual average wages among STEM jobs in 2013, respectively. In fact, Figure 1.6 also predicts that, in the USA, computer programming jobs will be the mostly advertised STEM jobs for the time period from 2012 to 2022.

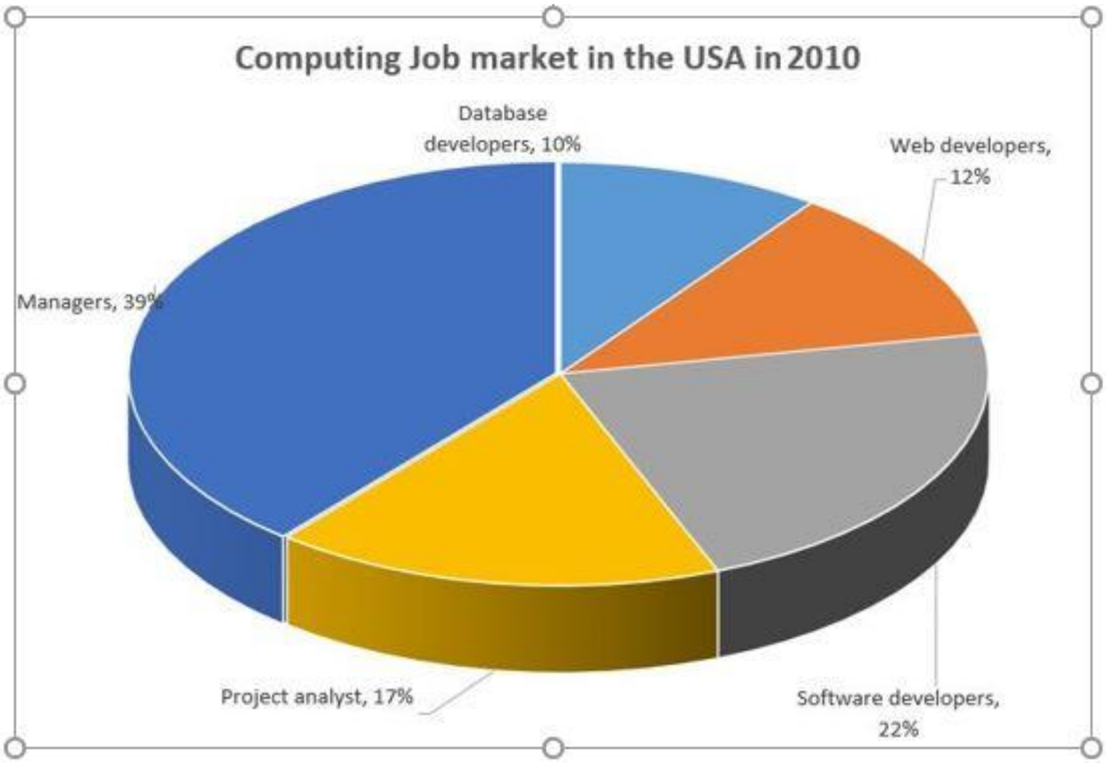


Figure 1.2: Computing Job market in the USA in 2010 (U.S. Bureau of Labor Statistics, 2010)

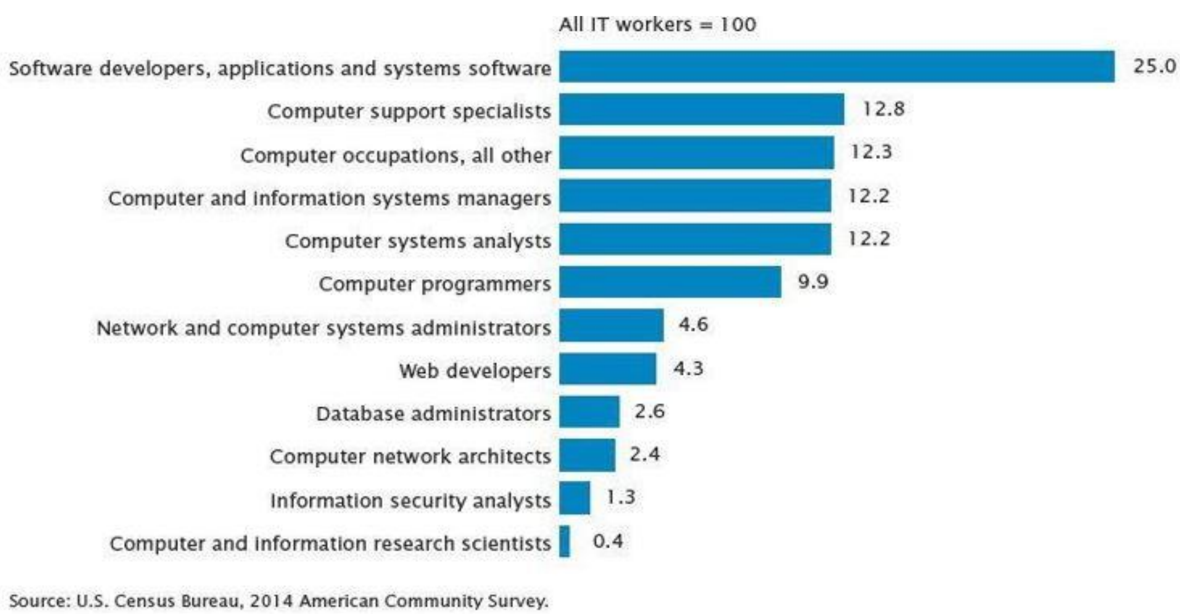


Figure 1.3: Computing job market in the USA in 2014 (U.S. Bureau of Labor Statistics, 2014)

| Rank | S&E Occupation | Projected Average Annual Job Openings[a] |
|---|---|---|
| 1 | Software developers, applications | 85,500 |
| 2 | Computer user support specialists | 55,400 |
| 3 | Computer systems analysts | 44,800 |
| 4 | Software developers, systems software | 32,700 |
| 5 | Computer and information systems managers | 32,500 |
| 6 | Civil engineers | 27,000 |
| 7 | Operations research analysts | 25,900 |
| 8 | Computer occupations, all other | 22,300 |
| 9 | Mechanical engineers | 21,200 |
| 10 | Industrial engineers | 19,700 |

Figure 1.4: Projected average annual job openings from 2014 to 2020 in Europe (OECD, 2014)

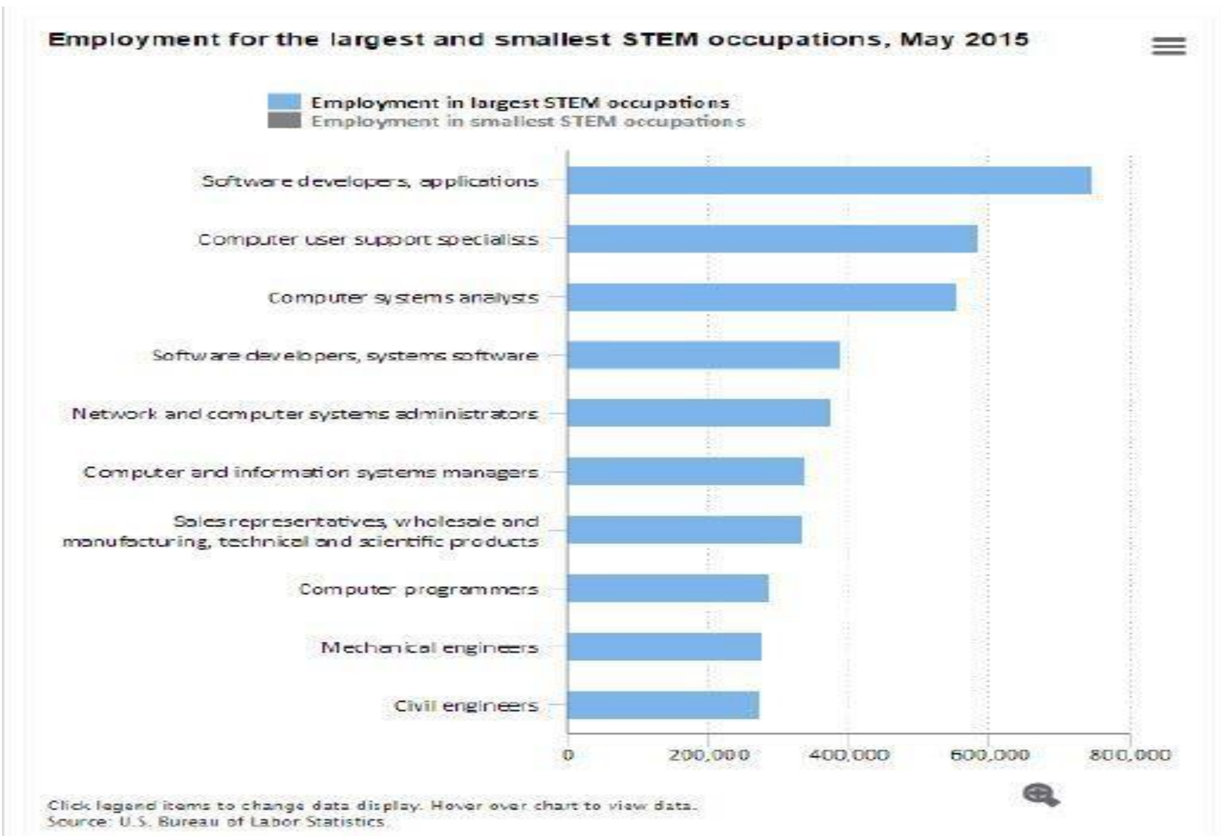


Figure 1.5: Employment for STEM occupations in 2015 (U.S. Bureau of Labor Statistics, 2015)

| Occupation | Job openings, projected 2012–22 | Employment | | Median annual wage, May 2013 | Typical entry-level education[1] |
|---|---|---|---|---|---|
| | | 2012 | Projected 2022 | | |
| Software developers, applications | 218,500 | 613,000 | 752,900 | $92,660 | Bachelor's degree |
| Computer systems analysts | 209,600 | 520,600 | 648,400 | 81,190 | Bachelor's degree |
| Computer user support specialists[2] | 196,900 | 547,700 | 658,500 | 46,620 | Some college, no degree |
| Software developers, systems software | 134,700 | 405,000 | 487,800 | 101,410 | Bachelor's degree |
| Civil engineers | 120,100 | 272,900 | 326,600 | 80,770 | Bachelor's degree |
| Computer programmers | 118,100 | 343,700 | 372,100 | 76,140 | Bachelor's degree |
| Sales representatives, wholesale and manufacturing, technical and scientific products[2] | 111,800 | 382,300 | 419,500 | 74,520 | Bachelor's degree |
| Network and computer systems administrators | 100,500 | 366,400 | 409,400 | 74,000 | Bachelor's degree |
| Mechanical engineers | 99,700 | 258,100 | 269,700 | 82,100 | Bachelor's degree |
| Computer and information systems managers[3] | 97,100 | 332,700 | 383,600 | 123,950 | Bachelor's degree |
| Industrial engineers | 75,400 | 223,300 | 233,400 | 80,300 | Bachelor's degree |
| Architectural and engineering managers[3] | 60,600 | 193,800 | 206,900 | 128,170 | Bachelor's degree |
| Web developers | 50,700 | 141,400 | 169,900 | 63,160 | Associate's degree |
| Electrical engineers | 44,100 | 166,100 | 174,000 | 89,180 | Bachelor's degree |
| Computer network architects[3] | 43,500 | 143,400 | 164,300 | 95,380 | Bachelor's degree |

Figure 1.6: STEM occupations with many job openings, projected 2012–22 (2010 Standard Occupational Classification (SOC) System)

## 1.2 Problem Statement and Research Gaps

Unfortunately, the above identified importance, excitement and benefits of computer programming are not sufficient enough to counter the stubborn problem of academic failure in computer programming. A proof of the stubbornness of this academic failure problem can be found from the existing literature where Watson and Li (2014: 1) posit that *“Learning to program can be an incredibly difficult task, to the point where the phrases failure rate and programming course are almost synonymous”.*

The same authors found that failure rates in introductory computer programming are as high as sixty (60) percent or more in many countries all over the world. They also found that Finland, Brazil, Germany, Portugal and South Africa have the highest failure rates in computer programming in their sample of fifteen (15) countries.

According to McCracken et al. (2001: 125), *“Many students do not know how to program at the conclusion of their introductory courses”.* Similarly, Dehnadi *et al.* (2009: 1) are adamant that *“Programming is hard to learn. The search for predictors of programming ability has produced no significant results. The problem is international and longstanding”.* The same authors posit that the computer programming problem is indeed general and persistent, despite the advances made by in the field of computing.

Existing teaching approaches have also not succeeded in improving these computer programming problems. A study by Vihavanen et al. (2014) on the influence of different teaching approaches (collaboration and peer programming, the use of visual programming environment, such as Scratch and Alice, the use of media computation and gamification, and the use of a combination of other hybrid teaching interventions) on academic performance in introductory programming found that such approaches were only able to improve the overall worldwide average pass rates in introductory programming by 16%.

A review of the existing research on the above identified failure rate problem led to the identification of the following research gaps that are further described in the next chapter. The basket of theories on the examination of academic performance in introductory programming is quite limited. Moreover, the teaching approaches explored by these studies disregard the culturally sensitive teaching methods of other STEM subjects. Furthermore, students from the African continent are largely underrepresented in the research populations of the existing studies on this problem. The existing literature is also usually silent on its types of time horizons, as well as its reliability and validity methods.

## 1.3 Overview of Current Programming Teaching Approaches

It seems important to mention that computer science education can be divided into two approaches, i.e., the culturally neutral approach, and the culturally sensitive approach. Culturally sensitive teaching approaches refer to teaching methods that recognize the importance of including elements of the learners' cultural preferences in all aspects of learning, while culturally neutral teaching approaches ignore such cultural elements (Ortiz, 2012). This section will describe some of these methods that have so far been used for the teaching of programming, and for the teaching of other STEM subjects, in order to explore possible new solutions to the above identified stubborn problem of academic failure in computer programming.

### 1.3.1 Culturally neutral teaching approaches and methods

According to Mohorovicic and Strcic (2011), computer programming teaching approaches can be classified into five main culturally neutral approaches: problem-based teaching approach; puzzle-based teaching approach; pair programming approach; prerecorded lectures approach; and game-themed programming approach.

#### a) Problem-based teaching approach (PBL)

In this instructional approach, students learn by actively engaging in practical real world problem scenarios. By engaging in the process of solving these real world problems, students are able to develop practical higher order thinking skills. PBL usually allows students to first work in groups in order to identify and discuss problems, learning goals and study materials. Thereafter, each student must work independently prior to their meeting where they discuss and apply together what they have learned in order to solve a particular problem (Mohorovicic and Strcic, 2011). PBL encourages increased retention of knowledge and students have better results in follow-up courses compared to their colleagues in traditional introductory programming courses. PBL also enhances students' communication skills, creative thinking, motivation and responsibilization (Nuutila *et al*., 2005; Wu, 2006).

### b) Puzzle-based teaching approach

In this instructional approach, students learn how to program by solving puzzles. This puzzle solving process involves a series of steps. First, a problem is presented to a student according to content that is being taught. Secondly, a complete solution of the program of the problem is then divided into many pieces of programs depending on the desired difficulty. Thereafter, students must attempt to reconstruct the entire program, by selecting the correct program pieces and by placing them in the right order. The puzzle-based teaching approach has been shown to significantly increase students' interest and level of participation in programming courses, as well as their critical thinking abilities to solve programming problems (Merrick, 2010; Yoneyama *et al*., 2008; Falkner *et al*., 2010).

### c) Pair programming approach

In the pair programming approach, two programmers collaborate or work together on the same code and on the same computer for the design, development and testing of a program. This process requires that the two programmers who are working as a pair assume the two roles of a driver and of a navigator. Here, the driver is the person that actively writes the code, while the role of the navigator is to scrutinize the code of the driver and to make relevant suggestions, where necessary. The pair programming approach leads to faster code writing compared to when individual students work alone, as well as to programs that are well designed and have few errors (Zacharis, 2010; Chaparro *et al*., 2005).

#### d) Prerecorded lectures teaching approach

In this instructional approach, students learn programming through lectures that are prepared and delivered using digital multimedia recordings comprising of narrations on the process of writing computer programs. These digital recordings are meant to supplement the conventional lectures by providing step by step presentations, demonstrations, and explanations on the process of writing and testing programs with the use of appropriate examples. They also provide students with the possibility of reviewing all the concepts that they may have missed or misunderstood during conventional lectures (Mohorovicic and Strcic, 2011; Smith and Fidge, 2008).

#### e) Game-based programming teaching approach

In the game-based programming approach, students learn programming concepts by exploring and programming small and simple interactive game applications. In other words, the game-based approach teaches students basic computer programming concepts by engaging them in game-like activities that consist of graphical and functional user interaction modules with the aim of teaching them programming concepts through understanding how games work (Sung *et al*., 2010).

### 1.3.2 Culturally sensitive teaching approaches and methods

Ethnoscience seems to be the main culturally sensitive teaching approach. It came into existence in the 1960s with its adoption for teaching and learning purposes in Arizona (USA) between 1960 and 1965 for life and environmental science subjects (Snow, 1972). It uses materials that are based on the culture and the history of a particular ethnic group to illustrate scientific principles (Table 1.1). According to Abonyi (1999), one of the basic reasons for the use of ethnoscience approaches for teaching and learning is because people have a strong affinity with their culture.

Hiwatig (2008: 40) also recalls the following recommendations given by UNESCO (United Nations Educational, Scientific and Cultural Organization) in 1991 for the implementation of ethnoscience teaching approaches in schools:

(a) *The content, language, symbols, designs, and purpose of the curriculum should be linked to day-to-day experiences and goals of the children;*

(b) *Theory should be linked to practice, human purpose, the quality of life, and in-school experience to out-of-school experience; and*

(c) *Teaching and learning should begin from the beliefs, interests, and learning skills that students bring to the classroom and should help each of them extend and revise their ability and understanding".*

Ethnoscience uses indigenous knowledge and it is often referred to as a culturally relevant science. D'Ambrosio (1985:44) cites D'Ambrosio (1977) to define it as "the study of scientific and, by extension, technological phenomena in direct relation to their social, economic and cultural backgrounds". Ethnoscience can also be viewed as the amalgamation of different systems of explanations and ways of doings that have been "accumulated through generations in distinct cultural environments" (D'Ambrosio, 1998: 1). The fundamental idea behind ethnoscience is that many basic scientific concepts and practices are enshrined in culturally reinforced knowledge and myths (Abonyi, 1999). Similarly, Peni (2011) posits that cultural practices with a direct bearing to science can be used by ethnoscience. For Livingston (2016), citing Auge (1999:118), ethnoscience is an attempt to recognize what indigenous people view as their science, namely, "their practices of looking after themselves and their bodies, their botanical knowledge, but also their forms of classification, of making connections". Ethnoscience embraces several disciplines (ethnomedicine, ethnobiology, ethnochemistry, ethnophysics, ethnomathematics, and ethnoagriculture) that are working together to negate the common belief that the western cultural heritage is particularly favourable to scientific development (Mathew and Smith, 2006) and that most of the science curriculum should reflect this orientation towards the western culture (Auge, 1999).

According to Muhammad (2011), the above mentioned common belief unfortunately enhances inferiority and negatively influences students' academic performance in non-western countries, especially in STEM subjects. This is the reason why ethnoscientists, such as Peni (2011), are calling for that unfortunate situation to be changed so that students can to be taught with the view that science is something that happens within and around them.

Table 1.1: Some examples of use of ethnoscience teaching approaches

| **Field** | **Ethnoscience teaching approach used** |
|---|---|
| Mathematics | Cultural artefacts found in the immediate environment, e.g., clay bed, local basket, native drum, native drum, round house, calabash and plates (Abiam *et al*., 2016) |
| Mathematics and computing | Elements from Latin American, Caribbean, American and African American cultural heritages (Eglash *et al*., 2013) |
| Mathematics | "Culturally Situated Design Tools" (CSDT), programmable Culturally Situated Design Tools" (pCSDT), Ghanaian Adinkra and Kente textiles symbols (Babbit *et al*., 2015) |
| Basic science and technology | Common beliefs, folk knowledge, myths and cultural practices of the indigenous people of Nsukka in Enugu state, Nigeria (Abonyi, 1999) |
| Biology | Common myths, indigenous views and cultural practices of the people of Nsukka in Enugu state, Nigeria (Ugwuanyi, 2016) |
| Chemistry | Common practices for making local soap of the indigenous people of Akwa Ibom, Nigeria (Ugwu and Diovu, 2016) |

Computing applications are becoming more and more popular worldwide; and this also calls for a multicultural view of computing, including for its teaching and learning, in general, and for the teaching and learning of computer programming, in particular; and that is the rationale behind the culturally sensitive approaches for the teaching and learning of computing. According to Morales-Chicas *et al*. (2019), culturally sensitive teaching approaches for computing education can be classified into three main teaching strategies: ethnocomputing; culturally situated design tools; and culturally relevant computing.

**a) Ethnocomputing**

Tedre (2002: 32) claims that ethnocomputing can be viewed from three different perspectives: from a constructivist perspective; from a multicultural educational or culturally relevant education perspective; and from an ethnosciences perspective. Social constructivism focuses on the "subjective, culturally bound, and usually hidden knowledge" that is transmitted through "languages and other social processes" in order to develop science. The aim of the multicultural educational perspective of ethnocomputing is to develop the necessary "skills for observing [the] computational phenomena that have their roots in a distinct cultural setting". As for ethnosciences, they "are a corpora of knowledge established as systems of explanations" and "ways of doing", which have been accumulated through generations in distinct cultural environments" (D'Ambrosio, 1998: 16). D'Ambrosio (1998: 32) is also adamant that the above multicultural perspective of ethnocomputing has the potential to "lead to new viewpoints into computer science which can be used to improve the cultural sensitivity in teaching computing" in general, and specifically for teaching computer programming through ethnoprogramming. According to Laiti (2006), ethnoprogramming basically requires that programming be done from an ethnological point of view, i.e., programming in a native language rather than in the English language. This is quite different from the current situation where English is the main language of programming, irrespective of the programming language used, and irrespective of the fact that, for example, in many African countries, English is not the first language for most of the students. In fact, ethnoscience studies are adamant that it is critical for the medium of instruction to combine students' native language with the English language (Sung *et al*., 2010; Bühmann and Trudell, 2008).

### b) Culturally Situated Design Tools

Culturally Situated Design Tools (CSDTs) are based on a constructionist type of programmable software that are used to teach computing and mathematics concepts to students through the construction of cultural artifacts (Eglash *et al*., 2013). CSDTs originated from a set of JAVA and Adobe Flash programs with a primary focus of teaching the mathematics concepts embedded in cultural practices through visual programming techniques (Babbitt *et al*., 2012). The creation of these CSDTs requires collaborating with the natives of a particular culture in order to identify from their surrounding environments their cultural symbols and artefacts that can be related to computing (Eglash *et al*., 2006). Examples of such CSDTs include the use of Cornrow Curves used in cornrow hair braiding. The aim of applying these CSDTs, as a teaching approach for computer programming, is to empower students to learn programming concepts by leveraging on the artefacts that can be found in their communities rather than by relying on the traditional programming platforms (Lachney, 2017; Lachney *et al*., 2016).

### c) Culturally responsive computing

Culturally responsive computing (CRC) is based on the principles of culturally relevant education theories. These theories aim to motivate students to view computing/computer programming from a cultural perspective. In other words, CRC encourages students to collectively engage in computing activities in a way that is different from the existing conventional computing approaches (Eglash *et al*., 2013; Scott *et al*., 2014). The ultimate goal of CRC is to achieve equity in STEM education through computing activities by adapting the curriculum in such a way that it will consider students' culture, their language, gender, race, as well as other social attributes that can provide a better understanding and appreciation of their identities, background and culture (Scott *et al*., 2015; Morales-Chicas *et al*., 2019).

## 1.4 Rationale and scope of the study

It has been established from the preceding sections that computer programming is a very important but difficult subject to teach and to learn; and, as a result, academic performance in introductory computer programming subjects in higher education generally remains poor, despite the use of a variety of culturally neutral teaching strategies and approaches. Moreover, the above sections have identified important theoretical, contextual and methodical gaps in the existing research in their attempt to solve this stubborn academic failure problem for introductory computing. It has also been established that culturally sensitive teaching approaches, such as the ethnoscience teaching method, have the proven ability to have improved academic performance in STEM subjects, such as mathematics, chemistry, biology, and even computer programming, for primary and secondary education. This study will, therefore, attempt to examine the impact of an ethnocomputing teaching approach on the academic performance of higher education students for introductory computer programming with the hope of contributing towards improving academic performance in this difficult but very important subject, because of the crucial role that it is playing in the currently emerging fourth industrial revolution (4IR). Even though this study has been located study within the broader background of STEM subjects and programming in the fourth industrial revolution (4IR), it is important to keep in mind that the scope of this study is restricted to the issue of academic performance in these subjects, with a focus on introductory programming.

## 1.5 Research aim, objectives, and questions

The above identified research problem and gaps from the existing literature have highlighted that academic failure in introductory computer programming in higher education is a stubborn problem.

The basket of theories used by the studies on the examination of this academic failure problem is limited. The teaching approaches explored by these studies disregard culturally sensitive teaching methods used for other STEM subjects. Students from the African continent are largely underrepresented in the research populations of these studies. The existing literature on academic failure in introductory computer programming in higher education is usually silent on its types of time horizons, its reliability and validity methods.

Bearing in mind the above identified research problem and gaps, the aim of this study is to propose the ethnocomputing teaching method as a new teaching approach that will improve academic performance for introductory computer programming in higher education. This aim can be subdivided into the following research objectives:

- To identify the theories that can support the ethnocomputing teaching method as an effective teaching approach for introductory computer programming in higher education;
- To examine the factors that affect the influence of the ethnocomputing teaching method on academic performance in introductory programming for a group of African students, and test these factors with a suitable research methodology and design; and
- To make recommendations on how to improve the use of the ethnocomputing method as a solution to the stubborn problem of academic failure in introductory computer programming in higher education.

The above listed research objectives can also be formulated in the form of a set of research questions:

- Which theories can support the ethnocomputing teaching method as an effective teaching approach for introductory computer programming in higher education?
- Which tested factors influence the impact of the ethnocomputing teaching approach on academic performance in introductory programming for selected African students?
- How can the use of the ethnocomputing method be improved as a solution to the stubborn problem of academic failure in introductory computer programming in higher education?

## 1.6 Structure of thesis

This thesis on the impact of the ethnoscience teaching philosophy on students' academic performance in introductory computer programming will consist of six chapters, as outlined below.

### Chapter One: General Introduction

This chapter has discussed the importance of STEM and computer programming in this emerging fourth industrial revolution era, and the excitement that computer programmers experience during their programming activities. It has also contrasted this excitement against the generally reported high failure rates and the research gaps on that problem where culturally sensitive teaching methods are ignored, despite the inefficiency of the culturally neutral approaches. The aim, research questions, objectives and rationale of the study are then, consequently, presented.

### Chapter Two: Literature Review

This chapter will review the existing literature on the factors that are affecting academic performance in introductory programming in higher education. It will also review the existing literature on this problem for high school STEM subjects.

### Chapter Three: Theoretical foundations in Education

This chapter will give an overview of the main teaching and learning theories. The researcher will then propose a theoretically supported conceptual model of the factors that are affecting academic performance in introductory computer programming, both for culturally neutral and for culturally sensitive teaching and learning approaches.

### Chapter Four: Research Methodology

This chapter will provide a comprehensive description of the quasi-experiment, i.e., the research strategy used for the partial empirical validation of the model presented in chapter 3.

### Chapter Five: Research Results

This chapter will present the findings of the quasi-experiment conducted by this study on the factors that are affecting academic performance in introductory computer programming both for culturally neutral and for culturally sensitive teaching and learning approaches. Such findings will include the results on students' preferred teaching philosophy or approach, and the ones on their performance in programming for their preferred teaching philosophy or approach.

### Chapter Six: Discussion, Recommendations and General Conclusion

This chapter will compare the current study against the reviewed literature. It will also discuss possible strategies and recommendations for the improvement of students' academic performance in introductory computer programming. A summary of this study will also be provided in this chapter.

## 1.7 Conclusion

STEM fields, in general, and computer programming, in particular, are crucial in this emerging 4IR (Fourth Industrial Revolution) era. In fact, computer programming, or coding, is seen as one of the most important skills that one can acquire today in this 4IR era because it is the foundation and the key knowledge area for all the other five core “pillars” of the IT curriculum. Computer programming activities elicit different intrinsic excitement facets and rewards for practitioners. They also attract numerous job opportunities around the world, despite the fact that it is reputed to be a difficult subject to teach and to learn, especially at the introductory level, due to the fact that it is a very challenging and complex intellectual activity, despite the use of various teaching and learning approaches.

These teaching and learning difficulties are the reason why this study aims to examine the impact of an ethnoscience teaching philosophy on students’ academic performance in introductory programming in higher education, because of claims from existing research that ethnoscience has contributed to the reduction of high failure rates in STEM subjects, such as mathematics, chemistry, biology, and even computing, for primary and secondary education learners. This study will attempt to achieve this aim by designing and testing a theoretically supported conceptual model and the factors that are affecting academic performance in introductory computer programming both for culturally neutral and for culturally sensitive teaching and learning approaches, in order to be able to recommend relevant remedial strategies. The next chapter describes the literature review to be used in this study for the achievement of its first objective.

# CHAPTER TWO

# LITERATURE REVIEW

The aim of this chapter is to review the existing literature on the impact of the ethnoscience teaching approach on academic performance, and on the factors that affect academic performance in introductory computer programming; having in mind that the purpose of this study is to propose the ethnocomputing culturally sensitive teaching approach as a new teaching method for introductory computer programming. It appears that the existing studies on academic performance in introductory computer programming are culturally neutral, and they focus on university students, while the existing ethnoscience culturally sensitive studies are focusing on the academic performance of high school learners for STEM subjects. This chapter can, therefore, be seen as a comparative description of the reviewed culturally neutral studies against the reviewed culturally sensitive studies in order to identify key research gaps in these two types of studies. It is important to note that this review was conducted according to a detailed literature analysis methodology, not presented here because of space constraints, but whose emerging themes are used for the overall presentation of this review. Existing culturally neutral studies and existing culturally sensitive ones are hereby compared in terms of their prevalence and contexts, their theories, their methodologies and their academic performance factors. The identification of these theories and reviewed factors play a key role in the deductive nature of this research. The chapter ends with a summary of the research gaps identified by this literature review.

## 2.1 Prevalence and Contexts of the Reviewed Studies

The prevalence and the contexts of the reviewed studies are hereby presented in terms of their frequencies as well their places and years of publications.

**Prevalence of the studies.** This review found that there are far more culturally neutral studies compared to the number of culturally sensitive studies. The same imbalance prevails between these two types of studies for the number of authors.

The only few culturally sensitive studies found by this review include Abiam et al. (2016), Abonyi (1998), Ajayi et al. (2017), Aktuna (2013), Achor et al. (2009), Babbitt (2014), Eglash et al. (2013), Eglash et al. (2011), Ibe and Nwosu (2017), Odili and Okpobiri (2011), Okwara and Upu (2017), Ugwanyi (2015), Ugwu and Diovu (2016), and Unodiaku (2013), all of whom focus on academic performance in chemistry, biology, basic science and technology, and mathematics in high school. However, this study did not find any existing culturally sensitive study on the factors that affect academic performance in introductory programming, even though computing is also part of STEM.

In fact, even though several authors have examined the problem of academic performance in introductory programming, they did not do so in the context of culturally sensitive education. For example, Vihavainen *et al*. (2014) reviewed thirty-two (32) papers on the influence of teaching and learning approaches on students' academic performance in introductory programming, but all these papers are anchored in culturally neutral education.

Similarly, Zhang, *et al*. (2013) investigated the effects of two different teaching approaches on academic performance in introductory programming in an urban public university, but both of these teaching and learning approaches were culturally neutral. The study by Kunkle and Allen (2016) is another example of a culturally neutral study that investigates the impact of different teaching approaches and programming languages on academic performance in introductory programming. Although the study conducted by Fasasi (2017) on the impact of the ethnoscience teaching approach on students' attitude towards a basic science and technology module is culturally sensitive, its scope is on attitude towards basic science and technology and not on academic performance in introductory computer programming.

The content of this subsection seems to point to a research gap on the need for more culturally sensitive research on academic performance in STEM subjects. It also specifically alludes to the need for culturally sensitive studies on the factors that affect academic performance in introductory programming.

**Places and years of publications.** This literature review found that most of the reviewed culturally neutral studies on academic performance in introductory computer programming were conducted either in Europe or in North America, with only a few in the African continent. In contrast to the reviewed culturally neutral studies, this literature review found that most of the reviewed culturally sensitive studies on academic performance in STEM subjects, e.g., Ugwu and Diovu (2016), Odili and Okpobiri (2011), and Abonyi (1999), were conducted in Africa. This is an indication that more authors are becoming interested in conducting research on the adoption of the culturally sensitive teaching approach in Africa. The culturally neutral studies on academic performance in introductory computer programming that were conducted in Europe include Bennedsen and Caspersen (2005), and Bergin and Reilly (2006), while Byrne and Lyons (2001), Hall *et al*. (2006) and Katz *et al*. (2006) are some examples of the culturally neutral studies on academic performance in introductory computer programming that were conducted in North America. This review also found that the reviewed culturally sensitive studies are more recent compared to the reviewed culturally neutral studies. Byrne and Lyons (2001), Buerck *et al*. (2003), Chamillard and Braun (2000), Goold and Rimmer (2000), Katz *et al*. (2003) and McDowell *et al*. (2003) are some examples of culturally neutral studies published in the early 2000s; while Ibe and Nwosu (2017), Okwara and Upu (2017), Ugwanyi (2015), Ugwu and Diovu (2016), Abiam *et al*. (2016) and Ajayi *et al*. (2017) are examples of recently published culturally sensitive studies.

The content of this subsection seems to point to a research gap on the need for more culturally neutral studies on academic performance in introductory programming in Africa and in the world, in general. This content also alludes to the need for more culturally sensitive studies on academic performance in STEM subjects outside of Africa.

## 2.2 Reviewed Theories

This review found that the basket of theories underpinning the reviewed culturally neutral studies on academic performance in introductory programming is bigger than the one of the reviewed culturally sensitive studies on academic performance in STEM subjects. The theoretical foundations for the reviewed culturally neutral studies include theories, such as Kolb learning style theory, Piaget theory of cognitive development, human cognitive theory, Davis's theory on knowledge acquisition, Frame theory, self-regulated learning theory, motivation theory, creativity theory, problem solving theory, and the adult learning theory. On the other hand, the theoretical foundations of the reviewed culturally sensitive studies include theories, such as constructivism, cognitive evaluation theory, Ausubel's meaningful learning theory, situated learning theory and ethnomathematics.

It, however, appears that Kolb learning style's theory is the theoretical foundation of the majority of the reviewed culturally neutral studies, while ethnomathematics is the theoretical foundation of most of the reviewed culturally sensitive studies. Byrne and Lyons (2001), Buerck *et al.* (2003), Allert (2004), Cakiroglu (2016), Campbell and Johnstone (2010) and Amoako et al. (2013) are examples of culturally neutral studies framed on Kolb learning style's theory; while Abiam et al. (2016), Aktuna (2013), Achor et al. (2009), Odili and Okpobiri (2011) and Unodiaku (2013) are some examples of culturally sensitive studies framed on the ethnomathematics theory.

The content of this subsection seems to point to a research gap on the need for culturally sensitive research to identify more theories on the factors that affect academic performance in STEM subjects.

## 2.3 Reviewed Methodologies

The research methodologies of the reviewed studies are hereby presented in terms of their research designs, research strategies, types of research data, data collection methods, types of time horizons, research population, sample and sample sizes, sampling methods, methods of data analysis, as well as their data validity and reliability testing methods.

**Research designs.** This literature review found that all the reviewed culturally sensitive studies on academic performance in STEM subjects are purely quantitative. This finding contrasts with the reviewed culturally neutral studies on academic performance in introductory programming that are either purely quantitative, or a mix of quantitative and qualitative studies. Ambrosio et al. (2014), Bennedsen and Caspersen (2006), Chamillard and Braun (2000), Rountree et al. (2002), Shaw (2012), Abonyi (1999), Ibe and Nwosu (2017) and Eglash et al. (2013) are examples of purely quantitative culturally neutral studies; while Cutts et al. (2006), Kinnunen and Malmi (2006), Duran (2016), Ranjeet (2011), Ranjeet (2008) and Simon et al. (2006) are some examples of mixed research design studies.

The content of this subsection seems to point to a research gap on the need for more qualitative culturally sensitive research on academic performance in STEM subjects.

**Research strategies.** This literature review found that all the reviewed culturally sensitive studies on academic performance in STEM subjects are experiments. This finding contrasts with the reviewed culturally neutral studies on academic performance in introductory programming that are either surveys, experiments, or a combination of surveys and experiments. Jones and Burnett (2008) and Rountree et al. (2002) are examples of the culturally neutral studies that are surveys; while Chamillard and Braun (2000), Katz et al. (2003), and Bennedsen and Caspersen (2008) are examples of the culturally neutral studies that are experiments.

On the other hand, Buerck et al. (2003), Duran (2016) and Golding et al. (2006) are examples of culturally neutral studies that combined surveys and experiments. The content of this subsection seems to point to a research gap on the need for more survey-based culturally sensitive research on academic performance in STEM subjects.

**Types of research data.** This literature review found that all the reviewed culturally sensitive studies on academic performance in STEM subjects exclusively rely on their primary data. This finding contrasts with the reviewed culturally neutral studies on academic performance in introductory programming that are making use of either primary data, secondary data, or a mix of both. Bergin and Reilly (2005), Golding et al. (2006), Amoako et al. (2013) and Law et al. (2011) are examples of culturally neutral studies with primary data only; while Chamillard and Braun (2000) and Katz et al. (2006) are examples of culturally neutral studies with secondary data only. On the other hand, Bennedsen and Caspersen (2006), Cutts et al. (2006), Ranjeet (2011) and Longi (2016) are examples of culturally neutral studies with a mix of primary and secondary data.

The content of this subsection seems to point to a research gap on the need for more culturally sensitive studies on the analysis of secondary data on academic performance in STEM subjects.

**Data collection methods**. This literature review found that all the reviewed culturally sensitive studies on academic performance in STEM subjects exclusively collected their data via standardized tests. This finding contrasts with the reviewed culturally neutral studies on academic performance in introductory programming that collected their data both via questionnaires, standardized tests or a combination of questionnaires and standardized tests. Cakiroglu (2014), Caspersen and Bennedsen (2007), Kinnunen and Malmi (2006), Bennedsen and Caspersen (2008), Ambrosio et al. (2014), and Chamillard and Braun (2000) are examples of culturally neutral studies that exclusively collected data via questionnaires.

On the other hand, Katz et al. (2003), Katz et al. (2006), Law et al. (2011) and Amoako et al. (2013) are examples of culturally neutral studies that exclusively collected data via standardized tests. This review also found that some culturally neutral studies, such as Rountree et al. (2002), Campbell and Johnstone (2010), Shaw (2012), Allert (2004) and Alturki (2016) made use of a combination of these two data collection methods.

The content of this subsection seems to point to a research gap on the need for more questionnaire-based culturally sensitive studies on academic performance in STEM subjects.

**Types of time horizons.** This literature review found that none of the reviewed culturally sensitive studies on academic performance in STEM subjects specified their types of time horizons. Similarly, none of the reviewed culturally neutral studies specified their type of time horizons, except for only two, namely, Bergin and Reilly (2006), and Bennedsen and Caspersen (2008), which both specified their type of time horizons as longitudinal studies.

The content of this subsection seems to point to a research gap on the need for academic performance studies to specify their type of time horizons, both for introductory computing and for STEM subjects, in general.

**Research population:** This literature review found that all the reviewed culturally sensitive studies are exclusively using secondary school learners as participants, while the reviewed culturally neutral studies are exclusively using undergraduate students as participants. However, there seems to be far more culturally neutral studies on the academic performance of first year undergraduate students compared to other undergraduate students above the first year level. Similarly, there seems to be far more culturally sensitive studies on the academic performance of senior secondary school learners compared to secondary school learners below the senior secondary school level.

Campbell and Johnstone (2010), Ambrosio et al. (2014), Bennedsen and Caspersen (2006), Cutts et al. (2006) and Rodrigo et al. (2009) are examples of some of the culturally neutral studies having first-year undergraduates as their research populations; while Allert (2004), Alturki (2016), Rountree et al. (2002) and Shaw (2012) are examples of culturally neutral studies having other undergraduate students as their research populations. As for the culturally sensitive studies, Abonyi (1999), Ajayi et al. (2017), Aktuna (2013), Achor et al. (2009), Eglash et al. (2011), Ibe and Nwosu (2017), Odili and Okpobiri (2011) and Babbitt (2014) are examples of the ones having senior secondary learners as their research populations; while Odili and Okpobiri (2011), Abiam et al. (2016) and Eglash et al. (2013) are examples of studies having junior secondary school learners as their research populations.

The content of this subsection seems to point to a research gap on the need for culturally sensitive studies on the academic performance of introductory programming university students. This content also alludes to the need for culturally neutral studies on the academic performance of STEM subjects as high school learners.

**Sample sizes.** This literature review found that the average sample sizes of the reviewed culturally neutral studies on academic performance in introductory programming seem to be bigger than the ones of the reviewed culturally sensitive studies on academic performance in STEM subjects. Law *et al.* (2011), McDowell *et al.* (2003) and Rountree *et al.* (2002) are examples of large size culturally neutral studies, while Babbitt (2014) and Eglash *et al.* (2011) are examples of small size culturally sensitive studies.

The content of this subsection seems to point to a research gap on the need for large sample size culturally sensitive studies on academic performance in STEM subjects.

**Sampling methods.** This literature review found that all the reviewed culturally sensitive studies on academic performance in STEM subjects exclusively rely on probability sampling methods, while the culturally neutral studies rely either on probability or non-probability sampling methods. Duran (2016), Ranjeet (2011), and Ranjeet (2008) are examples of culturally neutral studies that adopted probability sampling methods, while Katz et al. (2003), Longi (2016), Ranjeet (2011), and Ranjeet (2008) adopted non-probability sampling methods.

The content of this subsection seems to point to a research gap on the need for non-probability sampling culturally sensitive studies on the academic performance in STEM subjects.

**Methods of data analysis.** This literature review found that all the reviewed culturally sensitive studies on academic performance in STEM subjects exclusively relied on parametric data analysis methods, while the reviewed culturally neutral studies on academic performance in introductory programming relied on either parametric data analysis methods, or on a mix of parametric and non-parametric data analysis methods. Byrne and Lyons, (2001), Caspersen et al. (2007), Alturki, (2016), Buerck et al. (2003), Bennedsen and Caspersen, (2005), Kinnunen and Malmi, (2006), and Norwawi et al. (2009) are examples of culturally neutral studies that made use of parametric data analysis methods, while Sheard et al. (2008), Jones and Burnett (2008), Katz et al. (2006) and Shaw (2012) are examples of culturally neutral studies that made use of a mix of parametric and non-parametric data analysis methods.

The content of this subsection seems to point to a research gap on the need for non-parametric culturally sensitive studies on academic performance in STEM subjects.

**Data validity testing methods.** This literature review found that only a few of the reviewed culturally neutral and culturally sensitive studies did specify their types of data validity testing methods; and, amongst the few that did it, there were still more culturally neutral studies than the culturally sensitive ones.

In fact, the only culturally sensitive study that specified its data validity testing method as exploratory factor analysis is Abonyi (1999), while Law et al. (2011) and Shaw (2012) are the two culturally neutral studies that also specified the same type of data validity testing method. On the other hand, Caspersen and Bennedsen (2007), Hall et al. (2006), Longi (2016), Bennedsen and Caspersen (2008) are the culturally neutral studies that specified their data validity testing method as Pearson's correlation coefficients.

The content of this subsection seems to point to a research gap on the need for academic performance studies to specify their data validity testing methods, both for introductory computing and for STEM subjects, in general.

**Reliability of testing methods.** This literature review found that only a few of the reviewed culturally neutral and culturally sensitive studies did specify their types of reliability testing methods; and, amongst the few that did it, there were more culturally neutral studies than the culturally sensitive ones. In fact, Bergin and Reilly (2006), Cakiroglu (2014) and Law et al. (2011) are the culturally neutral studies that specified Cronbach's alpha coefficient method as their reliability testing method, while Ugwanyi (2015), and Ugwu and Diovu (2016) are the culturally sensitive studies that also specified the same method. On the other hand, Abiam et al. (2016), Abonyi (1999) and Ajayi et al. (2017) are the culturally sensitive studies that specified the test/retest approach, while Allert (2004), and Campbell and Johnstone (2010) are the culturally neutral studies that specified the same method. As for the studies that adopted the Cohen's kappa coefficient, this review found that only the culturally neutral study by Katz et al. (2003), and the culturally sensitive studies of Achor et al. (2009), Okwara and Upu (2017), and Unodiaku (2013) specified the Cohen's kappa coefficient method.

The content of this subsection seems to point to a research gap on the need for academic performance studies to specify their data reliability testing methods, both for introductory programming and for STEM subjects, in general.

## 2.4 Reviewed Academic Performance Factors

This section is a presentation of the categorization of the introductory programming and STEM subjects reviewed academic performance factors into independent research variables or themes. These research variables are: demographics, academic background, intellectual abilities, learning style and behaviour, teaching approach and philosophy, and psychological strength. This section will ultimately present the influence or absence thereof of these research variables on academic performance as per the reviewed studies.

**Demographics.** A fair amount of the reviewed studies has examined the influence of demographics on academic performance, both for introductory programming (CNS) and for STEM subjects (CSS), in general. Demographic variables refer to students' or learners' characteristics, such as gender, age, year of study, field of study or major, and first language. However, gender is the only demographic factor that was examined by the reviewed culturally sensitive studies (CSS), and it was also examined by the reviewed culturally neutral studies (CNS). The other demographic factors examined by the reviewed culturally neutral studies (CNS) include students' age, and their first language, even though the number of such reviewed studies is limited. For example, Rountree et al. (2002) and Sheard et al. (2008) found a negative correlation between age and academic performance in introductory programming. On the other hand, Su (2008) found that older students perform better than their younger counterparts in introductory programming, but Longi (2016) found that there is no relationship between age and academic performance in introductory programming. Rountree et al. (2002) also found that the first language of a student positively influences his or her academic performance in introductory programming.

As for the gender demographic factor, an overwhelming majority of the findings from the reviewed culturally sensitive studies (CSS) seems to indicate that learners' gender does not affect their academic performance in STEM subjects, except for Unodiaku (2013), who found that male learners perform better than female learners in STEM subjects.

The findings from the reviewed culturally neutral studies (CNS) also seem to be divided as to whether or not gender affects academic performance in introductory programming.

For example, Amoako et al. (2013), Byrne and Lyons (2001), Golding et al. (2006), Gould and Rimmer (2000), Katz et al. (2003), and Pillay and Jugoo (2005) found that male students perform better than their female counterparts in introductory programming. However, according to Bennedsen and Caspersen (2005), Bergin and Reilly, (2005), Buerck *et al*. (2003), Jones and Burnett (2008), Longi (2016) and McDowell *et al*. (2003), there is no relationship between students' gender and their academic performance in introductory computer programming.

The content of this subsection seems to point to a research gap on the need for more research on the influence of gender on academic performance in introductory programming when using culturally neutral teaching approaches. This content also alludes to the need for more research on the relationship between students and learners' demographics (beyond the gender factor) and their academic performance in introductory programming and in STEM subjects, in general.

**Academic Background.** None of the reviewed CSS examined the influence of academic background on academic performance in STEM subjects, and the current subsection, therefore, only applies to the reviewed CNS. In fact, a reasonable number of the reviewed CNS has examined the influence of academic background on academic performance. Academic background variables refer to students' previous academic performance from their secondary school for Mathematics, Physics, Chemistry, Biology, Information Technology and Languages. However, high school mathematics grades are the main academic background factor examined by the reviewed studies. Bergin and Reilly (2005) is one example of a study that found that previous academic performance in secondary school physics and biology positively influences academic performance in introductory programming.

Gould and Rimmer (2000) also found that previous academic performance in high school information technology positively influences academic performance in introductory programming. On the other hand, Bergin and Reilly (2005) found that previous academic performance in high school chemistry and biology has no influence on academic performance in introductory computer programming.

Byrne and Lyons (2001) also found that previous academic performance in high school foreign language has no influence on academic performance in introductory programming.

As for the influence of high school mathematics on students' academic performance in introductory programming, the reviewed CNS are unanimous that such influence is positive.

The content of this subsection seems to point to a research gap on the need for research on the influence of academic background on academic performance in STEM subjects within the culturally sensitive context. There is also a need for more CNS beyond the high school mathematics grades academic background factor.

**Intellectual Abilities.** The reviewed CSS did not examine the influence of intellectual abilities on academic performance for STEM subjects, except for Ajayi *et al*. (2017), and Achor *et al*. (2009) who found that memory retention abilities positively influence academic performance in secondary school mathematics and chemistry, respectively. On the other hand, there is a fair amount of reviewed CNS who examined the influence of intellectual abilities' factors on students' academic performance in introductory programming. Students intellectual abilities are described in this review in terms of students' abstraction abilities, their cognitive abilities, arithmetic reasoning abilities, spatial visualization and reasoning abilities, mental model, perceived understanding of the subject, perceptions on the complexity and difficulty of the subject, general intelligence and academic ability, creativity, map drawing skills, digital search articulation skills, and perceived comfort levels.

All the reviewed CNS are in agreement that intellectual abilities positively influence academic performance in introductory programming, except for the findings from Su (2008), Caspersen et al. (2007), Bennedsen and Caspersen (2006), Bennedson and Casperson (2008), and Hall et al. (2006) where it was found that students' abstraction ability has no relationship with their academic performance in introductory programming.

Similarly, perceptions on complexity and difficulty of course is the only intellectual ability factor that was found by Alturki (2016) to have a negative relationship with students' academic performance in introductory computer programming, while creativity and the mental model are the intellectual ability factors that were found by Su (2008) and Caspersen et al. (2007) to have no relationship with students' academic performance in introductory computer programming. The same finding applies for the contradictory relationships between abstraction and cognitive ability and students' academic performance in introductory computer programming, where Bennedsen and Caspersen (2006) and Bennedson and Casperson (2008) found that students' abstraction abilities have no relationship with their academic performance in introductory programming, while Gould and Rimmer (2000) found that they have a positive relationship with it. Similarly, Bergin and Reilly (2005) and Ranjeet (2008) found that cognitive ability positively influences academic performance in introductory programming, while Hall et al. (2006) found that it does not.

Gould and Rimmer (2000) also found that students' problem solving abilities positively influence their academic performance in introductory programming. Similarly, Amoako et al. (2013), Pillay and Jugoo, (2005) and Su (2008), respectively, found that general intelligence and academic ability, arithmetic reasoning ability, and spatial visualization and reasoning ability positively influence academic performance in introductory programming.

The same applies for Ambrosio et al. (2014), Fincher et al. (2006) and Simon et al. (2006) who also reported that intellectual abilities' components, such as map drawing skills, digital search articulation skills and perceived understanding of module significantly improve academic performance in introductory programming. Cutts et al. (2006) and Bergin and Reilly (2005) also found that students' perceived understanding of the module as well as their perceived comfort levels have a positive relationship with their academic performance in introductory computer programming.

The content of this subsection seems to point to a research gap on the need for research on the influence of intellectual abilities on academic performance in STEM subjects within the culturally sensitive context.

**Learning Style and Behaviour.** None of the reviewed CSS examined the influence of learning style and behaviour on academic performance in STEM subjects, and the current subsection, therefore, only applies to the reviewed CNS. In fact, a reasonable number of the reviewed CNS has examined the influence of learning style on introductory programming. On the other hand, only a limited number of the reviewed CNS examined the influence of other learning behaviour factors such as students' participation level and type, their affective and behavioral state, and their self- regulated learning ability. For example, Rountree et al. (2002) and Shaw (2012) found that students' participation levels positively influence their academic performance in introductory programming, and the same applies to Rodrigo et al. (2009) who also found that affective and behavioral states positively influence academic performance in introductory programming. As for the influence of self-regulated learning abilities, Bergin and Reilly (2006) found that it has no influence on academic performance in introductory computer programming.

Coming back to the effect of learning style on academic performance, most of the studies found a positive influence, except for Buerck et al. (2003), Cakiroglu (2014), Gould and Rimmer (2000), Pillay and Jugoo (2005), and Shaw (2012), who found that learning style has no influence on academic performance in introductory programming, while Fincher et al. (2006), Ranjeet (2011) and Simon et al. (2006) found that learning style has a negative influence on academic performance in introductory programming.

Allert (2004), Byrne and Lyons (2001), Campbell and Johnstone (2010), Norwami et al. (2009), Amoako et al. (2013), Pillay and Jugoo (2005), Ranjeet (2011), Fincher et al. (2006), Shaw (2012) and Simon et al. (2006) are examples of CNS reporting that learning style positively influences academic performance in introductory programming.

The content of this subsection seems to point to a research gap on the need for research on the influence of learning style and behaviour on academic performance in STEM subjects within the culturally sensitive context. There is also a need for more CNS on how students' learning behaviour affect their performance in introductory programming.

**Teaching Approach and Philosophy.** A fair number of the reviewed studies has examined the influence of teaching approaches and philosophies on academic performance both for introductory programming (CNS) and for STEM subjects (CSS), in general. However, the ethnoscience teaching method is the only teaching approach and philosophy that was examined by the reviewed CSS. In fact, most of the reviewed studies found that the ethnomathematics teaching approach significantly improves academic performance in mathematics (Abiam et al., 2016; Aktuna, 2013; Achor et al., 2009; Odili and Okpobiri, 2011; Unodiaku 2013; Babbitt, 2014; Eglash, et. al., 2011; Eglash, et al., 2013). On the other hand, only a few of the reviewed studies found that the ethnochemistry teaching approach improves academic performance in chemistry (Ugwu and Diovu, 2016; Ajayi et al., 2017).

The same applies for Ibe and Nwosu (2017), and Ugwanyi (2016), who both found that the ethnobiology teaching approach improves academic performance in biology, and also for Abonyi (1999), and Okwara and Upu (2017), who also found that the ethnoscience teaching approach improves academic performance in basic science and technology.

The other teaching approaches examined by the reviewed CNS include teachers' involvement, peer tutoring, the use of computer game-based instruction methods, the adoption of pair programming, the learning environment, and the perceived helpfulness of course materials, even though the number of such reviewed studies is quite limited. For example, Golding et al. (2006), Su (2008), McDowell et al. (2003) and Allert (2004) all found that peer tutoring, computer game-based instruction methods, pair programming and perceived helpfulness of course materials positively influence academic performance in introductory computer programming.

Similarly, Golding et al. (2006), Su (2008), McDowell et al. (2003) and Allert (2004), respectively, found that peer tutoring, the computer game-based instruction method, the adoption of pair programming and perceived helpfulness of course materials positively influence academic performance in introductory programming. On the other hand, Golding et al. (2009) and Buerck et al. (2003), respectively, found that teacher's involvement and learning environment have no influence on academic performance in introductory computer programming.

The content of this subsection seems to point to a research gap on the need for more research on the influence of the ethnoscience teaching approach of academic performance beyond mathematics, chemistry and biology within the culturally sensitive context. This content also alludes to the need for more research on other teaching approaches and philosophies beyond the ethnoscience teaching approach for introductory programming and for STEM subjects, in general.

**Psychological Strength.** The reviewed CSS did not examine the influence of psychological strength on academic performance, except for Okwara and Upu (2017) and Aktuna (2013), who found that students' interest in basic science and technology as well as their attitude towards mathematics positively influence their academic performance in these subjects.

On the other hand, there is a fair amount of reviewed CNS who examined the influence of the following psychological strength factors on students' academic performance: students' dislike of programming, learning expectations from the course and from different situations, self-esteem, attention to details, personality, personal confidence, self-efficacy and the existence of a personal value system. All the reviewed CNS are in agreement that psychological strength positively influences academic performance in introductory programming, with Gould and Rimmer (2000) and Longi (2016), respectively, finding that dislike of programming and an extrovert personality negatively influence academic performance in introductory programming, while Sheard et al. (2008) and Golding et al. (2006) found that learning expectations from the course and from different situations have no influence on students' academic performance in introductory computer programming.

Jones and Burnett (2008), Rountree et al. (2002) and Hall et al. (2006), respectively, found that self-esteem, attention to details, existence of a personal value system and personal confidence positively influence academic performance in introductory computer programming. Similarly, Golding et al. (2006), Katz et al. (2006), Longi (2016) and Ambrosio et al. (2014), respectively, found that personal confidence, self-efficacy, self-esteem, and attention to details positively influence academic performance in introductory computer programming.

The content of this subsection seems to point to a research gap on the need for more research on the influence of psychological strength on academic performance in STEM subjects within the culturally sensitive context.

## 2.5 Conclusion

The conclusion summarises the study's identified research gaps, starting with the one for more culturally sensitive studies, especially in the field of introductory programming, and for more recent culturally neutral studies. Similarly, there is a need to conduct culturally sensitive studies outside of Africa and culturally neutral studies in Africa. More culturally sensitive studies also need to be conducted in universities, while culturally neutral studies must also be undertaken in high schools. There is also a need for more theories beyond Kolb’s learning style theory for the culturally neutral studies, and beyond the ethnomathematics theory for the culturally sensitive studies. More qualitative, secondary data, surveys, non-probability and big sample sizes’ culturally sensitive studies also need to be conducted, and such studies should specify their reliability and validity testing methods, as well as their types of time horizons, both for the culturally neutral and for culturally sensitive studies.

More culturally neutral studies and culturally sensitive studies should also focus on examining the influence of other demographic factors beyond gender on academic performance, and on taking a closer look at why gender has an influence in culturally neutral teaching methods but not in culturally sensitive methods. Similarly, more culturally sensitive studies should focus on examining the influence of academic background on academic performance, starting with the influence of mathematics, as well as on the influence of learning style. There is also a need for more research on the influence of learning behaviour on academic performance, both for culturally neutral studies and for the culturally sensitive studies. More culturally neutral studies should also focus on the influence of intellectual abilities on academic performance, beyond problem solving abilities. More culturally sensitive studies also need to be conducted on the influence of psychological abilities on academic performance, beyond the influence of personal confidence and self-efficacy on academic performance. Finally, it is imperative to conduct culturally neutral research on the influence of teaching approaches on academic performance, as well as culturally sensitive research on the same factor and beyond the ethnomathematics teaching approach. The next chapter focuses on the theoretical foundations in education.

# CHAPTER THREE

# THEORETICAL FOUNDATIONS IN EDUCATION

The deductive nature of this research was mentioned in the introduction of chapter 2. This approach proceeds "from a theory to hypotheses to data to add to or contradict the theory" (Creswell et al., 2007:23), cited by Soiferman (2010). The aim of this chapter is, therefore, to identify the theories that are translatable into hypotheses for the design of a theoretically supported conceptual model of the factors that are hypothesized to affect academic performance in introductory programming within an ethnocomputing teaching approach. The previous chapter showed that the Kolb learning style's theory is used by the majority of the reviewed culturally neutral studies, while ethnomathematics is used for the reviewed culturally sensitive studies. The current chapter will present the entire basket of theories identified in the reviewed literature for culturally neutral studies, culturally sensitive studies, and education research, in general. This presentation will enable the identification of suitable theories to hypothetically support the influence of the a range of factors on academic performance in introductory programming within an ethnocomputing teaching approach, in line with the themes that were described in the previous chapter. These factors are: students' demographics; their academic background; their intellectual abilities; learning style and behaviour; psychological strength; as well the teaching approach and philosophy. The list of the teaching and learning theories presented by this chapter includes the Kolb learning style theory, Piaget theory of cognitive development, knowledge acquisition theory, self-regulated learning theory, constructivism, cognitive evaluation theory, Ausubel's meaningful learning theory, situated learning theory, ethnomathematics, Walberg's theory of educational productivity, sociocultural theories, behaviourism, cognitivism, structuralism and functionalism, nativism, empiricism, cognitive information processing theories, and parallel distributed processing theories.

## 3.1 Teaching and learning theories

This section presents the basket of education theories that are relevant for this study for the improvement of academic performance in introductory programming.

### 3.1.1 Adaptive control of thought (ACT) theory

According to the ACT theory, there are two types of knowledge acquired during learning: declarative knowledge and procedural knowledge. Declarative knowledge refers to the type of knowledge that is factual in nature. Procedural knowledge is knowledge inferred from the way an individual performs a task. According to this theory, learners first acquire declarative knowledge about the subject they are learning in the form of general facts about that subject before proceeding to apply that knowledge through practice. Learners then acquire and apply procedural knowledge by building on this declarative knowledge through searching and retrieving information from previously acquired procedural knowledge and analogies to past examples (Anderson, 1982).

Furthermore, according to Anderson (1982), when declarative knowledge is developed into procedural knowledge, it is further refined in the third stage of knowledge acquisition called tuning, which, in turn, has three phases: generalization; discrimination; and strengthening. Generalization is the process of expanding or replacing known facts in a production with new information to broaden the production's scope of applicability. Discrimination is the result of narrowing the selection of production rules. Strengthening is the process through which competing productions are weighted, based on the feedback on their applicability (Chen, 2006). Regardless of their domain knowledge about a specific subject, learners may be able to employ strategic knowledge to achieve knowledge acquisition. Strategic knowledge is a special type of procedural knowledge that controls the process of knowledge acquisition, and also regulates people's thinking and performance (Alexander and Judy, 1988). As a result, knowledge acquisition is achieved when learners actively participate in the processes of knowledge integration.

### 3.1.2 Motivation theories

The central idea behind motivation theories is that there are some underlying motives that influence the learning needs of a learner for a particular subject, which, in turn, influence the amount of effort they put into learning that subject. Motivation can be explained from two major perspectives: from the perspective of needs; and from the perspectives of the main contemporary motivation theories. According to Lynch (2012), there are five basic needs that motivates learners. The first is the learners' physiological needs, such as their ability to afford essential needs, including food, water and shelter. The second is their safety needs which involve feeling their physical and emotional security, their need for job security, health insurance, performance benefits, etc. The third is the learners' esteem needs which include internal feelings, such as self-respect and external factors, such as job recognition and attention. The fourth is the need for self-actualization which refers to learners' needs for self-fulfillment and for the attainment of their full potential. The fifth is learners' needs for achievement which referto their willingness to excel or strive to exceed expectations; and, lastly, their reward needs which refer to their willingness to be rewarded for achieving the expected outcome (Lynch, 2012). In summary, the need-based perspectives of motivation identify that the three aspects of motivation, namely, value, expectation and emotions influence learning outcomes and achievements.

According to Cook and Artino (2016), learners' motivation to learn can also be examined from the perspective of the following five theories: Expectancy-value theory, Attribution theory, Social-cognitive theory, Goal orientation theory and Self-determination theory. In the expectancy-value theory, learners are motivated by their expectation of success. The attribution theory focuses on the reasons learners give to explain the results of an activity, or the outcome of a task in which they engage. The expectancy-value model of motivation determines whether an individual can generate learning motivation.

This model can also help individuals to identify their learning objectives, to take the initiative to learn, to understand their own reasons for sticking to learning, to actively participate and make efforts to overcome the difficulties that they encounter during the process so as to improve their academic performance (Wang et al., 2019). The social-cognitive theory emphasizes that learners' motivation largely depends on their level of self-efficacy as well as on their self-regulated learning abilities. Furthermore, Bandura's social cognitive theory emphasizes that motivational incentives (rewards) influence learners' level of cognitive performance and behaviour during cognitive tasks (Worthy, 2011). For the goal orientation theory, learners are motivated by a 'growth' mindset which is the desire to perform better than others, and to avoid failure. Finally, the self-determination theory proposes that learners are motivated either by their intrinsic interests or by extrinsic values (Cook and Artino, 2016).

### 3.1.3 Kolb learning style theory

According to Kolb (1984), learning can be defined as a process whereby learners' acquire knowledge by the transformation of their experiences. This theory also posits that learners progressively learn through four main ways, namely, concretely, reflectively, abstractly, and actively. According to Kolb, learners learn effectively by progressing through all the four stages. In the first stage of learning, learners acquire a concrete experience followed by a second stage of observation of and reflection on that initial learning experience. This then leads to a third stage of formation of abstract concepts which enables the learner to be able to adapt and actively use these concepts in future learning situations and experiences. Kolb further categorized learners according to four types of learning styles: Accommodating accommodating learners learn best through independent discovery processes and they are active participants during learning; Diverging diverging learners learn best when collaborating with other learners during lectures; Converging converging learners learn best through hands-on practical instructional activities such as laboratory and field work; and Assimilating assimilating learners learn best by independently engaging in lectures. Kolb's learning style theory further categorizes the learning cycle into four stages (concrete experience, abstract experience, reflective observation, and active observation), each with its own individual learning style preference (Kolb, 1984; Sirin and Guzel, 2006). Concrete experience refers to the process where a learner learns by actively experiencing an activity. This is sometimes referred to as learning through hands-on experience. As for reflective observation, it is when a learner learns through the conscious reflection on the learning activity. Abstract conceptualization, on the other hand, refers to the situation where a learner learns by being presented with a theory or a model that has to be carefully observed. Finally, in active observation, learners learn by participating in the process of testing a theory or a model.

Kolb’s learning theory has been one of the best-known and most influential educational theories for higher education. It has been credited as the foundation for all learning styles’ models (Honey and Mumford, 2000) due to its use in diverse fields of study, such as education, management, computer science, psychology and medicine. Kolb’s theory emphasizes that learning mainly depends on experience, i.e., learners’ knowledge and understanding of a particular subject field depends on how they can grasp and transform their learning experience (Kolb, 1984).

### 3.1.4 Cognitive evaluation theory

According to Deci et al. (1975), academic performance is dependent on a learners’ internal motivation as well as on external rewards. The same author also posits that learners’ internal motivation is usually negatively influenced by the attraction of external rewards, due to the fact that external rewards usually place limits on the individual’s motivation and performance level. If a learner approaches a task with intrinsic motivation alone, then he or she will do so with increased energy and drive to succeed in that task. However, external rewards usually place or put the learner under undue pressure and limits his or her energy and drive to succeed in that task.

It is paradoxical because, according to Deci et al. (1975), extrinsic rewards usually have more influence on an individual's performance compared to his/her internal motivation because when an individual becomes dependent on the influence of external rewards, he or she tends to lose intrinsic motivation which limits the individual's energy and drive for a task, and ultimately undermines his/her potential and performance (Kim, 2013). In other words, the central idea behind this theory is that an individual's desire to feel competent intrinsically motivates his or her behaviour, because individuals who are considered to be intrinsically motivated participate in activities for the pleasure derived from the activity itself, and not for any external rewards. Similarly, this theory explains that, in order to feel competent and self-determined, an individual must effectively interact with his/her environment, as well as seek out other forms of challenges for him or her to feel competent and self-determined in handling those situations (Youren, 1998). In other words, Deci and Ryan's Cognitive Evaluation Theory (CET) addresses the social and environmental factors that facilitate and undermine intrinsic motivation in learners and points out to three significant psychological needs that influence their self-motivation (Riley, 2016). These needs are competence, autonomy and relatedness. According to Deci and Ryan (1985), a sense of competence comes from experiencing a positive feeling and success about an activity. It is linked to the concept of overcoming a challenge, and can best be explained by observing young children explore their environment. A sense of competence and the ability to take on challenges all foster the development of intrinsic motivation (Ryan and Deci, 2000). On the other hand, any negative intrusion toward this process, whether be it in the form of criticism or control, may undermine feelings of intrinsic motivation (Deci and Ryan, 1985).

In order for intrinsic motivation to flourish, a sense of competence must also be accompanied by a sense of autonomy (Deci and Ryan, 1985). When an individual is given a sense of choice, an acknowledgment of feelings, or an opportunity for self-direction, feelings of intrinsic satisfaction are enhanced. However, when a reward is offered as an incentive, learning and autonomy decrease, together with self-motivation (Rigby et al., 1992; Ryan and Deci, 2000).Creating a choice and an opportunity for self-direction is one of the many ways educators can provide autonomy support; thereby enhancing a student's intrinsic motivation (Deci et al., 1991; Ryan and Powelson, 1991). By creating learning opportunities that take into consideration a student's personal interests, and by providing choices, those responsible for a child's education can reap the benefits of intrinsic motivation in their students (Cordova and Lepper, 1996). Autonomy support and relatedness go hand in hand, as both of these needs influence the cognitive and affective outcomes of education (Deci and Ryan, 2009; Ryan and Powelson, 1991).

### 3.1.5 Ausubel's meaningful learning theory

According to Ausubel (1963), meaningful learning depends on two main factors: the educational materials; and learners' ability to acquire new knowledge. The adopted instructional materials must have a logical meaning for learners to be able to understand them. Learners must also be willing to acquire new knowledge and to think logically using previously assimilated concepts. In that case, a meaningful learning experience will influence learners to further seek such learning experiences. On the other hand, when a learning experience is not meaningful, learners tend to develop a rejection towards learning. Meaningful learning allows new learning blocks to become an integral part of already established learning clusters. In other words, Ausubel's theory explains that students learn through a meaningful process of relating new events to what they have already previously learnt, i.e., by cognitively representing new learning concepts in their memory, which leads to the acquisition of new knowledge and enhances retention abilities. Therefore, as a learner learns new concepts, he or she interacts with related elements in his or her cognitive structure, which accounts for its meaningfulness. Similarly, according to Ausubel (1963a, 1968), if knowledge is to be meaningful to a learner, then it has to be incorporated into his or her existing knowledge. Meaningfulness occurs when new knowledge is tied to the relevant concepts and propositions in the learner's cognitive structure. It is from these ties with pre-existing concepts that new concepts are understood.

### 3.1.6 Behaviourism

The central idea behind behaviorism is that a behaviour is learnt by observing and repeating it as performed by someone else, up until when one is able to adjust to and acquire that behaviour. There are four major groups of behaviourism theories: Thorndyke's connectionism; Pavlov's classical conditioning; Skinner's operant conditioning; and Guthrie's contiguous conditioning. According to Thorndyke (1913), a learner instinctively forms a connection to a behaviour through trial-and-error repetitive learning, regardless of whether or not he or she is deliberately performing such a behaviour. Thorndyke further explains that the strength of the connection to a new behaviour increases with the frequency of the performance of that behaviour, as opposed to Guthrie's (1935) contiguous conditioning for which the behaviour is immediately acquired, to the point where this new behaviour will ultimately become second nature. As for Skinner's (1953) operant conditioning, organisms learn by adapting their behaviour to the consequences of their previous behaviour in past stimuli, which are the confirmation or disconfirmation of their expectations within their environment (Tolman, 1948). According to Pavlov's (1927) classical conditioning theory, organisms learn by forming unique reflex responses to new stimuli, and these responses are automatically triggered when faced with the same stimuli. Both Watson's (1930) methodological behaviourism and Skinner's (1956) radical behaviourism link such reflex responses to the influence of external events, such as environmental changes, rather than the internal ones, e.g., thoughts and feelings. However, Hull's (1943) neo-behaviourism posits that thoughts, feelings and the environment influence behaviour.

Imenda (2018) recommends the following practices for behaviourism: 1) Learning outcomes should be given to learners for them to judge for themselves whether or not they have achieved these outcomes; 2) Learners must be tested through self-assessment activities to determine whether or not they have achieved the learning outcomes; 3) Learning materials must be sequenced appropriately from simple to complex learning outcomes in order to promote learning; and 4) Learners must be provided with feedback so that they can monitor their performance and take corrective action if required.

### 3.1.7 Cognitivism

Cognitivism is mainly concerned with the mental processes that facilitate learning, e.g., memorizing, critical thinking and problem solving. There are five main leading cognitivism theorists: Piaget, Bruner, Vygotsky, Bandura, Atkinson and Shiffrin. According to Piaget (1978), cognitive development depends on four factors: biological maturation; experience with the physical environment; experience with the social environment; and equilibration. Piaget (1978) further describes the following cognitive development stages. A child starts to develop the ability to solve simple problems before becoming two years old. A child develops the ability to speak and understand languages between the ages of 2 and 7. A child develops logical reasoning abilities between the age of 7 and the age of 11. A child starts developing abstraction capacities from the age of 11. For Bruner (1966), cognitive development heavily depends on the ability to master language and on the availability of systematic instruction opportunities. He believes that behaviour of children is influenced by internal cognitive processes, such as their thoughts and beliefs, rather than by new stimuli as claimed by Vygotsky (1978). In fact, according to Vygotsky (1978), it is the interaction of the child with his or her environment that stimulates his or her cognitive growth. Similarly, the above described social cognitive theory from Bandura emphasizes the influence of cognition on learning.

The teaching and learning characteristics of cognitivism can be summarized as follows: 1) Effective strategies should be used to allow learners to perceive and process information for it to be transferred into their memory (colour, graphics, size of text, etc.); 2) Appropriate strategies should be used to allow learners to retrieve existing information from long-term memory and make sense of the new information; 3) Information should be chunked to prevent memory overload; 4) Other strategies that promote deep processing should be used to help the long-term storage of information; 5) Learning materials should include activities for different learning styles, so that learners can select appropriate activities based on their preferred style.

### 3.1.8 Structuralism and Functionalism

Structuralism posits that learning happens by reflecting on and mapping the meaning of learning objects during learning experiences. It is that reflection and mapping that play a crucial role in the stimulation of students' understanding and their learning attitude (Carlson, 2020). For functionalism, students' understanding is reinforced by the repetitive execution of well-designed sequences of actions during learning experiences. There are three main structuralism theorists: Chomsky; Atkinson; and Shiffrin. Chomsky's work was in the context of language acquisition. As for Atkinson and Shiffrin, their work was presented as a metaphor of the modus operandi of computers. Similarly, there are four main functionalist theorists: Newell, Simon, Bourdieu and Vygotsky. Newell and Simon's functionalism is called the problem solving theory. Bourdieu's theory is called the social practice theory, and Vygotsky's theory is called the activity theory.

According to Malatji (2017), structuralism emphasizes a practical way of learning by discovering, i.e., the principle of relating theory to practice, which is one of the major principles governing academic activity. It also recognizes the purpose of learning and the need to apply acquired knowledge to adapt it to different learning situations. Functionalism posits that individual behaviour depends on individual needs and social balance in the same way that learning depends on the interconnectivity between an individual and his or her environment, as well as on how an individual interacts within the societal groups and institutions (Onyeneke 1996). In summary, from the perspective of the functionalism, learning depends on the socio-cultural context (Malatji, 2017).

### 3.1.9 Nativism, Empiricism, and Constructivism

Nativism posits that we are all born with “preinstalled” or innate knowledge, and learning simply requires an inner reflection in order to uncover the knowledge already within us. This is contrary to empiricism for which knowledge is not innate, but it is acquired through experiences and exposure to the world (Chahine, 2013). Constructivism also posits that knowledge is not innate, but it further explains that knowledge is constructed by individuals as a consequence of their interactions with their social and physical environment. Nativism, empiricism, and constructivism all focus on the process of learning from evidence. Piaget's theory of constructivism originated as an alternative to both nativism and empiricism. The central idea is that children develop their knowledge of the world by constructing intuitive theories. In contrast to empiricism, it proposes that children may be born with innate knowledge, but unlike nativism, it proposes that this knowledge may be radically transformed as children learn more about the world (Feigelman, 2011). Plato is considered as the father of nativism as opposed to Aristotle who is considered as the father of empiricism. As for constructivism, there are two main constructivist theorists, i.e., Piaget and Vygotsky. Piaget’s work was in the context of the cognitive development of children, while Vygotsky’s work was on the impact of the social environment on development and learning. Imenda (2018) summarizes the teaching and learning characteristics of constructivism as follows: 1) Learning should be an active process. Keeping learners active during meaningful activities results in a high level thinking, which facilitates the creation of personalized meaning; 2) Learners should construct their own knowledge rather than merely accepting the one from the instructor; 3) Collaborative and cooperative learning should be encouraged because it gives to learners the real-life experience of working in a group and it allows them to use their metacognitive skills; 4) Learners should be given control of the learning process. There should be a guided discovery process where learners are allowed to make decisions on the learning goals, but with some guidance from the instructor; 5) Learners should be given time and opportunity to reflect; 6) Learning should be made meaningful for learners. The learning materials should include examples that relate to students, so that they can make sense of the information. Assignments and projects should allow learners to choose meaningful activities to help them apply and personalize learning; and 7) Learning should be interactive enough to promote higher-level learning and social presence, and to help develop personal meaning.

### 3.1.10 Cognitive information processing theories (CIP)

CIP theories define learning as a process of cognitive operations where learners acquire knowledge, store it in their long-term memory, and retrieve it when necessary. CIP theories are objectivist in the sense that they conceive knowledge as an external truth which does not change according to learners. Learning strategies used by these theories involve memory processes, such as pattern recognition and rehearsal, and learners are simply required to apply these learning strategies, while instructors are required to provide support to learners. This is made possible with adequate practice and self-control for the learner (Dabbagh, 2009). According to the CIP view, the human learner is conceived to be a processor of information, just like a computer. When learning occurs, information is input from the environment, processed and stored in memory, and output in the form of a learned capability (Moos, 2016). In other words, learning is influenced by the learners' mental structures as well as by the learning context or environment (Eggen and Kauchack, 2007). This theory posits that effective learning begins with the attention phase after which students will develop their own individual interpretation of the observed information in order to be able to store it in their memory (Eggen and Kauchack, 2007).

According to Atkinson and Shiffrin (1968), the information processing theory states that the mind is analogous to a computer, and it operated in input, storage and output cycle. This theory assumes that the information coming from the environment is processed by a series of temporary sensory memory systems in the human brain. This information is then fed into a limited capacity short-term storage which is the working memory. This working memory is responsible for holding the information and transferring it to the long-term memory for storage and retrieval. Yahaya (2010) asserted that, in recent years, psychologists have attempted to develop theories of memory using the computer as a model. Information processing theories are based on the similarities between the operation of the human brain and that of the computer (Hess, 2000; Lutz and Huitt, 2003).

### 3.1.11 Parallel distributed processing (PDP) theories

PDP learning theories define learning as a process where learners acquire knowledge by using their prior learning experiences as well as their background knowledge to interpret and understand new content. PDP theories are pragmatist in the sense that they conceive knowledge as a reflection of reality. Learning strategies used by these theories are based on the gradual accumulation and reconstruction of knowledge, and learners are simply required to adapt such knowledge to different learning contexts, while instructors are required to help learners adjust to different learning conditions. This is made possible by the tracking of learners' mental models and by the provision of realistic and meaningful instructions to learners (Dabbagh, 2009). In fact, this model stresses that learning and other cognitive activities occur during the creation and storage of memory by modifying the strength of connections between neural units in the brain. It also posits that, when behaviours and mental processes are frequently engaged, they create strong connections between them; but learners' memory strength weakens if they stop interacting (Varughese, 2007).

PDP theories explain that learning and development are the result of context-sensitive representations of learners' cognitive functions, and many cognitive changes happen during learning and development (McClelland et al., 1989; Plaut and Shallice, 1994).

Furthermore, Rogers and McClelland (2008) describe the parallel distributed processing learning approach as a process where learning abilities are developed by the gradual activation of neuron-like processing units in the learners' brains in response to the learning experience.

### 3.1.12 Situated learning theories

Situated learning theories define learning as a process where learners construct their own knowledge based on their activities and experiences. Situated learning is constructivist in the sense that it considers knowledge as an outcome of the learning constructs assembled by learners. The learning strategies that are used by these theories are based on the social interaction of learners with their cultural and environmental surroundings, with the assumption that learners are the owners of the learning process, and instructors are guides or mentors (Dabbagh, 2009).

Lave and Wenger (1991:15) also proposed a new situated learning process with the name of "legitimate peripheral participation" which posits that teaching and learning should occur within a realistic and authentic context where learners acquire knowledge in authentic settings, apply it by making use of culturally relevant artefacts, and socially interact and collaborate with one another within a "community of practice". However, learners should gradually move away from this community of practice to become independent and engage in more complex learning activities up to when they completely master the subject matter and become experts.

This theory also claims that learning must be adapted to the current environmental context because it occurs daily; and teaching must be "interactive", "situated" and "relevant" to "a physical setting", through the adoption of social activities via which knowledge is developed (Clancey, 1995.).

### 3.1.13 Self-regulated learning theory

This theory describes the impact of students' use of self-regulated learning approaches on their academic performance. According to the self-regulated learning theory, self-regulated learners are those who take an active responsibility for their own learning and academic achievement (Borkowski et al., 1986; Zimmerman and Martinez-Pons, 1990). Zimmerman (1986) also describes self-regulated leaners as those who approach learning by actively participating in the learning environment by using three different approaches: metacognitive; motivational; and behavioural (Zimmerman, 1986). In the metacognitive aspect of the self-regulated learning process, learners plan and organize their own learning, they set their learning goals, they monitor their own learning, and they evaluate themselves during and after learning (Pressley and Ghatala, 1990).Consequently, learners become self-aware of what they had previously learnt, and what they still have to learn. In the motivational aspect of the self-regulated learning process, learners develop a high level of self-confidence to learn how to accomplish a task. They also develop a high level of interest in their learning tasks; and they constantly display high levels of effort and persistence (Zimmerman, 2002). As for the behavioural aspect of the self-regulated learning process, it simply posits that self-regulated learners usually learn in an environment that is suitable for the improvement of learning (Zimmerman and Martinez-Pons, 1990). Similarly, according to Chaves-Barboza et al. (2015), the self-regulated learning process is divided into three main stages: forethought; performance; and self-reflection. In the forethought stage, the subject sets his or her learning goals and plans the necessary strategies for such goals. This requires them to trust their previous knowledge and capacities. In the performance stage, the subject then implements the strategies planned in the previous stage. Additionally, he or she performs the necessary controls. Finally, in the self-reflection stage, the subject uses all the information and experiences obtained from the previous stage for the resumption of the self-regulated learning cycle.

### 3.1.14 Sociocultural learning theories

Sociocultural learning theorists posit that learning is a “social endeavor” and it occurs through social interactions between learners (Lerman, 2001). They further support that “individual learning and development is constructed through a process of internalization and transformation” of the collective experiences gained from interactive processes (John-Steiner, 1996:7). This confirms the inter-dependency between individual and collective learning processes: “learners actively influence learning environments, just as learning environments actively influence learners”. These theories are based on the assumption that learning takes place in the cultural context, and it is mediated by culturally constructed tools, such as language, objects, signs and symbols. These culturally constructed tools create singular human forms of higher-level thinking. Vygotsky is considered as the father of the sociocultural learning theory, and his work influenced other prominent sociocultural theorists, such as Lave, Wenger and D’Ambrosio. Vygotsky’s theory is called the sociocultural theory of human learning. Wenger’s theory is called the situated learning theory. Lave’s theory is called the legitimate peripheral participation theory. Lave and Wenger’s combined theory is called the community of practice theory, and D’Ambrosio’s theory is called ethnomathematics. In fact, the sociocultural perspective of learning suggests that children develop literacy through social interactions and participation in both their home and school settings (Shume and Blatt, 2019). It also posits that individuals learn through a process of observation, rehearsal and reinforcement, there is an interconnectivity between social and individual processes (Liesener, 2017).

The sociocultural learning theory also states that learning processes must give more focus on social, language and cultural interactions to ensure individual developments in the social environment (Hung and Nichani, 2002). Knowledge is acquired and constructed in a social setting, and learning is a social interaction whereby the learning process involves the social, language and cultural individual development of the learner (Lantolf et al., 2015).

### 3.1.15 Walberg’s theory of educational productivity

Walberg’s theory of educational productivity describes three groups of nine factors that affect learning outcomes: the school and the home environment; educators’ instructional approaches; and students’ aptitude. However, both students’ aptitude and educators’ instructional approaches significantly contribute more to learners’ academic achievement compared to the school and the home environment. Students’ aptitude refers to their intellectual ability, their prior academic performance, and their level of development, as indicated by their age or their level of maturity. Students’ aptitude also refers to psychological drivers, such as their motivation and their personality. Educators’ instructional approaches refer to the general strategies or methods used for teaching and learning. The school and home environment refers to the student’s home or family background, to the high or low morale of his or her classmates, and to the positive or negative influence of his or her peers. For example, if a student possesses high intellectual ability and he or she is also provided with an adequate amount of instruction, the student may still fail if he or she is not motivated to learn. The environment also plays an important role in influencing students' learning, in the sense that learners’ classmates as well as their classroom environment influence learning and academic performance. Similarly, learners' peer groups outside of their schools, their family members, and the way they utilize their after school hours also influence their learning ability, their motivation to learn, as well their learning approach (Walberg, 1980).

In summary, Walberg’s theory of academic achievement posits that a student’s cognitive, behavioural, and attitudinal educational outcomes are influenced by his or her psychological characteristics and immediate environment (Reynolds and Walberg, 1992). This includes their cognitive, behavioural and attitudinal compositions as well as by their learning environment (Gantt, B.J., 2019).

### 3.1.16 Ethnoscience

According to Banister (1999), the central idea around ethnoscience is that a social group's knowledge is mostly reflected in its language. Ajayi et al. (2017) also defined ethnoscience as knowledge that is indigenous to a particular culture. The term ethnoscience originates from the word "ethnos", which means nation, and "scientia", which denotes knowledge (Melyasari et al., 2018). Abonyi (2002) also defined ethnoscience as the knowledge that is indigenous to a particular culture and is concerned with natural objects and events that may have potentially the same branches as Western science. This means that branches of ethnoscience would include ethnochemistry, ethnophysics, ethnobiology, ethnomathematics, etc. Readers are reminded that ethnoscience is a social cultural theory.Within the context of teaching and learning, ethnoscience means the use of students' homes, communities, lives and cultural experiences to teach science concepts (Dewi et al., 2019).

The focus of this study is limited to ethnoprogramming, which originates from ethnomathematics and ethnocomputing. D'Ambrosio (2001) defined ethnomathematics as the study of mathematical concepts embedded in cultural practices, in recognition of the fact that all cultures and all people develop unique methods and sophisticated explications to understand and transform their own realities. In fact, the term ethnomathematics was invented by D'Ambrosio in 1985 to describe the mathematical practices of different cultural groups and it can refer to the study of mathematical ideas found in any culture. This includes materials, cultural artifacts, symbols, languages and other objects created by members of a specific cultural group. The central idea behind the ethnomathematics teaching approach is the inclusion of learners' cultural backgrounds, prior knowledge, experiences, languages, activities, their social background and their environment as components in the teaching and learning of mathematics (D'Ambrosio, 2001). This perspective provides an important opportunity for teachers to make use of these cultural artifacts and objects in the teaching and learning of mathematics in a culturally sensitive context (Rosa and Orey, 2011).

Ethnomathematics influenced the development of ethnocomputing which, in turn, influenced ethnoprogramming, or programming in indigenous languages apart from English, with the assumption of teaching computer programming within a culturally sensitive context since computing has roots in mathematics and it is interdisciplinary by nature (Laiti, 2016). Ethnocomputing assumes that computing processes and usage are influenced by their socio-cultural context (Tedre et al., 2002). Tedre (2002) also defined ethnocomputing as the knowledge developed by the members of distinct cultural groups by means of the study of computational phenomena located within their sociocultural environment. For Babbit (2014), it is a constructionist approach that seeks to teach computer science concepts and ideas to students through cultural artifacts.

## 3.2 Hypotheses and supporting theories

Even though sixteen major learning theories have been presented in this chapter for their possible relevance, this study has selected three theories for its theoretical foundation: Walberg's theory of educational productivity, self-regulated learning theory and the ethnoscience theory. These three theories are the building blocks of the conceptual model of the factors that are hypothesized to influence academic performance in introductory computer programming, both in culturally neutral and culturally sensitive education.

### 3.2.1 Walberg's theory

The above described Walberg's theory of educational productivity postulates that students' academic performance is affected by their school and home environment, their aptitude and by the instructional approaches of their educators. Walberg stated that students' home environment can be described in terms of their family background, hereby extended to their demographics. The following hypothesis can, therefore, be formulated on the basis of this extension of Walberg's theory.

H1: Students' academic performance is affected by their demographics (Walberg's extended theory).

Equating students' aptitude to their academic background also leads to the formulation of the following hypothesis.

H2: Students' academic performance is affected by their academic background (adaptation of Walberg's theory).

Similarly, the following hypothesis can also be formulated when one considers that students' intellectual abilities also contribute to their aptitude.

H3: Students' academic performance is affected by their intellectual abilities (adaptation of Walberg's theory).

Finally, according to Walberg, academic performance depends on the quality and quantity of instruction that are assimilated to the teaching approach and philosophy for the formulation of the following hypothesis.

H4: Students' academic performance is affected by the teaching approaches and philosophies (adaptation of Walberg's theory).

It is also important to note that, for Walberg's theory, home and school environment, students' aptitude, and the quality and quantity of instruction affect learning, which, in turn, affects academic performance. This study restricts this learning concept to students' learning style and behaviour for the formulation of the following hypothesis:

H5: Students' academic performance is affected by their learning style and behaviour (adaptation of Walberg's theory).

### 3.2.2 Self-regulated learning theory

The above described self-regulated learning theory portrays self-regulated learners in terms of their meta-cognitive abilities, their motivations and their behaviour. Students' motivation refers to their level of confidence, their interests, and their willingness to persist despite the difficulties. This study extends this motivational factor under the general theme of students' psychological strength for the formulation of the following hypothesis.

H6: Students' academic performance is affected by their psychological strength (adaptation of self-regulated learning theory).

### 3.2.3 Ethnoscience

The above formulated hypothesis (H4) postulates that teaching approaches and philosophies affect academic performance. The ultimate goal of this research is to propose the ethnocomputing teaching approach for introductory programming: H4 will be instantiated into hypothesis H7 as follows, with the acknowledgment that ethnoscience is socio-cultural theory.

H7: Students' academic performance is affected by the adoption of the ethnocomputing teaching approach (ethnoscience theory).

## 3.3 Theoretically supported conceptual model of academic performance factors for introductory programming

The above formulated hypotheses can be summarized by the theoretically supported conceptual model of factors affecting academic performance in introductory computer programming illustrated by Figure 3.1.

## 3.4 Conclusion

The theoretically supported conceptual model presented in this chapter hypothesizes that academic performance in introductory programming is affected by six reviewed factors, namely: demographics; academic background; intellectual abilities; learning style and behaviour; psychological strength; and teaching approaches and philosophies, such as the adoption of the ethnoscience teaching approach. Walberg's theory of academic achievement supports most of these reviewed academic performance factors, except for the teaching approach and philosophy factor, and the psychological strength factor, which are, respectively, supported by the ethnoscience theory and by the self-regulated learning theory. Other important supporting theories such as behaviourism, cognitivism and constructivism were also presented in this chapter. The next chapter addresses the methodology used in this study.

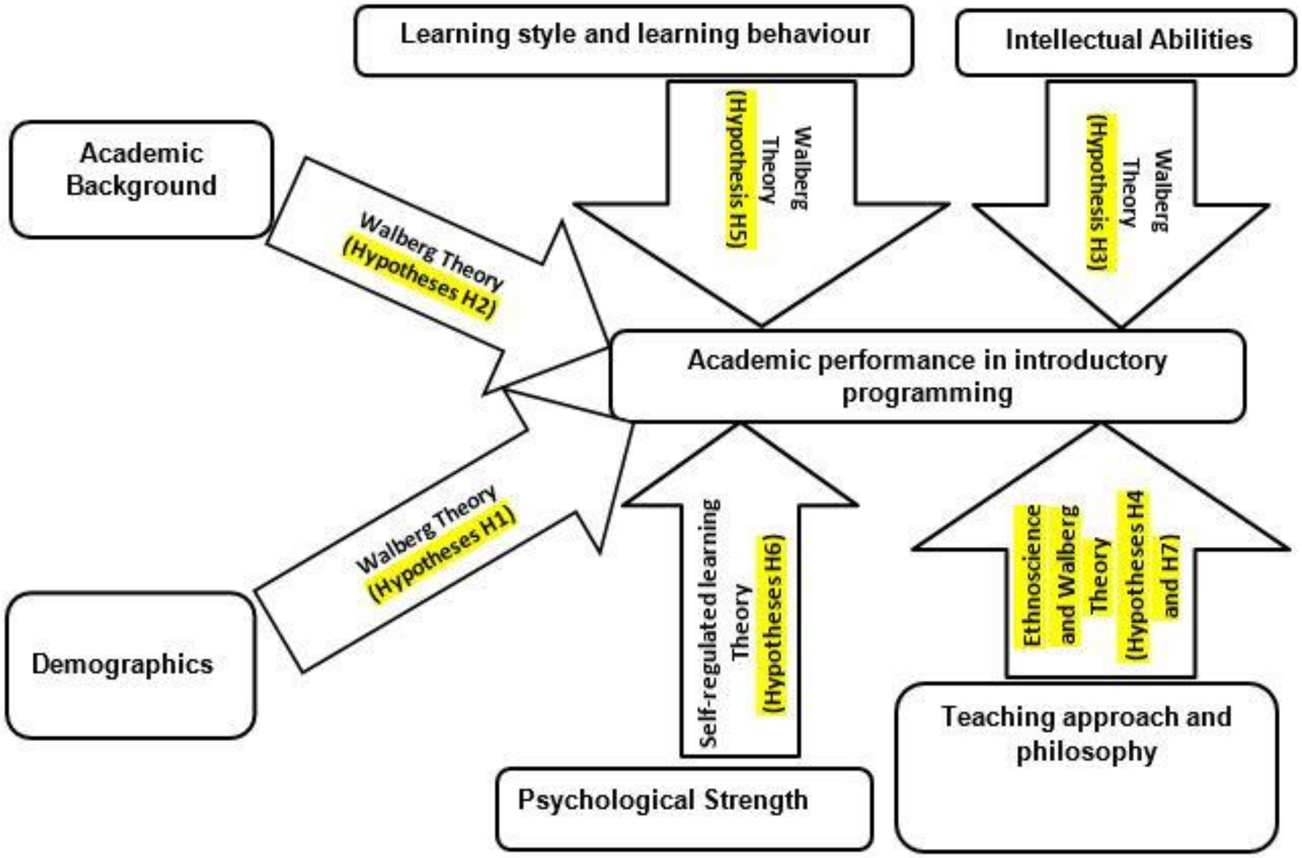


Figure 3.1: Theoretically supported conceptual model of factors affecting academic performance in introductory computer programming.

# CHAPTER FOUR

# RESEARCH METHODOLOGY

The purpose of this chapter is to describe the methodologies used for the achievement of the aim of the current study on the impact of the ethnoscience teaching approach on academic performance in introductory computer programming. The philosophical assumption of this research is the relational methodology, as described by Gaotlhobogwe et al. (2018), because of its closeness to the ethnoscience philosophy. According to these authors, "relational methodologies are […] methodologies that draw from Indigenous knowledge, histories, languages, metaphors, world views, philosophies, and experiences of former colonized and historically marginalized communities". This philosophical assumption is embodied in an integrative (adaptive) evaluation framework where "Western evaluation models, theories and instruments are adapted, contextualized, and made culturally relevant and inclusive of local stakeholders" (Gaotlhobogwe et al., 2018:54). The methodologies presented in this chapter include the ones for the content analysis and the ones for the quasi-experiment. Content analysis was used for the literature review presented in chapter 2, and the quasi-experiment methodology was used for the empirical validation of part of the conceptual model presented in chapter 3. This partial validation's option was adopted for financial reasons and it is fully acknowledged that this constitutes a limitation for this study, having in mind that the rest of the model can be validated by future studies.

## 4.1 Content Analysis

According to Smith (2000), content analysis is a technique that is commonly used for the extraction of desired information from existing sources of information by systematically and accurately identifying specific characteristics from these sources of information. The choice of the content analysis in this research is justified by the fact that it enables the researcher to quantify and analyze the presence, meanings and relationships between certain words, themes, or concepts within a body of literature on a certain subject, before making inferences about the messages within the text (Elo et al., 2014). This was done in line with the first, second and third research objectives and questions of this study, as presented in section 1.5 of chapter 1. Content analysis was used for the analysis of the existing empirical studies included in the literature review presented in chapter 2, according to the following steps, as described by Gaur and Kumar (2018: 13).

1) *Select database(s) according to the objective of the review.*
2) *Select the literature sample according to the review objective's criteria. Selection criteria may include the time period, domain definition for the literature review, or type of manuscript.*
3) *Develop a valid coding scheme.*
4) *Code the entire sample.*
5) *Assess coding accuracy and inter-coder reliability using reliability test methods, such as Cohen's kappa or Krippendorf's alpha (Potter and Levine-Donnerstein, 1999).*
6) *Summarize and interpret the coded text".*

### 4.1.1 Selection of the databases of the studies to be reviewed

Even though the studies included in this review were collected from google scholar, it is interesting to note that this review found most of its papers from the following research databases: the ACM Digital library; Current Contents; EBSCOhost; IEEEXplore; ISI Web of Science; Inspec; ISI Proceedings; ProQuest; Sage Full Text Collections; Science-Direct; Springer Link; Taylor and Francis; Wiley online library; Research gate; Elsevier; Proquest; SAGE; CiteSeerX; and Scopus. Moreover, the majority of the papers were collected from the ACM Digital library and from the IEEEXplore database. The choice of these databases was mainly due to the assumption that these are the some of the most popular and common databases that index scientific scholarly journal articles.

### 4.1.2 Selection criteria of the sample of the reviewed studies

The first selection criterion for the inclusion of studies in this literature review was the inclusion of the following keywords in those studies: “computer programming” and “academic performance”; “computer programming” and “academic achievement”; "ethnoscience" and "achievement"; "ethnoscience" and "academic achievement"; and "ethnoscience" and "academic performance". The second selection criterion was the publication of such studies between the year 2000 and the year 2018, and that of their empirical nature, either as case studies, surveys, experiments, observations or interviews. The choice of the time period between the year 2000 and the year 2018 is due to the fact that the current study needed to identify the current state of the art of research in the fields of introductory computer programming and in the field of ethnoscience. This does not necessarily dismiss the fact that programming started long before the year 2000 because, in research, new findings usually acknowledge the old ones. The third selection criterion was the free availability of such studies on Google Scholar. This was done because of financial constraints as well as in support of open access scholarly research, while acknowledging that it could be a constraint and a limiting factor for this content analysis.

The first two selection criteria led to the identification of 76 articles published between the year 2000 and the year 2018 and with the required keywords: 50 culturally neutral studies and 26 culturally sensitive studies. The final selection criteria led to the identification, selection and collection of a total of fifty-four freely available and downloadable studies (40 culturally neutral studies and fourteen 14 culturally sensitive studies). It is important to remind readers at this point that culturally sensitive studies made use of different types of culturally relevant teaching approaches, such as the ethnoscience teaching approaches, while culturally neutral studies made use of different conventional or traditional teaching approaches.

### 4.1.3 Coding scheme of the review

Each of the studies included in this review was analyzed and described according to the following list of attributes in line with the content analysis technique: theories, contexts, methodologies, and academic performance factors. These theories, contexts, methodologies and academic performance factors were assigned meaningful codes for the purpose of analyzing and identifying important theoretical, contextual and methodical gaps in the existing research body on the stubborn academic failure problem for introductory computing. This review decided to first analyze the culturally neutral studies because there were apparently a higher number of identifiable factors contributing to the improvement of academic performance in culturally neutral studies, judging from the larger number of academic research publications compared to those of the culturally sensitive studies.

#### 4.1.3.1 Theories

The coding scheme that was adopted by this study to identify the theoretical foundations of the reviewed studies, in line with the content analysis methodology, is hereby presented. These theories were randomly assigned the codes 1 to 15, while code 0 was used to represent the absence of theories in a given reviewed study. For example, code 2 was used to represent Piaget theory of cognitive development. The above described 1 to 15 codes were used to compare and contrast the theories of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible theoretical research gaps to be filled by the current study.

#### 4.1.3.2 Contexts

This section will present the coding scheme that was adopted by this study to identify the contexts of the reviewed studies in line with the content analysis methodology. These contexts were described in terms of the author(s) of each of the reviewed studies, and their place and year of publication. These codes were assigned in an increasing incremental sequence corresponding to the alphabetical order of the names of the authors of the studies both for the culturally neutral and culturally sensitive studies. The same applies to the years of publication of the reviewed studies, where the codes were also assigned in an incremental sequence from the least recent publications to the most recent ones. The places of publication were randomly assigned codes based on the continents where the study was published. For instance, the least recent study in this review was published in 1998, and it was assigned the code 1. On the other hand, the most recent ones were published in 2017 and were assigned the code 4. The above described 1 to 4 codes were used to compare and contrast the contexts of the reviewed culturally neutral studies against the ones of the culturally sensitive studies so as to identify the possible contextual research gaps to be filled by the current study.

#### 4.1.3.3 Methodologies

The methodologies of the reviewed studies are described in terms of the following list of characteristics: research designs; research strategies; types of research data; type of research data; data collection methods; type of time horizons; research populations; sample and sample sizes; sampling methods; research variables; method for data analysis; validity testing methods; and reliability testing methods. This section will present the coding scheme that was adopted by this study to identify the methodologies of the reviewed studies. For each of these attributes, a numeric code was assigned to a reviewed study according to the time when a decision was taken for the inclusion of that study in the review. It is important to note that this review first analyzed culturally neutral studies before analyzing cultural sensitive studies, and that decision had an impact on the coding scheme of this review.

**Research designs.** The purpose of this section is to present the coding scheme that was adopted by this study to identify the research designs of the reviewed studies in line with the content analysis methodology.

The reviewed research designs were randomly assigned the codes 1, 2 and 3, both for culturally neutral and culturally sensitive studies. For example, code 1 was used to represent the quantitative research design. The above described 1 to 3 codes were used to compare and contrast the research designs of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible research designs' gaps to be filled by the current study.

**Research strategies.** The coding scheme adopted by this study to identify the research strategies of the reviewed studies is hereby presented, in line with the content analysis methodology. Each of the different types of reviewed research strategies was randomly assigned an integer code between 1 and 6, both for culturally neutral and culturally sensitive studies. For example, code 1 was used to represent surveys. The above described 1 to 6 codes were used to compare and contrast the research strategies of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible research strategies' gaps to be filled by the current study.

**Types of research data.** This section presents the coding scheme that was adopted by this study to identify the types of research data of the reviewed studies, in line with the content analysis methodology. The reviewed types of research data were randomly assigned codes 1, 2 or 3, both for culturally neutral and culturally sensitive studies. For example, code 2 was used to represent secondary data. The above described 1 to 3 codes were used to compare and contrast the research data types of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible data types of research gaps to be filled by the current study.

**Data collection methods.** The coding scheme adopted by this study to identify the data collection methods of the reviewed studies is hereby presented, in line with the content analysis methodology. Different types of data collection methods were randomly assigned codes for the reviewed culturally neutral studies and for the culturally sensitive ones.

These data collection methods were, respectively, assigned integer codes between 1 and 6. For example, code 1 was used to represent questionnaires, while code 2 was used to represent standardized tests. The above described 1 to 6 codes were used to compare and contrast the data collection methods of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible data collection research gaps to be filled by the current study.

**Types of time horizons.** The purpose of this section is to present the coding scheme adopted by this study to identify the types of time horizons of the reviewed studies, in line with the content analysis methodology. Each identified type of time horizon, both from the reviewed culturally neutral and the culturally sensitive studies were randomly assigned an integer code value of 0 or 1. For example, code 1 was used to represent longitudinal studies. The above described 0 and 1 codes were used to compare and contrast the types of time horizons of the reviewed culturally neutral studies against the ones of the culturally sensitive studies so as to identify the possible time horizons' research gaps to be filled by the current study.

**Research population.** The coding scheme adopted by this study to identify the research populations of the reviewed studies is hereby presented, in line with the content analysis methodology. Each identified type of research population was randomly assigned an integer code between 1 and 4, both for the reviewed culturally neutral studies and for the culturally sensitive ones. For example, code 1 was used to represent first year undergraduate students, while the code 3 was used to represent senior secondary school learners. The above described 1 to 4 codes were used to compare and contrast the types of research population of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible populations' research gaps to be filled by the current study.

**Sample sizes.** This section presents the coding scheme adopted by this study to identify the sample sizes of the reviewed studies, in line with the content analysis methodology. The reviewed sample sizes were categorized into six intervals that were coded by randomly assigned integer values between 1 and 6, both for the reviewed culturally neutral studies and the culturally sensitive ones.

For example, code 2 was used to represent sample sizes of between 30 to 100 students, while the code 6 was used to represent sample sizes above 1500 students. The above described 1 to 6 codes were used to compare and contrast the sample sizes of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible sample sizes' research gaps to be filled by the current study.

**Sampling methods.** The purpose of this section is to present the coding scheme adopted by this study to identify the sampling methods of the reviewed studies, in line with the content analysis methodology. Each of the reviewed sampling methods was randomly assigned an integer code between 1 and 6, both the reviewed culturally neutral studies and for culturally sensitive ones. For example, code 6 was used to represent the stratified sampling method, while code 3 was used to represent random sampling. The above described 1 to 6 codes were used to compare and contrast the sample methods of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible sample methods' research gaps to be filled by the current study.

**Methods of data analysis.** The coding scheme adopted by this study to identify the statistical data analysis methods of the reviewed studies is hereby presented, in line with the content analysis methodology. Each reviewed data analysis method was randomly assigned an integer code between 1 and 3, both for the culturally neutral and for the culturally sensitive studies. For example, code 2 was used to represent the parametric data analysis method.

The above described 1 to 3 codes were used to compare and contrast the data analysis methods of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible data analysis methods' research gaps to be filled by the current study.

**Data validity testing methods.** This section presents the coding scheme adopted by this study to identify the data validity testing methods of the reviewed studies, in line with the content analysis methodology. The identified data validity testing methods were assigned code values of 1 or 2. For example, code 1 was used to represent Pearson correlation coefficients.

The above described 1 to 2 codes were used to compare and contrast the data validity testing methods of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible data validity testing methods' research gaps to be filled by the current study.

**Reliability of testing methods.** The purpose of this section is to present the coding scheme adopted by this study to identify the reliability testing methods of the reviewed studies, in line with the content analysis methodology. Each reviewed reliability testing method was randomly assigned an integer code between 1 and 3, both for the reviewed culturally neutral studies and for the culturally sensitive ones. For example, code 2 was used to represent the Cronbach's alpha coefficient reliability testing method. The above described 1 to 3 codes were used to compare and contrast the reliability testing methods of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible reliability testing methods' research gaps to be filled by the current study.

#### 4.1.3.4 Academic Performance Factors

The coding scheme adopted by this study to identify the academic performance factors of the reviewed studies is hereby presented, in line with the content analysis methodology.

Each of the identified academic performance factors was first classified into a category or theme, and each then randomly assigned an integer code value between 1 and 6, both for the reviewed culturally neutral studies and for the culturally sensitive ones. For example, code 1 was used to represent demographic factors. The above described 1 to 6 codes were used to compare and contrast the academic performance factors of the reviewed culturally neutral studies against the culturally sensitive studies so as to identify the possible academic performance factors' research gaps to be filled by the current study.

## 4.2 Quasi-Experiment

This section describes the methodology of the quasi-experiment conducted by this study, in line with the following five (5) requirements for experiments, as proposed by Asgari and Nunez (2011:38):

- "One or more control group(s) and experimental group (s);
- Random assignment of subjects in both control and experimental groups; pre-test of groups to check the equality;
- Post-test of groups to identify the impacts on dependent variables; one or more experimental treatment(s) on the experimental group/s;
- Isolation, control and manipulation over independent variables; and
- 'Non-contamination' between experimental and control group".

This study also took into account the following assertion from Bryman (2016: 37) and Cohen et al. (2013: 38): "if an experiment lacks any of these attributes, then it becomes a quasi-experiment, and this is not necessarily something negative". In fact, in some fields of study, quasi-experiments are seen as an improvement to true experimental designs, since not all phenomena can be studied in laboratory conditions (Bryman, 2016; Cohen et al., 2013).

This study followed a pre-test-post-test ‘Non-equivalent’ control group quasi-experimental design, which includes a combination of two groups, namely: a control group; and an experimental group (Bryman, 2016; Cohen *et al*., 2013). Moreover, because the above listed five (5) requirements do not mention any data collection or any data analysis methods, this study proposed more steps for the conduct of its quasi- experiment, inclusive of the above listed five (5) requirements, as hereby described.

### 4.2.1 Identification of the research population for the experiment

This study took place at the Durban University of Technology (D.U.T.) in Durban (South Africa). The research population of this study consisted of 672 first-year fresher-students enrolled for the Applications Development 1A module in the Department of Information Technology (I.T.) at D.U.T, in the first semester of the 2018 academic year. A first test was administered to a group of volunteering students on Input-Processing-Output (IPO) introductory programming concepts to assess their prior programming abilities. The choice of the above described population was motivated by its proximity to the geographical location of the researcher even though its representability can be questioned in the South African context.

### 4.2.2 Identification of the control group and the experimental group

It is important to first describe the two teaching philosophies used by the quasi-experiment conducted by this study, namely: the conventional teaching philosophy; and the ethnoscientific teaching philosophy. Since this study focuses on the teaching of introductory computer programming to first year students whose native language is isiZulu, but who were enrolled in a university whose medium of instruction was English, this study decided to use the English language and the isiZulu language as the differentiating factors between the experimental group and the control group of this quasi-experiment.

In fact, this study used this differentiating language factor both for the medium of instruction and for the language of the interface of the programming language for the introductory programming course. In other words, students from the control group were taught computer programming in English, and the code of their C# computer programs had to be written in English. On the other hand, students from the experimental group were taught computer programming in isiZulu, and the code of their C# computer programs had to be written in isiZulu. It was clearly the central intent of this study to use language as a differentiating factor between the control group and the experimental because of the fact that language is a cultural asset. This is in line with the aim of this study to explore the influence of a culturally sensitive teaching approach on academic performance in introductory programming.

The isiZulu language was chosen for the experimental group because this study was conducted in a university located within the KwaZulu-Natal province of South Africa where the isiZulu language is the main indigenous language, as spoken by the popular Zulu native tribe. It is also important to note that, even though the entire population of the study was entirely made up of isiZulu native students, the control group consisted of students whose preferred teaching philosophy was the conventional teaching philosophy, while the experimental group consisted of students whose preferred teaching philosophy was the ethnoscience teaching philosophy.

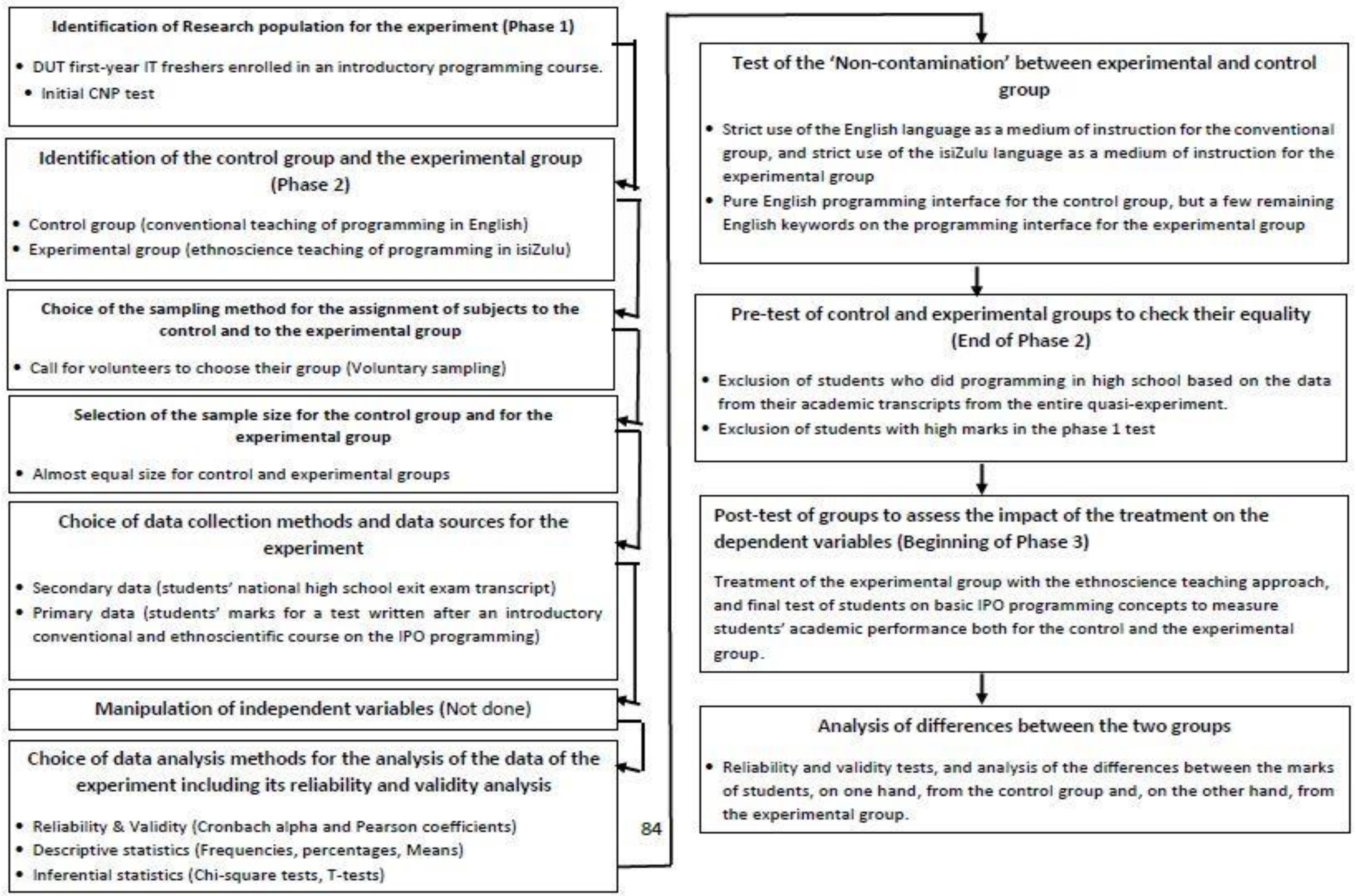


Figure 4.1: Schematic diagram of the quasi-experiment conducted by this study

### 4.2.3 Choice of the sampling method for the assignment of subjects to the control group and to the experimental group

For the second phase of this quasi-experiment, the phase with the necessary steps to ensure the equality of groups between the control group and the experimental group, volunteers were requested from the above mentioned first-year fresher-students in order to assign participants either to the initial control group or to the initial experimental group. This volunteering aspect of the assignment of participants either to the initial control or to the initial experimental group is one of the reasons why this study is not considered as a true experiment, but rather as a quasi-experiment, because a true experiment would have required a random assignment of students.

### 4.2.4 Selection of the sample size for the control group and for the experimental group

This study was conducted in three phases described in the above outline (Figure 4.1): A first phase to examine students' performance factors prior to any intervention (culturally neutral education); a second phase to examine students' preferred teaching philosophy, and a third phase to examine the influence of the ethnoscience teaching philosophy on academic performance.

For the first phase, the sample size was 21. For the second phase, the sample size was 31: 16 preferred the culturally neutral teaching approach, and 15 preferred the culturally sensitive one. Finally, the sample size for the third phase was 5 for the control group, and also 5 for the experimental one.

It is acknowledged that the above presented sample size is small and it is one of the limitations of this study.

### 4.2.5 Choice of the data type and data sources for the experiment

This quasi-experiment used secondary data from students' transcripts as well as primary data from the results of the test conducted after the treatment of its subjects. Secondary data were needed for the examination of the influence of learners' demographics and their academic background on their academic performance in introductory programming. Primary data were needed for the examination of the influence of the ethnocomputing teaching approach on academic performance in the same subject. These four variables (demographics, academic background, teaching approach and academic performance) are clearly linked in the earlier presented conceptual model.

#### 4.2.5.1 Secondary data

Secondary data from students' transcripts contained their demographic data, their compulsory subject choices for their national high school exit examination (or matriculation examination) and their grades for that examination.

**Demographic data.** Students' demographic data consisted of the following four items:

- **Matriculation examination year:** This refers to the year when a student passed his or her high school national exit examination;
- **School location:** This refers to the area of the high school where a student wrote his or her national exit examination. This could either be an urban area or a rural area:
- **Gender:** This refers to the gender of a student either as a male or as a female; and
- **Age:** This refers to the age of a student.

**Students' compulsory subject choices in their national high school exit examination.** Even though there are two types of subjects in the national high school exit examination in South Africa, i.e., compulsory subjects, and non-compulsory subjects, this study only used data from the following compulsory subjects:

- **Compulsory home language subject:** This refers to the language that a student chooses as his or her home language subject for the national high school exit examination (either English, IsiZulu, or IsiXhosa);

- **Compulsory additional language subject:** This refers to the language that a student chooses as his or her additional language subject for the national high school exit examination (either Afrikaans, English, or IsiZulu);
- **Compulsory mathematics subject:** This refers to the type of mathematics that a student chooses as his or her mathematics subject for the national high school exit examination (either mathematics core subject or mathematics literacy); and
- **High school computing subject:** Information Technology (IT), Computer Application Technology (CAT), or no computing subject.

**Students' academic performance for their national high school exit examination**

Students' levels (see Table 4.1) for each of the subjects identified by section 4.2.5.1 were used for the measurement of the academic background of the participants, as reflected by their academic performance in these subjects for the national high school exit examination. These measurements were not aggregated into a single variable, but each of them was analyzed individually.

Table 4.1: South African national senior certificate (matric) grading scheme

| **Scores** | **Level** |
|---|---|
| 80 - 100% | 7 |
| 70 - 79% | 6 |
| 60 - 69% | 5 |
| 50 - 59% | 4 |
| 40 - 49% | 3 |
| 30 - 39% | 2 |
| 0 - 29% | 1 |

### 4.2.5.2 Primary data

All the students were first taught some basic IPO strings programming concepts with the conventional method. Then, a first test on these basic IPO strings programming concepts was administered to them in the first phase of the study.

Thereafter, the students had to choose their preferred teaching approach, and the conventional group was consequently taught basic IPO integer programming concepts with the conventional method for the conventional group, and with the ethnoscience method (taught for the first time) for the experimental group. A second test on these basic IPO integer programming concepts was administered to them to assess their academic performance in introductory programming after treatment. The results of these two tests constituted the dataset for the primary data for this study and both tests were conducted for the sole purpose of this study. The fact that the ethnoscience method was taught for the first time should be acknowledged to recognize that different results could have been obtained if it was not the case, but that should not change the hypothetical theoretical model.

### 4.2.6 Manipulation of the independent variable (s)

According to Bryman (2016: 112), "manipulation refers to the treatment or intervention being changed purposely by the researcher to create treatment conditions, such as altering the environment, programme, or treatment". For the purpose of this quasi- experiment, there was no manipulation of the independent variable.

### 4.2.7 Choice of the analysis methods for the analysis of the data of the experiment including its reliability and validity analysis

Both the primary and the secondary data of the three phases of this study were analyzed using version 23.0 of SPPS (statistical package for social sciences) for the following constructs of the conceptual model and for the relationships from that model and the corresponding underlying hypotheses: Demographics, academic background, preferred teaching approach and academic performance. The reliability of the primary data of the third phase of this quasi-experiment (students' marks for the phase 3 basic programming test) was checked using the Cronbach's alpha coefficient and its validity was checked using the Pearson correlation coefficient (See associated results on Table 5.22 in chapter 5). On the other hand, secondary data were not included in these reliability and validity checks because secondary data items were never aggregated into a single variable, instead each of them was always analyzed separately. Moreover, descriptive statistics were analyzed in terms of proportions and means, both for the above mentioned primary data and for the above mentioned secondary data. This data were subjected to chi-square tests and to t-tests in order to assess their effect on students' preferred teaching philosophy and on their academic performance in introductory programming (See Sections 5.1.1 and 5.1.2 for more details).

### 4.2.8 Test of the 'non-contamination' between experimental and control groups

According to Rhoads (2011: 77), "contamination occurs when interaction between individuals randomly assigned to different treatment conditions causes some individuals to receive features of a treatment to which they were not assigned". There was no contamination between the experimental and the control groups of this study.

### 4.2.9 Pre-test of control and experimental groups to check their equality

As already stated above, this study consisted of three phases. During the second phase, students were asked to choose their preferred teaching philosophy for introductory computer programming: either the conventional teaching philosophy, or the ethnoscientific teaching philosophy. This allowed for the possibility to identify the factors that were affecting their choice. The examination of the academic background's secondary data of Phase 2's participants also served as a screening process to remove students with prior programming knowledge and experience from the quasi-experiment after that phase. Such examination also helped to ensure that the academic backgrounds' profiles of the students from the control group of Phase 3 were similar to the ones of the experimental group.

### 4.2.10 Post-test of groups to assess the impact of the treatment on the dependent variable (s)

A post-test was administered to the students that completed Phase 3 of the quasi-experiment. These participants were taught with the help of screencasts and recordings on how to code basic input-processing-output programming (IPO) patterns, with one set for the control group, and another set for the treatment or experimental group. These screencasts and recordings included a step-by-step presentation, demonstration and explanation of the process of writing and testing IPO programming patterns with the use of appropriate examples. They each had an approximate duration of twenty minutes. Students were also provided with code stories made up of documents attempting to fully describe some programming examples on IPO patterns. Students from the control group were taught how to write simple IPO programs in English, and the code of their C# computer programs had to be written in English (See an example in Figure 4.2). On the other hand, students from the experimental group were taught in the isiZulu language on how to write simple IPO programs, and the code of their C# computer programs had to be written in isiZulu (See an example in Figures 4.3 and 4.4). A post-test was conducted on both the control group and the experimental group in the form of basic C# codes in order to examine the impact of the ethnoscience teaching philosophy (isiZulu teaching of programming) on academic performance in introductory programming. Examples of such codes can be found in Figures 4.2, 4.3 and 4.4, both for the control group and for the experimental group.

### 4.2.11 Analysis of differences between the groups

An analysis of the performance of both the control group and the experimental group for the above described post-test was conducted in order to compare and contrast the academic performance of these two groups after having subjected them to their respective teaching approaches.

## 4.3 Conclusion

The two research methodologies used by this study were the above described six steps' content analysis and eleven steps' quasi-experiment. The next chapter will be dedicated to the presentation of the results of the analysis of the primary and secondary data of this study in order to empirically validate part of the theoretically supported conceptual model described in the previous chapter.

```
using System;
namespace MConvEx
{
 class Program
 {
  static void Main(string[] args)
  {
   //declaration of input variables
   uint father_no_of_gifts = 0;
   uint mother_no_of_gifts = 0;
   uint required_no_of_gifts = 0;
   //declaration of processing variables
   uint father_and_mother_no_of_gifts;
   //declaration of output variables
   string people_comment;
   //input instructions
   Console.WriteLine("Enter the father's number of gifts as a positive number or else you will have an error");
   father_no_of_gifts = Convert.ToUInt32(Console.ReadLine());
   Console.WriteLine("Enter the mother's number of gifts as a positive number or else you will have an error");
   mother_no_of_gifts = Convert.ToUInt32(Console.ReadLine());
   Console.WriteLine("Enter the required total number of gifts as a positive number or else you will have an error");
   required_no_of_gifts = Convert.ToUInt32(Console.ReadLine());
   //processing instructions
   father_and_mother_no_of_gifts = father_no_of_gifts + mother_no_of_gifts;
   people_comment = father_and_mother_no_of_gifts >= required_no_of_gifts ? "" : "not";
   people_comment = "They did " + people_comment + " receive enough gifts";
   //output instructions
   Console.WriteLine("\n" + "Father number of gift is " + father_no_of_gifts);
   Console.WriteLine("Mother number of gift is " + mother_no_of_gifts);
   Console.WriteLine("Required number of gift is " + required_no_of_gifts);
   Console.WriteLine("Father and Mother's number of gifts is:  " + father_and_mother_no_of_gifts);
   Console.WriteLine(people_comment);
   Console.WriteLine("Press any key");
   Console.ReadKey();
  }
 }
}
```

Figure 4.2: Conventional code segment example (main program)

```
using System;
using inombolo_engcwele = System.UInt32;
using igama = System.String;
using uhlamvu = System.Char;
using inombolo_exubile = System.Double;
namespace UtilityLibraries
{
    public class IkilasilesiZululabhiri
    {
        public static void umshini_Khuluma(string value)
        {
            System.Console.WriteLine(value);
        }
        public static void ciphiza_nanomayiliphi_inkinobho_kumshini()
        {
            System.Console.ReadKey();
        }
        public static string umshini_yamukela_umbhalo()
        {
            return (System.Console.ReadLine());
        }
        public static UInt32 umshini_yamukela_inombolo()
        {
            return (Convert.ToUInt32(System.Console.ReadLine()));
        }
        public static string phendula_inombolo_uyenze_igama(inombolo_engcwele n)
        {
            return (Convert.ToString(n));
        }
        public static char umshini_yamukela_uhlamvu()
        {
            return (Convert.ToChar(System.Console.ReadKey()));
        }
        public static double umshini_yamukela_inombolo_exubile()
        {
            return (Convert.ToDouble(System.Console.ReadLine()));
        }
    }
}
```

Figure 4.3: Ethnocomputing code segment example (Class libraries)

```
using inombolo_engcwele = System.UInt64;
using igama = System.String;
using uhlamvu = System.Char;
using inombolo_exubile = System.Double;
namespace UtilityLibraries
{
 class Program
 {
  static void Main(string[] args)
  {
  //indawo yokubeka izinto ezingenayo inombolo_engcwele
  isiphiwo_sababa = 0; inombolo_engcwele isiphiwo_samama = 0;
  inombolo_engcwele okuncane_okumele_ukukhiphe = 0;
  // indawo yokubeka izinto ezisebenza inombolo_engcwele
  isiphiwo_sikababa_no_mama = 0;
  // indawo yokubeka izinto eziphumayo igama
  isingqumo_sokugcina_Ngezipho = "";
  //imiyalo yokufaka ezindaweni zokubeka
  IkilasilesiZululabhiri.umshini_Khuluma("Ubaba uzoletha izipho ezingaki : Inombolo oyifaka ibe ngaphezu kwa 0 ukuze kungabi yiphutha");
  isiphiwo_sababa = IkilasilesiZululabhiri.umshini_yamukela_inombolo();
  IkilasilesiZululabhiri.umshini_Khuluma("Umama uzoletha izipho ezingaki : Inombolo oyifaka ibe ngaphezu kwa 0 ukuze kungabi yiphutha");
  isiphiwo_samama = IkilasilesiZululabhiri.umshini_yamukela_inombolo();
  IkilasilesiZululabhiri.umshini_Khuluma("Ngokwesiko zingaki izipho ezindingekayo : Inombolo oyifaka ibe ngaphezu kwa 0 ukuze kungabi yiphutha");
  okuncane_okumele_ukukhiphe = IkilasilesiZululabhiri.umshini_yamukela_inombolo();
  //imiyalo yokusebenza
  isiphiwo_sikababa_no_mama = isiphiwo_sababa + isiphiwo_samama;
  isingqumo_sokugcina_Ngezipho = (isiphiwo_sikababa_no_mama < okuncane_okumele_ukukhiphe) ? "bathole izipho ezincane" : "bathole izipho ezanele";
  //imiyalo yokukhipha
  IkilasilesiZululabhiri.umshini_Khuluma("\n" + "Isiphiwo sababa : " + isiphiwo_sababa);
  IkilasilesiZululabhiri.umshini_Khuluma("isiphiwo samama : " + isiphiwo_samama); IkilasilesiZululabhiri.umshini_Khuluma("Izipho
  ezindingekayo : " + okuncane_okumele_ukukhiphe); IkilasilesiZululabhiri.umshini_Khuluma("Isipho sika baba nomama : " +
  isiphiwo_sikababa_no_mama); IkilasilesiZululabhiri.umshini_Khuluma("Imibono yabantu ngezipho : " + isingqumo_sokugcina_Ngezipho);
  IkilasilesiZululabhiri.umshini_Khuluma("\n" + "chofa noma iyiphi inkinombo");
  IkilasilesiZululabhiri.ciphiza_nanomayiliphi_inkinobho_kumshini();
  }
 }
}
```

Figure 4.4: Ethnocomputing code segment example (Main program)

# CHAPTER FIVE

# RESEARCH RESULTS

The findings of this study are presented in this chapter as the outcomes of the different tests described in chapter 4. Such findings include the results of the reliability and the validity tests of the data of the experiment conducted by this study, as well as the results of the descriptive and the inferential statistical analysis of that data. Readers are reminded that reliability and validity tests were only conducted on primary data collected for the measurement of the performance of the participants in the introduction to the programming test conducted at the end of the quasi-experiment. As for the inferential statistical analysis, its purpose was to empirically validate part of the theoretically supported conceptual model presented at the end of chapter 3, and to test the following hypotheses also presented in chapter 3:

H1: Students' academic performance is affected by their demographics;

H2: Students' academic performance is affected by their academic background; and

H7: Students' academic performance is affected by the adoption of the ethnocomputing teaching approach.

## 5.1 Academic performance factors for introductory programming prior to any intervention

The secondary data of this study were used to empirically test hypothesis 1 and hypothesis 2, respectively, on the influence of students' demographics and their academic background on their performance in introductory programming prior to any intervention (See conceptual model in chapter 3). This section, therefore, includes the findings of this study on the descriptive and inferential statistical analysis of the above mentioned data. There is no presentation of reliability or validity tests' results in this section because of the non-aggregation data in this first phase of the study.

### 5.1.1 Descriptive statistics for the first phase

The descriptive statistics of the first phase of this study on students' performance in introductory programming prior to any intervention are hereby presented with regards to the demographics of the participants, their academic background and their academic performance in the very first introduction to the programming test that was administered to them prior to any special intervention.

#### 5.1.1.1 Demographics of participants of the first phase

The demographics of the participants of this first phase of this study are hereby presented (Table 5.1) in terms of the year of their national high school exit examination, their school location, their gender and their age, having in mind that participants were different in each stage (See section 4.2.4 on the different samples).

Table 5.1: First phase: descriptive statistics of participants' demographics

| **Demographic items** | | **Nb. of Students** | **Percentage (%)** |
|---|---|---|---|
| High school exit examination year | 2012 | 1 | 4.8 % |
| | 2013 | 0 | 0.0 % |
| | 2014 | 1 | 4.8 **%** |
| | 2015 | 2 | 9.5 **%** |
| | 2016 | 7 | 33.3 **%** |
| | 2017 | 10 | 47.6 **%** |
| School location | Urban | 9 | 42.9 **%** |
| | Rural | 12 | 57.1 **%** |
| Gender | Male | 13 | 61.9 **%** |
| | Female | 8 | 38.1 **%** |
| Age | Above 21 years | 13 | 61.9 **%** |
| | 18-21 years | 8 | 38.1 **%** |

According to Table 5.1, the distribution of the participants who volunteered for this first phase of the study contains more male students (13 students or 61.9%), more students whose age is above 21 years (13 students or 61.9%), more students from rural schools (12 students or 57.1%), and more students who graduated in 2017 (10 students or 47.6%) (This study was conducted during the 2018 academic year).

#### 5.1.1.2 Academic background: Matric subjects' choices of the participants

The academic background of the participants of this first phase of this study is hereby presented for the secondary data described by section 4.2.5.1 on their subject choices for their national high school exit examination for the following compulsory subjects: home or first language; first additional language; computing where applicable; and mathematics. Table 5.2 shows that isiZulu (13 students or 61.9%) is the first choice for the home language subject choice for this phase of the study with English (6 students or 28.6%) being its second choice. On the other hand, for the first additional language subject choice, isiXhosa (15 students or 71.4%) is the first choice for the home language subject choice for this phase of the study with isiZulu (6 students or 28.6%) being its second choice. Out of the twenty-one (21) students who participated in this first phase, only two (2) of them (9.5%) did a computing subject in high school, i.e., CAT.

Table 5.2: Descriptive statistics of participants' academic background choices

| **Academic back ground items** | | **Number of Students** | **Percentage (%)** |
|---|---|---|---|
| Home language | English | 6 | 28.6 **%** |
| | IsiXhosa | 2 | 9.5 **%** |
| | IsiZulu | 13 | 61.9 **%** |
| Additional language | IsiXhosa | 15 | 71.4 **%** |
| | English | 1 | 4.8 **%** |
| | IsiZulu | 5 | 23.8 **%** |
| Computing | IT | 0 | 0.0 **%** |
| | CAT | 2 | 9.5 **%** |
| | None | 19 | 90.5 **%** |
| Mathematics | Maths core | 21 | 100 **%** |

#### 5.1.1.3 Academic background: Subjects' marks of Matric participants

The academic background of the participants of this first phase of the study is hereby presented for the secondary data described by section 4.2.5.1 on their academic performances for their national high school exit examination for the following compulsory subjects: home or first language; first additional language; mathematics; and computing, where applicable.

**First Language subject.** Figure 5.1 shows that a very high proportion of students had a mark between 60% and 80% (levels 5 and 6) in their high school exit home language examination: 16 students out a total of 21. Overall, the mean value of students' high school exit national examination levels for their home language subject is 5.29 (mark between 60 to 69 percent) for this first phase of the study.

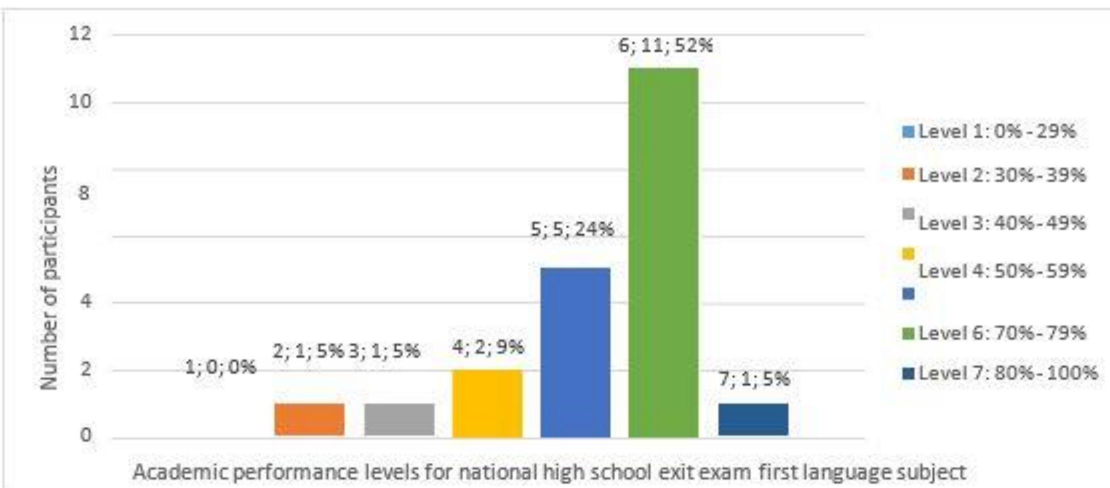


Figure 5.1: Descriptive statistics on home language subject scores for Phase 1

**First additional language subject.** Figure 5.2 shows that a very high proportion of students had a mark between 50% and 70% (levels 4 and 5) in their high school exit first additional language examination: 17 students out a total of 21. For the same subject, three students, out of a total of 21 students, had a level 7 score (between 80% and 100%). Overall, the mean value of students' high school exit national examination score for their home language subject is 4.71 (mark between 60 to 69 percent when 4.71 is rounded to 5) for this phase of the study.

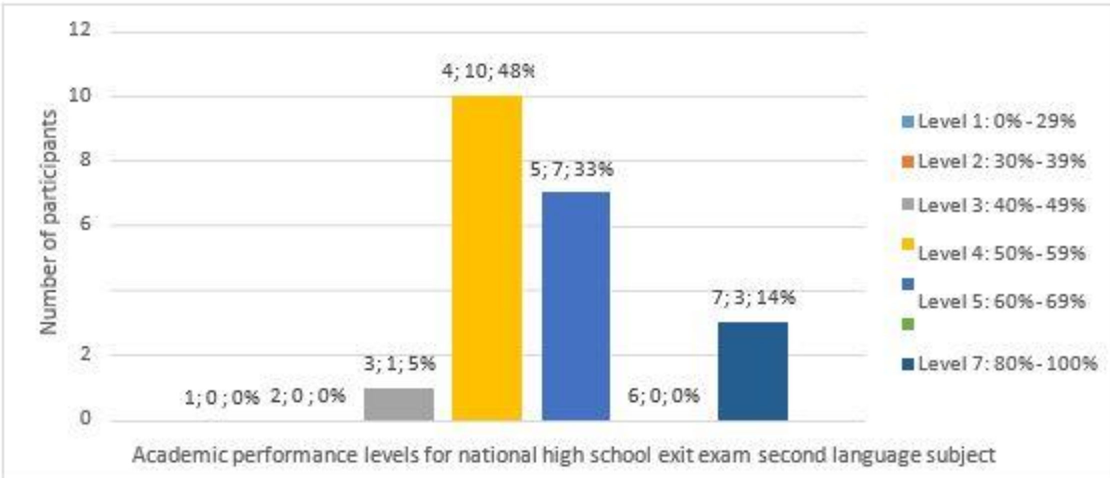


Figure 5.2: Descriptive statistics on additional language subject scores for Phase 1

**Mathematics subject.** Figure 5.3 shows that a very high proportion of students had a mark between 40% and 60% (levels 3 and 4) in their high school exit mathematics core examination: 18 students out a total of 21. Overall, the mean value of students' high school exit national examination levels for their mathematics core subject is 3.48 (mark between 40 to 49 percent) for this first phase of the study.

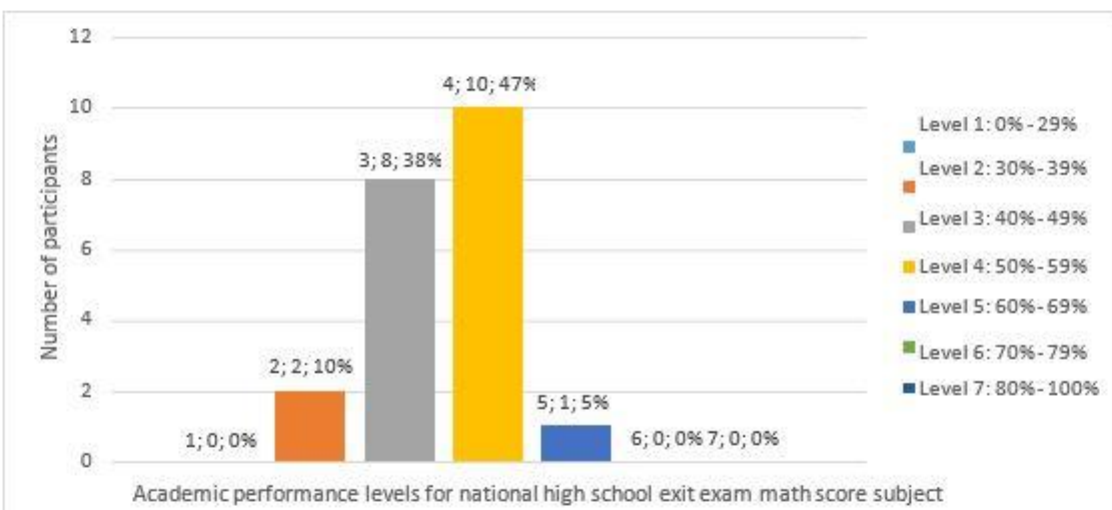


Figure 5.3: Descriptive Statistics on mathematics core subject scores for Phase 1

None of the students did IT in high school and the two participants who took CAT had level 6 and level 7 scores, respectively, between 70% and 79%, and between 80% and 100% for that subject.

#### 5.1.1.4 Descriptive statistics on students' performance in introductory programming prior to any intervention

The descriptive statistics of the results of this first phase of the study on students' performance in introductory programming prior to any intervention are illustrated by Figure 5.4. These statistics clearly indicate a poor academic performance, with a pass rate below thirty percent (29%) and a failure rate above seventy percent (71%).

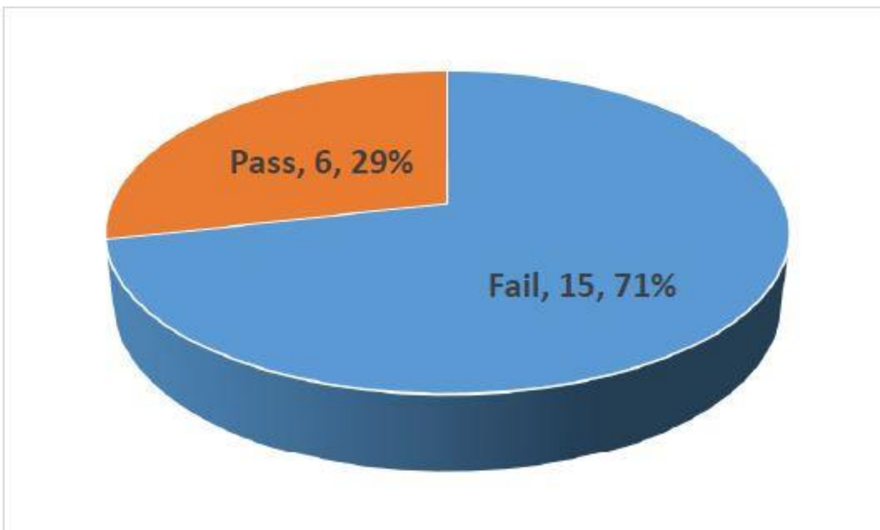


Figure 5.4: Descriptive statistics on introductory programming scores (Phase 1)

### 5.1.2 Inferential statistics on students' performance in introductory programming prior to any intervention

This section presents the results of the chi-square tests that were conducted by this first phase of this study on the identification of the factors affecting students' preferred teaching philosophy.

#### 5.1.2.1 Demographic factors

The chi-square tests' results on Table 5.3 indicate that no correlation was found between students' demographics (gender, age, school location and matric year) and their performance in introductory programming prior to any special intervention.

Table 5.3: Chi-square test results on students' demographics and their performance in introductory computer programming for Phase 1

| **STUENTS' DEMOGRAPHICS** | **Performance in introductory programming prior to any special intervention** | **Value** | **df** | **Asymptotic Significance (2- sided)** |
|---|---|---|---|---|
| GENDER | Pearson chi-square | .081[a] | 1 | .776 |
| | Likelihood Ratio | .082 | 1 | .775 |
| | Linear-by-Linear Association | .077 | 1 | .782 |
| | N of Valid Cases | 21 | | |
| AGE | Pearson chi-square | .081[a] | 1 | .776 |
| | Likelihood Ratio | .082 | 1 | .775 |
| | Linear-by-Linear Association | .077 | 1 | .782 |
| | N of Valid Cases | 21 | | |
| SCHOOL LOCATION | Pearson chi-square | .175a | 1 | .676 |
| | Likelihood Ratio | .174 | 1 | .677 |
| | Linear-by-Linear Association | .167 | 1 | .683 |
| | N of Valid Cases | 21 | | |
| MATRIC YEAR | Pearson chi-square | 3.710a | 4 | .447 |
| | Likelihood Ratio | 3.971 | 4 | .410 |
| | Linear-by-Linear Association | 1.871 | 1 | .171 |
| | N of Valid Cases | 21 | | |

#### 5.1.2.2 Academic background: Matric subjects' choices factors

The chi-square tests conducted by the first phase of this study on the relationship between students' academic background and their performance in introductory programming (prior to any special intervention) are presented below in terms of students' matric subject choices for the home language subject, the first additional subject and for the computing subject. According to Table 5.4, students' language choices for the home language subject and their choices for the computing subject are the two subject choices that were found by this study to affect students' performance in introductory programming prior to any special intervention.

Table 5.4: Chi-square test results on students' matric subjects' choices and their performance in introductory computer programming for Phase 1

| | **Performance in introductory programming prior to any special intervention** | **Value** | **Df** | **Asymptotic Significance (2-sided)** |
|---|---|---|---|---|
| HOME | Pearson chi-square | 6.174[a] | 2 | .046 |
| LANGUAGE | Likelihood Ratio | 6.327 | 2 | .042 |
| MARKS | Linear-by-Linear Association | 1.120 | 1 | .290 |
| | N of Valid Cases | 21 | | |
| FIRST | Pearson chi-square | 2.707a | 2 | .258 |
| ADDITIONAL | Likelihood Ratio | 2.726 | 2 | .256 |
| LANGUAGE | Linear-by-Linear Association | 1.164 | 1 | .281 |
| MARKS | N of Valid Cases | 21 | | |
| COMPUTING | Pearson chi-square | 5.526a | 1 | .019 |
| MARKS | Likelihood Ratio | 5.571 | 1 | .018 |
| | Linear-by-Linear Association | 5.263 | 1 | .022 |
| | N of Valid Cases | 21 | | |

A further analysis of these chi-square correlation test results is available on Table 5.5 and Table 5.6 where it can be seen that almost all the students {nine (9) students out of eleven (11)}, who chose isiZulu as their language choice for the home language subject, failed the first test that took place prior to any special intervention. On the other hand, all the students {two (2) students)} who choose CAT as a computing subject in high school passed this test together with four of the students that never did any computing subject in high school, compared to the fifteen (15) students who did not take any computing subject in high school and failed this test.

Table 5.5: Chi-square test on students' home language subject choices and their performance in introductory programming for Phase 1

| | | | HOMLANCH | | | Total |
|---|---|---|---|---|---|---|
| | | | ENGLISH | ISIXHOSA | ISIZULU | |
| TEST0MARKCODE | FAIL | Count | 4 | 0 | 11 | 15 |
| | | Expected Count | 4.3 | 1.4 | 9.3 | 15.0 |
| | PASS | Count | 2 | 2 | 2 | 6 |
| | | Expected Count | 1.7 | .6 | 3.7 | 6.0 |
| Total | | Count | 6 | 2 | 13 | 21 |
| | | Expected Count | 6.0 | 2.0 | 13.0 | 21.0 |

Table 5.6. Chi-square test on students' computing subject choices and their performance in introductory programming for Phase 1

| | | | COMCH | | Total |
|---|---|---|---|---|---|
| | | | NONE | CAT | |
| TEST0MARKCODE | FAIL | Count | 15 | 0 | 15 |
| | | Expected Count | 13.6 | 1.4 | 15.0 |
| | PASS | Count | 4 | 2 | 6 |
| | | Expected Count | 5.4 | .6 | 6.0 |
| Total | | Count | 19 | 2 | 21 |
| | | Expected Count | 19.0 | 2.0 | 21.0 |

#### 5.1.2.3 Academic background: Matric subjects' scores factors

The chi-square tests' results on Table 5.7 indicate that no correlation was found between students' performance in the matric compulsory subjects (home language, first additional language, mathematics and computing) and their performance in introductory programming prior to any special intervention.

Table 5.7: Chi-square test results on students' matric subjects' scores and their performance in introductory programming for Phase 1

| MATRIC SUBJECTS MARKS | PERFORMANCE IN INTRODUCTORY PROGRAMMING PRIOR TO ANY SPECIAL INTERVENTION | Value | Df | Asymptotic Significance (2-sided) |
|---|---|---|---|---|
| HOME LANGUAGE MARKS | Pearson chi-square | 1.979[a] | 5 | .852 |
| | Likelihood Ratio | 2.734 | 5 | .741 |
| | Linear-by-Linear Association | .013 | 1 | .908 |
| | N of Valid Cases | 21 | | |
| FIRST ADDITIONAL LANGUAGE MARKS | Pearson chi-square | 3.243a | 3 | .356 |
| | Likelihood Ratio | 3.349 | 3 | .341 |
| | Linear-by-Linear Association | .318 | 1 | .573 |
| | N of Valid Cases | 21 | | |
| MATHS MARKS | Pearson chi-square | 1.890a | 3 | .596 |
| | Likelihood Ratio | 2.670 | 3 | .445 |
| | Linear-by-Linear Association | .542 | 1 | .461 |
| | N of Valid Cases | 21 | | |
| COMPUTING MARKS | Pearson chi-square | 5.526a | 2 | .063 |
| | Likelihood Ratio | 5.571 | 2 | . 062 |
| | Linear-by-Linear Association | 5.229 | 1 | .022 |
| | N of Valid Cases | 21 | | |

## 5.2 Teaching philosophy choice factors for introductory programming

The secondary data of this quasi-experiment were used to empirically test the unplanned hypothesis 8 and hypothesis 9, respectively, on the influence of students' demographics and their academic background on their choice of a preferred teaching philosophy, either as conventional or as ethnoscientific, for introductory programming, as described by section 4.2.5.1. This section, therefore, includes the findings of this study on the descriptive and on the inferential statistical analysis of the above mentioned data. There is no presentation of reliability or validity tests' results in this section because of the non-aggregation data in the second phase of this study.

### 5.2.1 Descriptive statistics

The descriptive statistics of the second phase of this study on students' choice of a preferred teaching philosophy are hereby presented with regards to their demographics and their academic background. Readers are reminded that the academic performance variable is absent here, simply because section 5.2 deals with the second phase of this study on students' choice of a preferred teaching philosophy, while the academic performance dependent variable is examined in section 5.1 and in section 5.3.

#### 5.2.1.1 Demographics of participants

The demographics of the participants of the second phase of this study are hereby presented in terms of the year of their national high school exit examination, their school location, their gender and their age.

Table: 5.8: Second phase of descriptive statistics of participants' demographics

| | **Demographic items** | **Nb. of Students** | **Percentage (%)** |
|---|---|---|---|
| High school exit examination year | 2012 | 1 | 3.2 % |
| Additional language | 2013 | 2 | 6.5 % |
| | 2014 | 2 | 6.5 **%** |
| | 2015 | 3 | 9.7 **%** |
| | 2016 | 9 | 29.0 **%** |
| | 2017 | 14 | 45.2 **%** |
| School location | Urban | 14 | 45.2 **%** |
| | Rural | 17 | 54.8 **%** |
| Gender | Male | 20 | 64.5 **%** |
| | Female | 11 | 35.5 **%** |
| Age | Above 21 years | 11 | 35.5 **%** |
| | 18-21 years | 20 | 64.5 **%** |

According to Table 5.8, the distribution of the participants who volunteered for this second phase of the study is almost even between "gap year students" (before the year 2017: 54.8%) and the "non-gap year students" (year 2017: 45.2%), even though there are slightly more "gap year students". Readers are reminded that this quasi-experiment was conducted during the 2018 academic year. Similarly, the distribution of these participants is almost even in terms of the location of their high school, either as rural schools (54.8%) or urban schools (45.2%), even though there are slightly more students from rural schools. On the other hand, almost two thirds of participants are male (64.5%) and the same proportion of participants are above 21 years old (64.5%). From all these findings, the one on the gender distribution seems in line with current trends on gender imbalances in the world of technology, but all the other findings seem surprising, to say the least.

#### 5.2.1.2 Academic background: matric subjects' choices of the participants

The academic background of the participants of this second phase of the study is hereby presented for the secondary data described in section 4.2.5.1 on their subject choices for their national high school exit examination for the following compulsory subjects: home or first language; first additional language; computing, where applicable; and mathematics.

Table 5.9 shows that almost two thirds (61.3%) of the participants had isiZulu as their home language, with the rest of the participants having English (29.0%) as their home language, while a small minority of the participants had isiXhosa (9.7%) as their home language. As for the additional language subject, almost three quarters (71.0%) of the participants had English, with the rest having isiZulu (22.6) and Afrikaans (6.4). A huge proportion of the participants did not take any computing subject in high school (87.1%) even though a small proportion of the participants took CAT (9.7%), and a very small minority took IT (3.2%).

Table: 5.9: Phase 2: Descriptive statistics of participants' academic background choices

| Academic background items | | Nb. of Students | Percentage (%) |
|---|---|---|---|
| Home language | English | 9 | 29.0 **%** |
| | IsiXhosa | 3 | 9.7 **%** |
| | IsiZulu | 19 | 61.3 **%** |
| Additional language | Afrikaans | 2 | 6.4 **%** |
| | English | 22 | 71.0 **%** |
| | IsiZulu | 7 | 22.6 **%** |
| Computing | IT | 1 | 3.2 **%** |
| | CAT | 3 | 9.7 **%** |
| | None | 27 | 87.1 **%** |
| Mathematics | Maths Core | 31 | 100 **%** |

### 5.2.1.3 Academic background: matric subjects' marks of the participants

The academic background of the participants of this second phase of the study is hereby presented for the secondary data described in section 4.2.5.1 on their academic performances for their national high school exit examination for the following compulsory subjects: home or first language; first additional language;

computing, where applicable; and mathematics.

**First Language subject.** Figure 5.5 shows that a very high proportion of students had a mark between 60% and 100% (levels 5, 6 and 7) in their high school exit home language examination): 25 students out a total of 31. Overall, the mean value of students' high school exit national examination levels for their home language subject is 5.42 (mark between 60 to 69 percent).

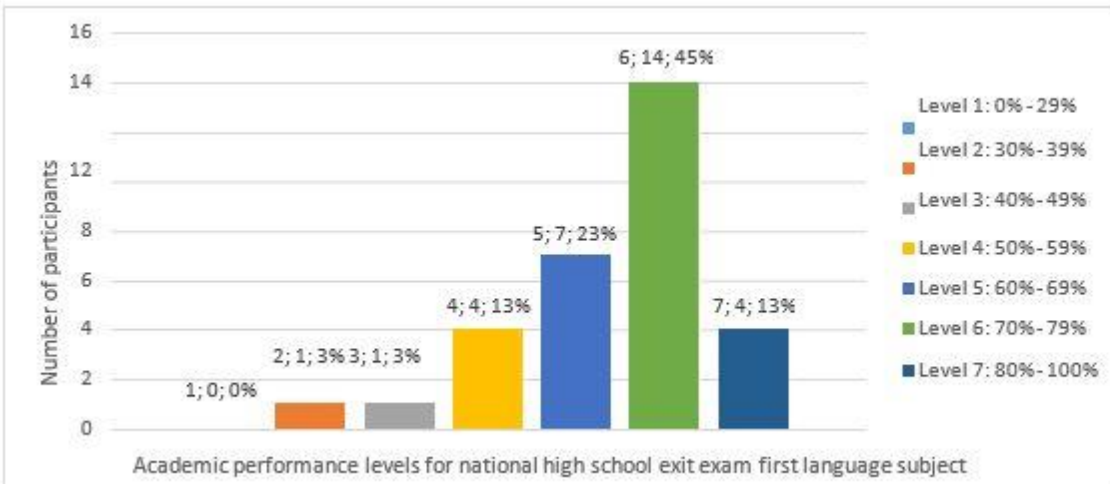


Figure 5.5: Descriptive statistics on home language subject scores for Phase 2

**First additional language subject.** Figure 5.6 shows that nearly three quarters of the students had a mark between 50 to 69 percent (levels 4 and level 5) in their high school exit additional language examination. For the same subject, almost one fifth of the students had a mark between 80 to 100 percent (level 7), a small proportion of the students had a mark between 40 to 49 percent (level 3), and a very small proportion of the students had a mark between 70 to 79 percent (level 6). Overall, the mean value of students' high school exit national examination score for their home language subject is 4.87 (mark between 60 to 69 percent).

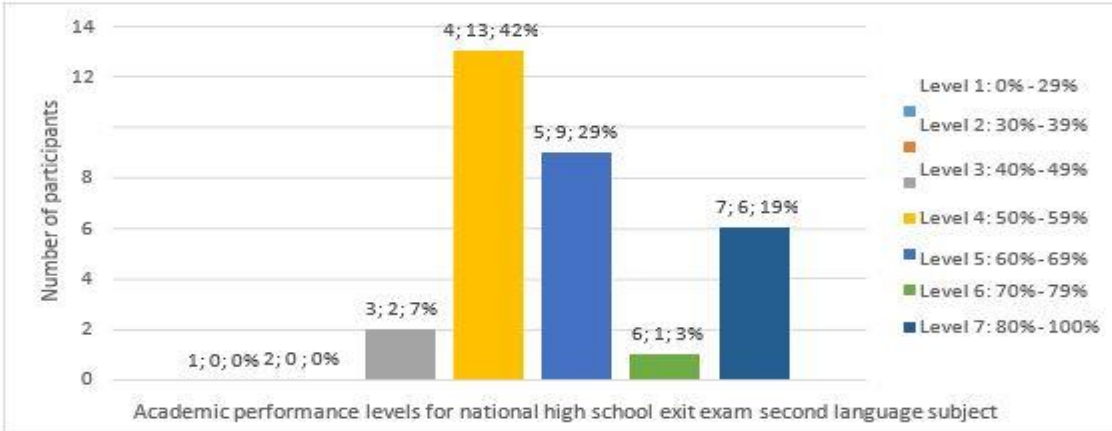


Figure 5.6: Descriptive statistics on additional language subject scores (Phase 2)

**Mathematics subject.** Figure 5.7 shows that more than three quarters of the students had a mark between 40 to 59 percent (level 3 and level 4) in their high school mathematics core examination, with a slight majority (42%) of these students having a mark between 40 and 49 percent (level 3) and the remaining 39 percent of the students having a mark between 50 and 59 percent (level 4). For the same subject, around one tenth of the students had a mark between 60 to 69 percent (level 5), and a very small proportion of the students had a mark between 30 to 39 percent (level 2). Overall, the mean value of students' high school exit mathematics core examination score is 3.58 (between 50 to 59 percent).

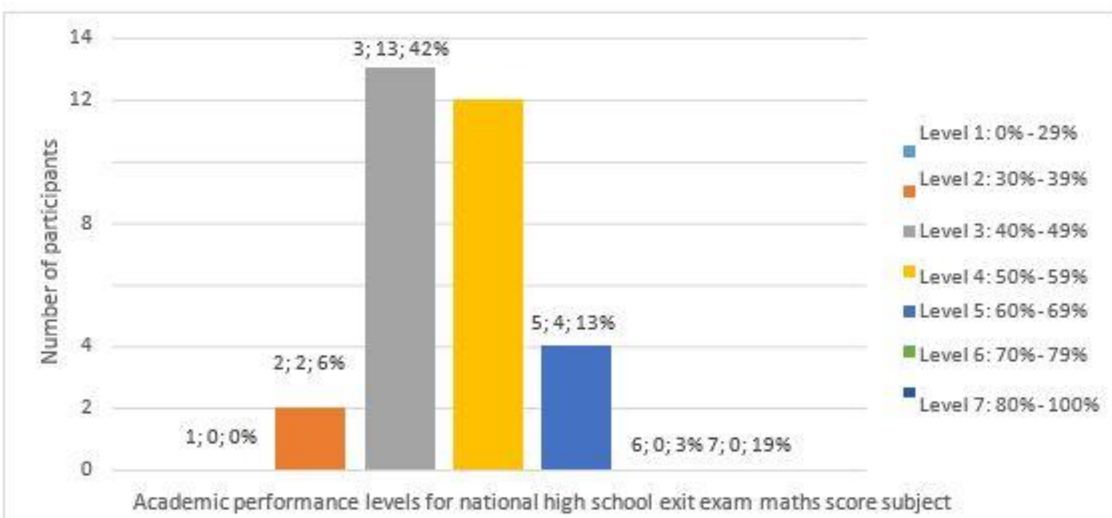


Figure 5.7: Descriptive statistics on mathematics core subject scores for Phase 2

The only one student who took IT had a level 4 score (between 50% and 59%) while the three participants who took CAT had level 5, level 6 and level 7 scores, respectively, between 50% and 69%, 70% and 79%, and between 80% and 100%.

#### 5.2.1.4 Descriptive statistics on students' choices of a preferred teaching philosophy

The descriptive statistics of the results of the second phase of this study on students' preferred teaching philosophy are illustrated by Figure 5.8. These descriptive statistics clearly indicate that, from a purely descriptive perspective and without any generalization beyond this restricted sample, students' preferred teaching philosophy was almost evenly distributed between the conventional teaching approach (52%) and the ethnoscience teaching approach (48%), but slightly in favour of the conventional teaching approach.

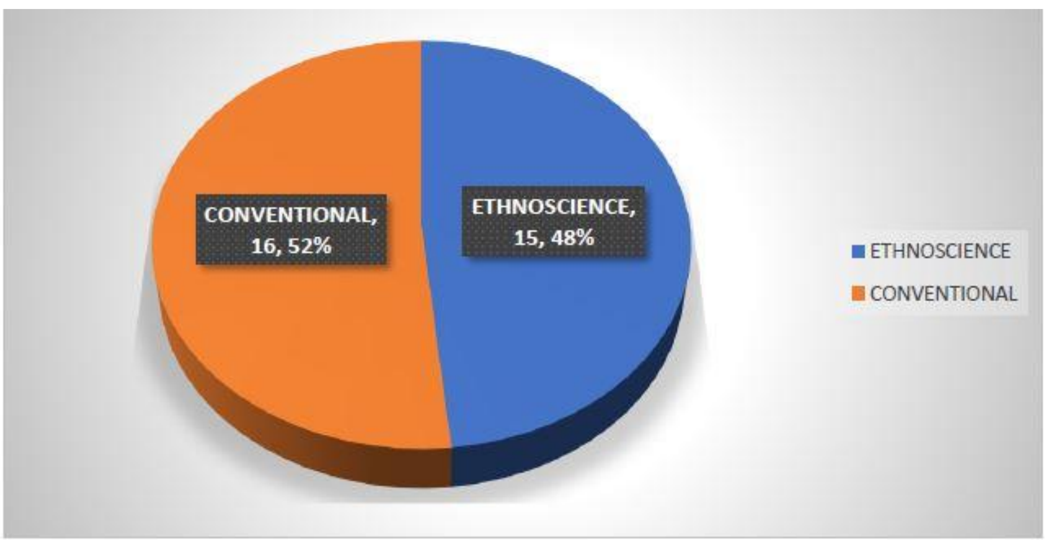


Figure 5.8: Descriptive statistics on students' preferred teaching philosophy for Phase 2

### 5.2.2 Inferential statistics on students' choices of a preferred teaching philosophy

This section presents the results of the chi-square tests that were conducted by the second phase of this study on the identification of the factors affecting students' preferred teaching philosophy.

### 5.2.2.1 Demographic factors

The chi-square results of the tests on Table 5.10 indicate that no correlation was found between students' demographics (gender, age, school location and matric year) and their choice of a preferred teaching philosophy for introductory computer programming.

Table 5.10: Chi-square test results on students' demographics and their choice of a preferred teaching philosophy for introductory computer programming (Phase 2)

| STUENTS' DEMOGRAPHICS | CHOICE OF A PREFERRED TEACHING APPROACH AND PHILOSOPHY | Value | df | Asymptotic Significance (2- sided) |
|---|---|---|---|---|
| GENDER | Pearson chi-square | .059[a] | 1 | .809 |
| | Likelihood Ratio | .059 | 1 | .808 |
| | Linear-by-Linear Association | .057 | 1 | .812 |
| | N of Valid Cases | 31 | | |
| AGE | Pearson chi-square | .059a | 1 | .809 |
| | Likelihood Ratio | .059 | 1 | .808 |
| | Linear-by-Linear Association | .057 | 1 | .812 |
| | N of Valid Cases | 31 | | |
| SCHOOL LOCATION | Pearson chi-square | 1.642a | 1 | .200 |
| | Likelihood Ratio | 1.659 | 1 | .198 |
| | Linear-by-Linear Association | 1.589 | 1 | .208 |
| | N of Valid Cases | 31 | | |
| MATRIC YEAR | Pearson chi-square | 3.416a | 5 | .636 |
| | Likelihood Ratio | 4.578 | 5 | .470 |
| | Linear-by-Linear Association | .020 | 1 | .888 |
| | N of Valid Cases | 31 | | |

#### 5.2.2.2 Academic background: Matric subjects' choices factors

The findings from the chi-square tests conducted by the second phase of this study on the relationship between students' academic background and the choice of a preferred teaching philosophy are presented below in terms of students' matric subject choices for the home language subject, the first additional subject and for the computing subject. According to Table 5.11, students' language choices for the home language subject are the only subject choices that were found by this study to affect students' choices of a preferred teaching approach and philosophy for introductory computer programming.

Table 5.11: Chi-square test results on students' matric subjects' choices and their choice of a preferred teaching philosophy for introductory computer programming for Phase 2

| MATRIC SUBJECTS CHOICES | CHOICE OF A PREFERRED TEACHING APPROACH AND PHILOSOPHY | Value | Df | Asymptotic Significance (2- sided) |
|---|---|---|---|---|
| Home language | Pearson chi-square | 8.333[a] | 2 | .016 |
| | Likelihood Ratio | 9.709 | 2 | .008 |
| | Linear-by-Linear Association | 5.938 | 1 | .015 |
| | N of Valid Cases | 31 | | |
| Additional language | Pearson chi-square | 3.985a | 2 | .136 |
| | Likelihood Ratio | 4.800 | 2 | .091 |
| | Linear-by-Linear Association | .083 | 1 | .773 |
| | N of Valid Cases | 31 | | |
| Computing | Pearson chi-square | 1.340a | 2 | .512 |
| | Likelihood Ratio | 1.731 | 2 | .421 |
| | Linear-by-Linear Association | .211 | 1 | .646 |
| | N of Valid Cases | 31 | | |

A further analysis of the chi-square correlation test results between home language subject choice and students' preferred teaching philosophy for computer programming shows that all the students who chose isiXhosa as their home language subject in their high school exit examination all chose English as their preferred teaching philosophy for computer programming (see Table 5.12).

Table 5.12: Chi-square test on students' home language and teaching philosophy choices for Phase 2

| | | | ENGLISH | ISIZULU | |
|---|---|---|---|---|---|
| HOMLANCH | ENGLISH | Count | 7 | 2 | 9 |
| | | Expected Count | 4.6 | 4.4 | 9.0 |
| | | Residual | 2.4 | -2.4 | |
| | ISIXHOSA | Count | 3 | 0 | 3 |
| | | Expected Count | 1.5 | 1.5 | 3.0 |
| | | Residual | 1.5 | -1.5 | |
| | ISIZULU | Count | 6 | 13 | 19 |
| | | Expected Count | 9.8 | 9.2 | 19.0 |
| | | Residual | -3.8 | 3.8 | |
| TOTAL | | Count | 16 | 15 | 31 |
| | | Expected Count | 16.0 | 15.0 | 31.0 |

On the other hand, slightly more than two thirds (13 out of 19) of the students who chose isiZulu as their home language subject in their high school exit examination also chose isiZulu as their preferred teaching philosophy for computer programming, and almost the same proportion (7 out of 9) of the students who chose English as their home language subject in their high school exit examination also chose English as their preferred teaching philosophy for computer programming.

### 5.2.2.3 Academic background: Matric subjects' scores factors

The chi-square tests' results on Table 5.13 indicate that no correlation was found between students' performance in the matric compulsory subjects (home language, first additional language, mathematics and computing) and their choice of a preferred teaching philosophy for introductory computer programming.

Table 5.13: Chi-square test results on matric subjects' scores and teaching philosophy choices for Phase 2

| MATRIC SUBJECTS MARKS | CHOICE OF A PREFERRED TEACHING APPROACH AND PHILOSOPHY | Value | Df | Asymptotic Significance |
|---|---|---|---|---|
| HOME LANGUAGE MARKS | Pearson chi-square | 6.403[a] | 5 | .269 |
| | Likelihood Ratio | 7.321 | 5 | .198 |
| | Linear-by-Linear Association | 5.544 | 1 | .019 |
| | N of Valid Cases | 31 | | |
| FIRST ADDITIONAL LANGUAGE MARKS | Pearson chi-square | 4.665a | 4 | .323 |
| | Likelihood Ratio | 5.845 | 4 | .211 |
| | Linear-by-Linear Association | 1.320 | 1 | .251 |
| | N of Valid Cases | 31 | | |
| MATHEMATICS MARKS | Pearson chi-square | .045a | 3 | .998 |
| | Likelihood Ratio | .045 | 3 | .998 |
| | Linear-by-Linear Association | .017 | 1 | .897 |
| | N of Valid Cases | 31 | | |
| COMPUTING MARKS | Pearson chi-square | 4.009a | 4 | .405 |
| | Likelihood Ratio | 5.550 | 4 | .235 |
| | Linear-by-Linear Association | .095 | 1 | .758 |
| | N of Valid Cases | 31 | | |

## 5.3 Academic performance factors in preferred teaching paradigm for introductory programming

The primary data of this quasi-experiment were used to empirically test hypothesis 7 on the influence of the ethnocomputing teaching philosophy on academic performance in introductory programming, as described in section 4.2.5.2. This section, therefore, consists of the presentation of the reliability, validity, descriptive statistics and inferential statistics of the primary data that were collected by this study on the performance of students in programming for their preferred teaching philosophy. The attention of readers is drawn on the fact that the assessment of the reliability and the validity of the data of the third phase of this quasi-experiment was done as described in section 4.2.7 of chapter four. This third phase also made use of the same data as the first phase for the assessment of its independent research variables, but for another slightly bigger sample. This section will, therefore, start by presenting its findings on the assessment of the reliability and the validity of its primary data for its dependent variable which measures students' academic performance in introductory programming both for the conventional teaching philosophy and for the ethnoscience teaching philosophy.

### 5.3.1 Reliability of the data on academic background and on the data on academic performance in programming

The value of the Cronbach's alpha ($\alpha$) coefficient of the variable representing the primary data on academic performance of students in programming is presented by Table 5.14, both for the control group and for the experimental group. That value is equal to 0.838, which is clearly greater than 0.7, and this clearly indicates that this primary data is reliable. On the other hand, because the secondary data were not aggregated into a single variable, there was no need for any reliability nor validity assessment for it, as already described above.

Table 5.14: Cronbach's alpha coefficient for the dependent variable of Phase 3

| Cronbach's Alpha | Number of items |
|---|---|
| .838 | 5 |

Table 5.15: Pearson coefficient for the dependent variable of Phase 3

| | | COMMENTS | VARIABLES | INPUT_INS | OUTPUT_INS | PROCESSING_INS |
|---|---|---|---|---|---|---|
| COMMENTS | Pearson Correlation | 1 | .997** | .998** | .998** | .997** |
| | Sig. (2-tailed) | | .000 | .000 | .000 | .000 |
| | N | 10 | 10 | 10 | 10 | 10 |
| VARIABLES | Pearson Correlation | .997** | 1 | .999** | .999** | 1.000** |
| | Sig. (2-tailed) | .000 | | .000 | .000 | .000 |
| | N | 10 | 10 | 10 | 10 | 10 |
| INPUT_INS | Pearson Correlation | .998** | .999** | 1 | 1.000** | 1.000** |
| | Sig. (2-tailed) | .000 | .000 | | .000 | .000 |
| | N | 10 | 10 | 10 | 10 | 10 |
| OUTPUT_INS | Pearson Correlation | .998** | .999** | 1.000** | 1 | .999** |
| | Sig. (2-tailed) | .000 | .000 | .000 | | .000 |
| | N | 10 | 10 | 10 | 10 | 10 |
| PROCESSING_INS | Pearson Correlation | .997** | 1.000** | 1.000** | .999** | 1 |
| | Sig. (2-tailed) | .000 | .000 | .000 | .000 | |
| | N | 10 | 10 | 10 | 10 | 10 |

**. Correlation is significant at the 0.01 level (2-tailed).

### 5.3.2 Data validity

The assessment of the validity of the primary data of this third phase of this quasi-experiment was done using the Pearson coefficient's validity method, and the results are presented by Table 5.15. These results show that all the items for the primary data of this third phase are inter-correlated with each other, and this indicates that the primary data are convergently valid.

### 5.3.3 Descriptive statistics

The descriptive statistics of the second phase of this study are hereby presented in terms of the demographics of the participants, and their academic background, in line with the theoretically supported academic performance model proposed by Figure 5.1

#### 5.3.3.1 Demographics of participants

The demographics of the participants of the third phase of this study are hereby presented in terms of their high school exit national examination year, their school location, their gender and their age group.

##### 5.3.3.1.1 Demographics of the control or conventional group

The demographics of the conventional group of the third phase of this study are hereby presented in terms of their high school exit national examination year, their school location, their gender and their age group.

Table 5.16: Phase 3: descriptive statistics of participants' demographics for the conventional group

| Participants' demographics | | Nb. of Participants | Percentage (%) |
|---|---|---|---|
| HIGH SCHOOL EXAMINATION YEAR | 2015 | 1 | 20.0 |
| | 2016 | 0 | 0.0 |
| | 2017 | 4 | 80.0 |
| SCHOOL LOCATION | Urban | 2 | 40.0 |
| | Rural | 3 | 60.0 |
| GENDER | Male | 3 | 60.0 |
| | Female | 2 | 40.0 |
| AGE | 18-21 years | 2 | 40.0 |
| | Above 21 years | 3 | 60.0 |

Table 5.16 shows that more than three quarters (80.0%) of the participants in the conventional group passed their high school exit national examination in 2017, but the rest of the participants (20.0%) passed their high school exit national examination in 2015. It is interesting to note that more than three quarters (80.0%) of the participants in the conventional group are male, two thirds (60.0%) of the participants are from rural schools, and their age ranges from 18 to 21 years.

#### 5.3.3.1.2 Demographics of the experimental group

Table 5.17 shows that two thirds (60.0%) of the participants in the experimental group passed their high school exit national examination in 2017, and the rest of the participants only registered at the university in 2018, even though they passed their high school exit national examination in 2016 (20.0%) or in 2015 (20.0%). Two thirds (60.0%) of these participants are from rural schools, are female (60%) and the age range for more than three quarters (80.0%) of them is between 18 and 21 years. Interestingly, there are more female participants that male participants in the experimental group, compared to the control group where there are more male participants, even though, overall, there are more male participants than female participants in this quasi-experiment.

Table 5.17: Phase 3 participants' demographics' descriptive statistics for the experimental group

| **Participants' demographics** | | **Nb. of Participants** | **Percentage (%)** |
|---|---|---|---|
| HIGH SCHOOL EXAMINATION YEAR | 2015 | 1 | 20.0 |
| | 2016 | 1 | 20.0 |
| | 2017 | 3 | 60.0 |
| SCHOOL LOCATION | Urban | 2 | 40.0 |
| | Rural | 3 | 60.0 |
| GENDER | Male | 2 | 40.0 |
| | Female | 3 | 60.0 |
| AGE | 18-21 years | 4 | 80.0 |
| | Above 21 years | 1 | 20.0 |

### 5.3.3.2 Academic background: Matric subjects' choices of the participants

The academic background of the participants of the third phase of this study is hereby presented for the secondary data described in section 4.2.5.1 on their subject choices for their national high school exit examination for the following compulsory subjects, first for the conventional group and, thereafter, for the experimental group: home or first language; first additional language; computing, where applicable; and mathematics.

#### 5.3.3.2.1.1 Matric subjects' choices of the conventional group

Table 5.18 shows an almost equal split of participants in the conventional group between isiZulu and English, both as a home language subject choice, or as a first additional language subject choice. In fact, it appears that the three (3) students that had isiZulu as a home language subject choice also had English as a second language subject choice, and the two (2) students that had English as a home language subject choice also had isiZulu as a second language subject choice. All these students did mathematics core, none of them did IT, and only one of them did CAT.

Table 5.18: Phase 3: Descriptive statistics of participants' academic background choices for the conventional group

| **Academic back ground items** | | **Number of Students** | **Percentage (%)** |
|---|---|---|---|
| Home language | English | 2 | 40.0 **%** |
| | IsiXhosa | 0 | 0.0 **%** |
| | IsiZulu | 3 | 60.0 **%** |
| Additional language | Afrikaans | 0 | 0.0 **%** |
| | English | 3 | 60.0 **%** |
| | IsiZulu | 2 | 40.0 **%** |
| Computing | IT | 0 | 0.0 **%** |
| | CAT | 1 | 20.0 **%** |
| | None | 4 | 80.0 **%** |
| Mathematics | Maths Core | 5 | 100 **%** |

#### 5.3.3.2.1.2 Matric subjects' choices of the experimental group

Table 5.19 shows that a very high percentage of students (4 students or 80%) from the experimental group had isiZulu as their home language subject choice and the same students had English as their first additional language subject choice. In return, only one (1) student (20%) had English as his or her home language subject choice and the same student had isiZulu as his or her first additional language subject choice. All these students did Mathematics core, and none of them did CAT, let alone IT.

Table 5.19: Phase 3: Descriptive statistics of participants' academic background choices for the experimental group

| Academic back ground items | | Number of Students | Percentage (%) |
|---|---|---|---|
| Home language | English | 1 | 20.0 **%** |
| | IsiXhosa | 0 | 0.0 **%** |
| | IsiZulu | 4 | 80.0 **%** |
| Additional language | Afrikaans | 0 | 0.0 **%** |
| | English | 4 | 80.0 **%** |
| | IsiZulu | 1 | 20.0 **%** |
| Computing | IT | 0 | 0.0 **%** |
| | CAT | 0 | 0.0**%** |
| | None | 5 | 100 **%** |
| Mathematics | Maths Core | 5 | 100 **%** |

#### 5.3.3.2.2 Academic background: Matric subjects' scores of the participants

The performance of the participants for their above mentioned matric subjects is hereby presented both for the experimental group and for the conventional group

#### 5.3.3.2.3 Academic background: Matric subjects scores of the control or conventional group

Figures 5.9 and 5.10 show that two thirds (60.0%) of the students in the conventional group had a mark between 70 to 79 percent (level 6) in their high school exit home language examination. The majority of students (80.0%) either had a mark between 60 to 69 percent (level 5) or between 50 to 59 percent (level 4) in their high school exit additional language examination. On the other hand, none of the students had a level seven (7) score for the home language subject, while one fifth (20%) of the students had a level seven (7) score in the additional language subject. Overall, the mean value of students' high school exit national examination score for both the home and additional language subjects is 5.00, which is a mark between 60 and 69 percent.

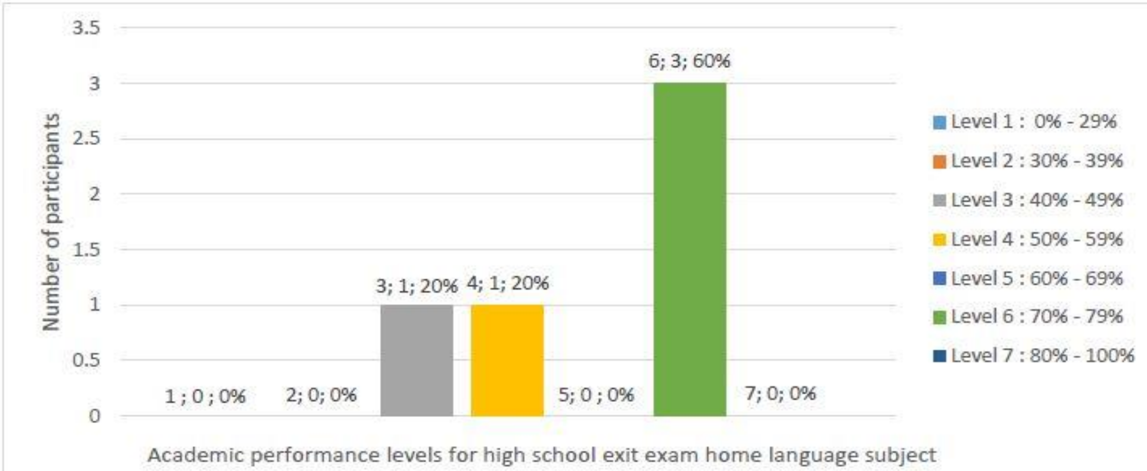


Figure 5.9: Descriptive statistics on home language subject scores of Phase 3 for the conventional group

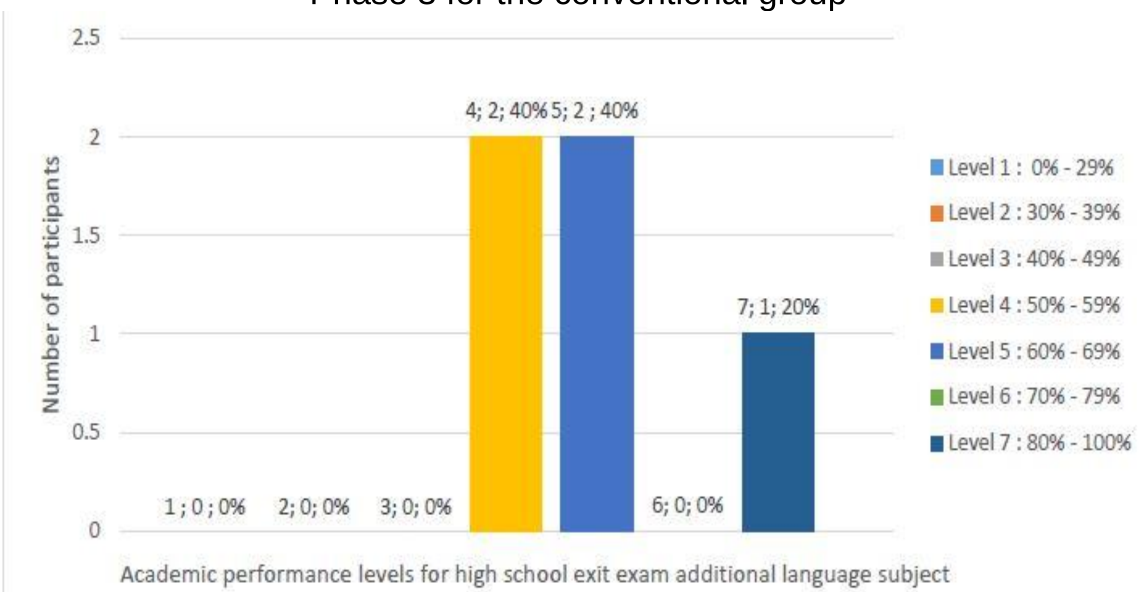


Figure 5.10: Descriptive statistics on additional language subject scores of Phase 3 for the conventional group

Figure 5.11 shows that almost two thirds (60.0%) of the students in the conventional group had a mark between 40 and 49 percent (level 3) in their high school exit examination for the mathematics core subject, while the remaining students (40.0%) either had a mark between 50 to 59 percent (level 4) or between 60 to 69 percent (level 5) for the same subject. Overall, the mean value of students' high school exit national examination scores for the mathematics core subject is 3.60, which is between level 3 (mark between 40 and 49 percent) and level 4 (mark between 50 and 59 percent).

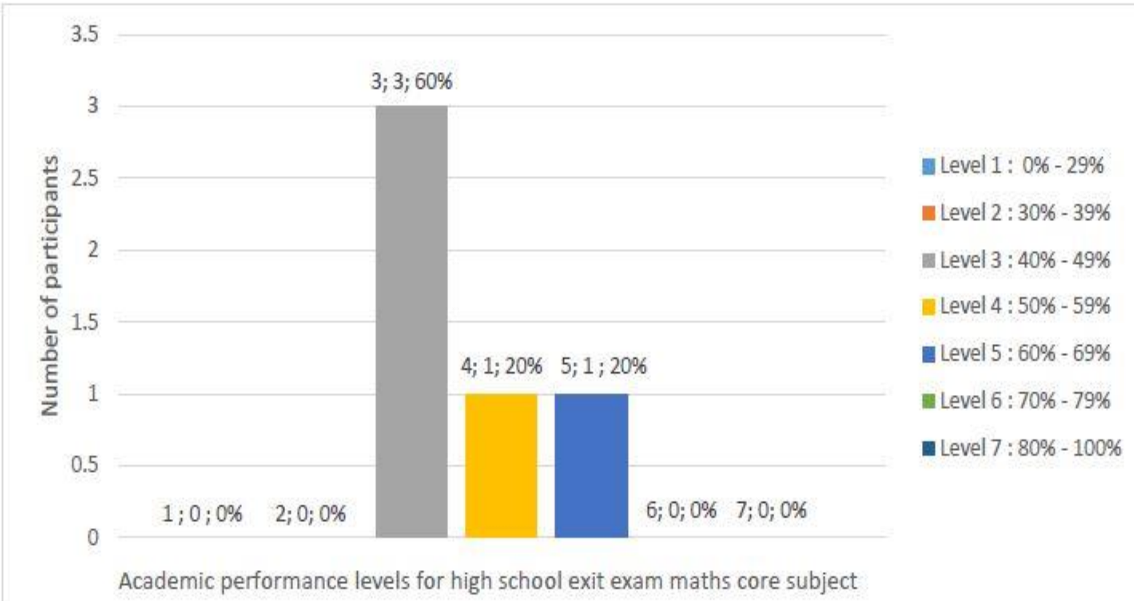


Figure 5.11: Descriptive statistics on mathematics core subject scores of Phase 3 for the conventional group

The only student in the conventional group who did CAT had a mark between 50 to 59 percent (level 4) in the high school exit computing subject examination, but none of them did IT.

Table 5.20: Descriptive statistics on average academic background scores of Phase 3 for the conventional group

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Home language | 5 | 3 | 6 | 5.00 | 1.414 |
| Additional language | 5 | 4 | 7 | 5.00 | 1.225 |
| Mathematics | 5 | 3 | 5 | 3.60 | .894 |
| Valid N (listwise) | 5 | | | | |

#### 5.3.3.2.4 Academic background: Matric subjects scores of the experimental group

Figures 5.12 and 5.13 show that an overwhelming majority (80.0%) of the students in the experimental group had a mark between 70 to 79 percent (level 6) in their high school exit examination for the home language subject. Similarly, the majority (80%) of students in the experimental group either had a mark between 50 to 59 percent (level 4) or between 60 to 69 percent (level 5) in their high school exit examination for the additional language subject. On the other hand, none of the students in the experimental group had a mark between 80 to 100 percent (level 7) in the home language subject, even though almost a fifth of them (20.0%) had a level seven (7) score in the additional language subject. However, overall, the mean value of students' high school exit national examination scores for the home language subject is 5.80, which is between level 5 (mark between 60 and 69 percent) and level 6 (mark between 70 and 79 percent), and the mean value of students' high school exit national examination scores for the additional language subject is 5.00, which is a mark between 60 and 69 percent.

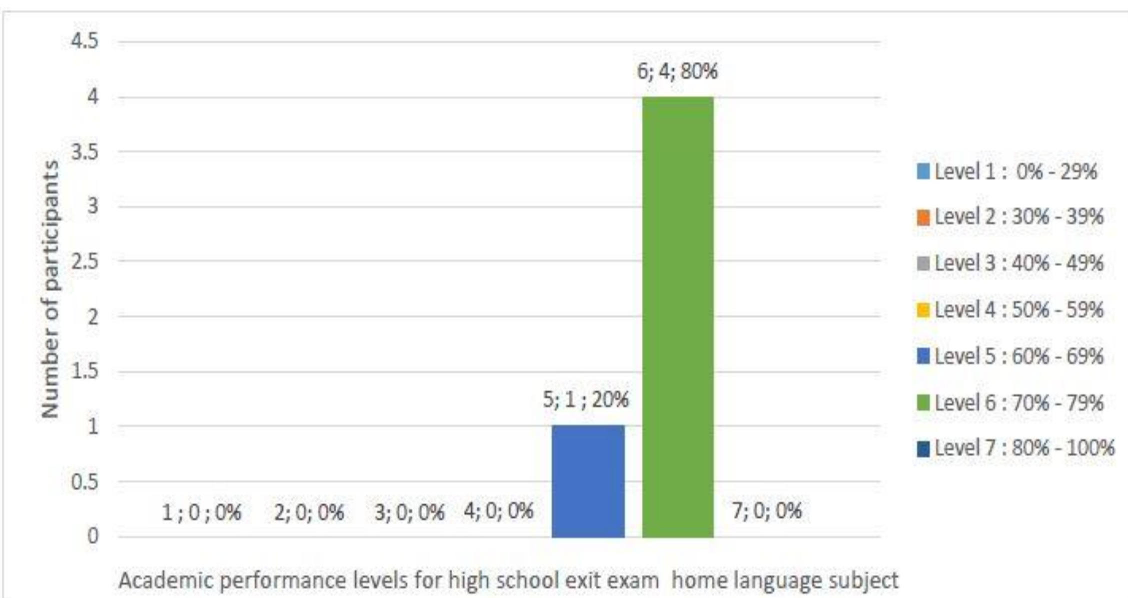


Figure 5.12: Descriptive statistics on home language subject scores of Phase 3 for the experimental group

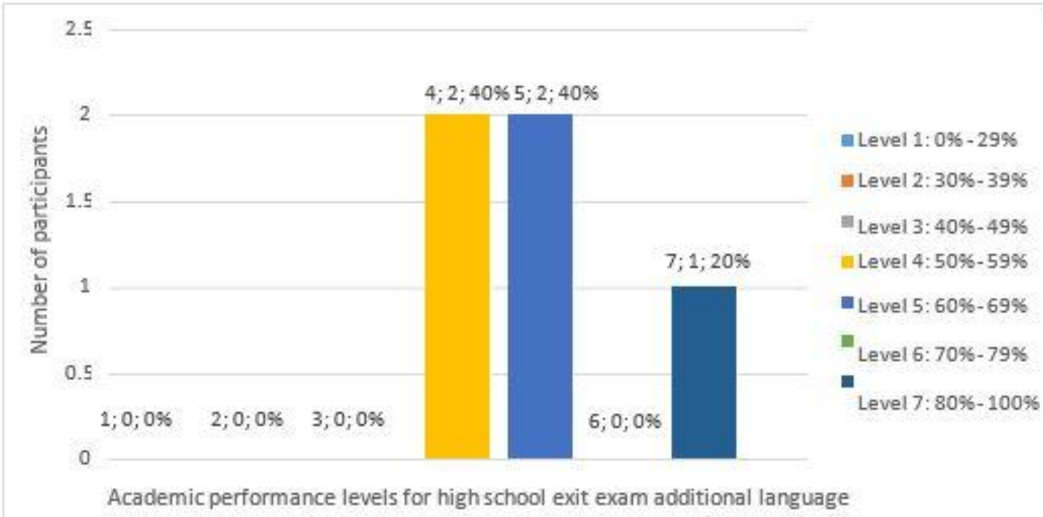


Figure 5.13: Descriptive statistics on additional language subject scores of Phase 3 for the experimental group

Figure 5.14 shows that two thirds (60.0%) of the students in the experimental group had a mark between 50 and 59 percent (level 4) in their high school exit examination for the mathematics core subject, while the remaining one third (40.0%) had a mark between 40 to 49 percent (level 3). It is interesting to note that none of the students had a mark higher than 60 percent in mathematics core. Overall, the mean value of students' high school exit national examination scores for the mathematics core subject is 3.80, which is between level 3 (mark between 40 and 49 percent) and level 4 (mark between 50 and 59 percent). See Table 5.21.

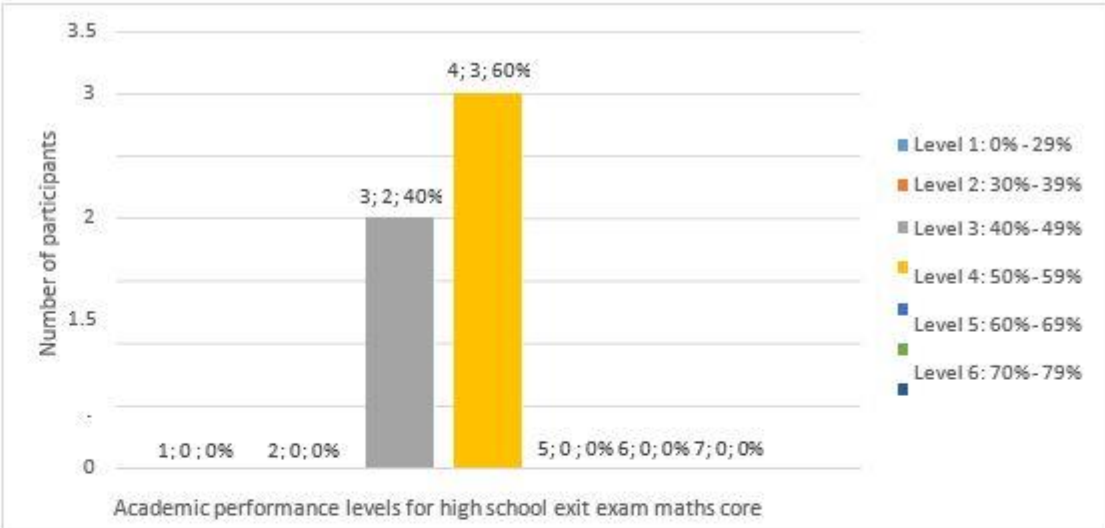


Figure 5.14: Descriptive statistics on mathematics core subject scores of Phase 3 for the experimental group

All the students in the experimental group did not write any computing subject (i.e., CAT or IT) in the high school exit computing subject examination.

Table 5.21: Descriptive statistics on average academic background scores of Phase 3 for the experimental group

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Home language | 5 | 5 | 6 | 5.80 | .447 |
| Additional language | 5 | 4 | 7 | 5.00 | 1.225 |
| Mathematics | 5 | 3 | 4 | 3.80 | .447 |
| Valid N (listwise) | 5 | | | | |

### 5.3.3.2.5 Students' performance in programming both for the control group and for the experimental group

The descriptive analysis of students' performance in programming is presented by Figures 5.15 and 5.16 and Tables 5.22, 5.23 and 5.24, both for the control group and for the experimental group.

Table 5.22: Phase 3 students' academic performance in introductory programming

| Std. | Group | Comments /25 | Variables /60 | Input Instr. /40 | Output Instr. /25 | Proc. Instr. /150 | Total /300 | Remark |
|---|---|---|---|---|---|---|---|---|
| 1 | Exp. | 25 | 60 | 40 | 25 | 150 | 300 | PASS |
| 2 | Exp. | 25 | 60 | 40 | 25 | 150 | 300 | PASS |
| 3 | Exp. | 25 | 60 | 30 | 20 | 150 | 285 | PASS |
| 4 | Exp. | 25 | 50 | 40 | 25 | 10 | 150 | PASS |
| 5 | Exp. | 25 | 60 | 40 | 25 | 150 | 300 | PASS |
| 6 | Conv. | 25 | 60 | 40 | 25 | 70 | 220 | PASS |
| 7 | Conv. | 25 | 20 | 20 | 20 | 20 | 105 | FAIL |
| 8 | Conv. | 20 | 20 | 20 | 20 | 10 | 90 | FAIL |
| 9 | Conv. | 10 | 10 | 10 | 10 | 10 | 50 | FAIL |
| 10 | Conv. | 20 | 20 | 20 | 20 | 10 | 90 | FAIL |

For the understanding of the concept of comments, input instructions, and output instructions in the context of programming, the experimental group had a pass rate of 100%, with mean values of 25.00 out of 25, 38.00 out of 40, and 24.00 out of 25, respectively; while the conventional group had a pass rate of 80%, with mean values of 20.00 out of 25, 22.00 out of 40, and 19.00 out of 25, respectively. As for the understanding of the concept of variables, and for the overall performance of students in this quasi-experiment, the experimental group also had a pass rate of 100%, with mean values of 58.00 out of 60, and 267.00 out of 300, respectively; while the conventional group had a pass rate of only 20% with mean values of 26.00 out of 60, and 111.00 out of 300, respectively. Finally, for the understanding of the concept of processing instructions, the experimental group had a pass rate of 80%, with a mean value of 122.00 out of 150, while the conventional group had a pass rate of 0% with a mean value of 24.00 out of 150.

Table 5.23: Descriptive statistics on academic performance of Phase 3 for the conventional group

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Processing instructions (150) | 5 | 10 | 150 | 122.00 | 62.610 |
| Comments (25) | 5 | 25 | 25 | 25.00 | .000 |
| Variables (60) | 5 | 50 | 60 | 58.00 | 4.472 |
| Input instructions (40) | 5 | 30 | 40 | 38.00 | 4.472 |
| Output instructions (25) | 5 | 20 | 25 | 24.00 | 2.236 |
| Total score (300) | 5 | 150 | 300 | 267.00 | 65.727 |
| Valid N (listwise) | 5 | | | | |

These results clearly indicate that students from the experimental group performed far better than those from the conventional group, from the mere analysis of these descriptive statistics, even though this still has to be confirmed by the use of relevant inferential statistics (See Tables 5.22-5.24).

Table 5.24: Descriptive statistics on academic performance of Phase 3 for the experimental group

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Processing instructions (150) | 5 | 10 | 70 | 24.00 | 26.077 |
| Comments (25) | 5 | 10 | 25 | 20.00 | 6.124 |
| Variables (60) | 5 | 10 | 60 | 26.00 | 19.494 |
| Input instructions (40) | 5 | 10 | 40 | 22.00 | 10.954 |
| Output instructions (25) | 5 | 10 | 25 | 19.00 | 5.477 |
| Total score (300) | 5 | 50 | 220 | 111.00 | 64.265 |
| Valid N (listwise) | 5 | | | | |

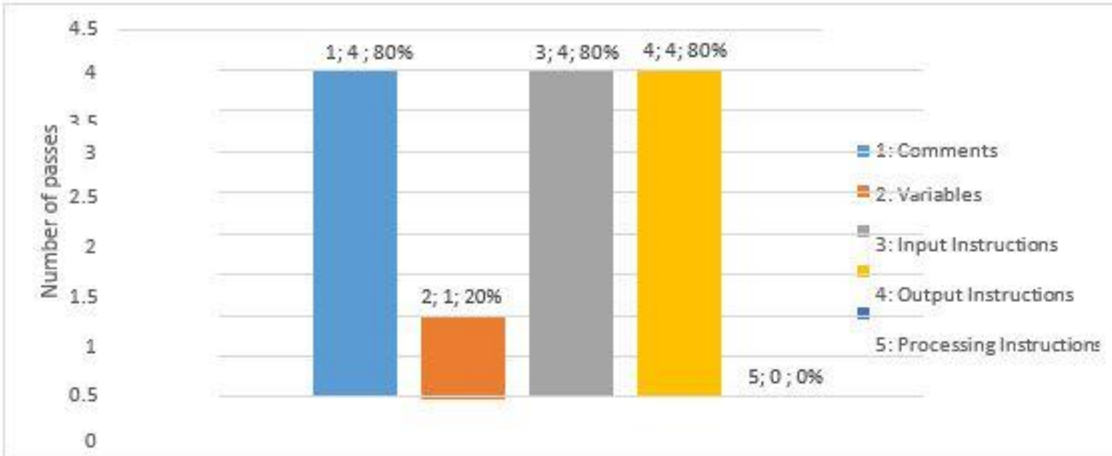


Figure 5.15: Phase 3 students' pass rate for the control group

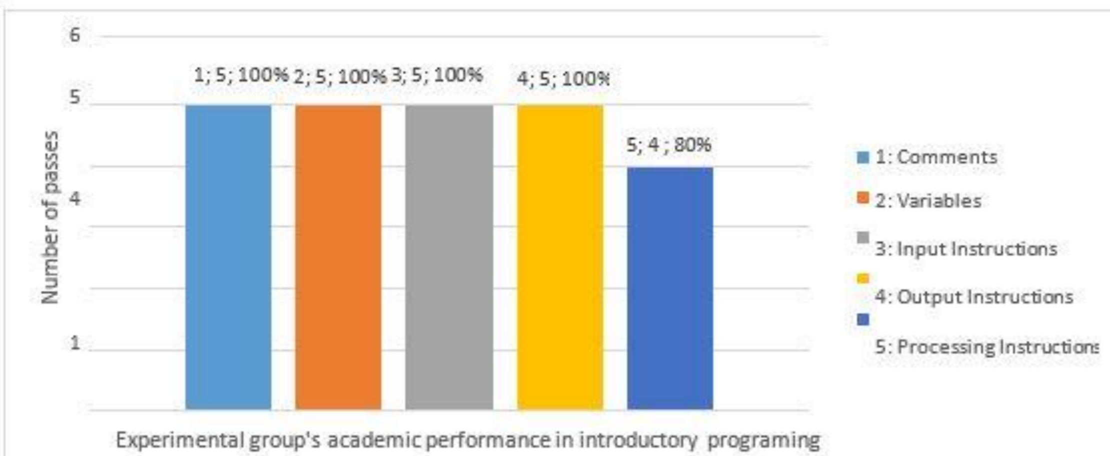


Figure 5.16: Phase 3 students' pass rate for the experimental group

### 5.3.4 Inferential statistics

This section presents the chi-square results of tests with a significance level p of 0.05 ($p<0.05$) on the factors that were hypothesized to affect academic performance in introductory computer programming, for the understanding of the concepts of comments, variables, input instructions, processing instructions and output instructions.

#### 5.3.4.1 Demographics and performance in preferred teaching philosophy

Tables 5.25 to 5.29 are the results of the chi- square tests conducted on the demographic factors that were hypothesized to affect academic performance in introductory computer programming when students are taught in their preferred teaching philosophy. Readers are reminded that the test that was administered to students aimed to assess their understanding of the concepts of comments, variables, input instructions, processing instructions and output instructions. Readers are also reminded that the demographics of students consist of their gender, age, their school location and their national high school examination (Matriculation/Matric) year. Among these demographics and programming concepts, gender is the only demographic factor that was found to correlate with academic performance in one of the introductory programming concepts, i.e., the concept of output instructions, with female students outperforming male students.

Table 5.25: Statistics of the chi-square test results for the relationship between Phase 3 students' gender and their performance on the concept of output instructions

| | | OUTPUT INSTRUCTIONS | | | |
|---|---|---|---|---|---|
| | | 10 | 20 | 25 | Total |
| GENDER | MALE | 1 | 4 | 1 | 6 |
| | FEMALE | 0 | 0 | 4 | 4 |
| Total | | 1 | 4 | 5 | 10 |

Table 5.26: Statistics of the chi-square test results for the relationship between Phase 3 students' gender and their academic performance in introductory computer programming

| | GENDER | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|---|
| COMMENTS | Pearson chi-square | 2.857[a] | 2 | .240 |
| | Likelihood Ratio | 3.900 | 2 | .142 |
| | Linear-by-Linear Association | 1.765 | 1 | .184 |
| | N of Valid Cases | 10 | | |
| VARIABLES | Pearson chi-square | 5.000a | 3 | .172 |
| | Likelihood Ratio | 6.730 | 3 | .081 |
| | Linear-by-Linear Association | 3.465 | 1 | .063 |
| | N of Valid Cases | 10 | | |
| INPUT INSTRUCTIONS | Pearson chi-square | 6.667a | 3 | .083 |
| | Likelihood Ratio | 8.456 | 3 | .037 |
| | Linear-by-Linear Association | 5.000 | 1 | .025 |
| | N of Valid Cases | 10 | | |
| OUTPUT INSTRUCTIONS | Pearson chi-square | 6.667a | 2 | .036 |
| | Likelihood Ratio | 8.456 | 2 | .015 |
| | Linear-by-Linear Association | 3.630 | 1 | .057 |
| | N of Valid Cases | 10 | | |
| PROCESSING INSTRUCTIONS | Pearson chi-square | 2.708a | 3 | .439 |
| | Likelihood Ratio | 3.416 | 3 | .332 |
| | Linear-by-Linear Association | .685 | 1 | .408 |
| | N of Valid Cases | 10 | | |
| TOTAL SCORE | Pearson chi-square | 7.222a | 6 | .301 |
| | Likelihood Ratio | 9.641 | 6 | .141 |
| | Linear-by-Linear Association | 1.815 | 1 | .178 |
| | N of Valid Cases | 10 | | |

Table 5.27: Statistics of the chi-square test results for the relationship between Phase 3 students' age and their academic performance in introductory computer programming

| | AGE GROUP | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|---|
| COMMENTS | Pearson chi-square | .816[a] | 2 | .665 |
| | Likelihood Ratio | 1.069 | 2 | .586 |
| | Linear-by-Linear Association | .126 | 1 | .723 |
| | N of Valid Cases | 10 | | |
| VARIABLES | Pearson chi-square | 1.111a | 3 | .774 |
| | Likelihood Ratio | 1.668 | 3 | .644 |
| | Linear-by-Linear Association | .202 | 1 | .653 |
| | N of Valid Cases | 10 | | |
| INPUT INSTRUCTIONS | Pearson chi-square | 1.111a | 3 | .774 |
| | Likelihood Ratio | 1.668 | 3 | .644 |
| | Linear-by-Linear Association | .357 | 1 | .550 |
| | N of Valid Cases | 10 | | |
| OUTPUT INSTRUCTIONS | Pearson chi-square | .714a | 2 | .700 |
| | Likelihood Ratio | .988 | 2 | .610 |
| | Linear-by-Linear Association | .640 | 1 | .424 |
| | N of Valid Cases | 10 | | |
| PROCESSING INSTRUCTIONS | Pearson chi-square | 2.857a | 3 | .414 |
| | Likelihood Ratio | 3.220 | 3 | .359 |
| | Linear-by-Linear Association | .012 | 1 | .912 |
| | N of Valid Cases | 10 | | |
| TOTAL SCORE | Pearson chi-square | 4.444a | 6 | .617 |
| | Likelihood Ratio | 5.626 | 6 | .466 |
| | Linear-by-Linear Association | .084 | 1 | .772 |
| | N of Valid Cases | 10 | | |

Table 5.28: Statistics of the chi-square test results for the relationship between Phase 3 students' school location and their academic performance in introductory programming

| SCHOOL LOCATION | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson chi-square | 2.857[a] | 2 | .240 |
| Likelihood Ratio | 3.900 | 2 | .142 |
| Linear-by-Linear Association | 1.765 | 1 | .184 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 2.222a | 3 | .528 |
| Likelihood Ratio | 2.911 | 3 | .406 |
| Linear-by-Linear Association | .923 | 1 | .337 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 2.222a | 3 | .528 |
| Likelihood Ratio | 2.911 | 3 | .406 |
| Linear-by-Linear Association | 1.250 | 1 | .264 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.875a | 2 | .392 |
| Likelihood Ratio | 2.231 | 2 | .328 |
| Linear-by-Linear Association | 1.500 | 1 | .221 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 5.833a | 3 | .120 |
| Likelihood Ratio | 7.915 | 3 | .048 |
| Linear-by-Linear Association | .849 | 1 | .357 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 7.222a | 6 | .301 |
| Likelihood Ratio | 9.641 | 6 | .141 |
| Linear-by-Linear Association | 1.132 | 1 | .287 |
| N of Valid Cases | 10 | | |

Table 5.29: Statistics of the chi-square test results for the relationship between Phase 3 students' matric year and their academic performance in introductory programming

| MATRICULATION YEAR | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson chi-square | 1.888[a] | 4 | .756 |
| Likelihood Ratio | 2.115 | 4 | .715 |
| Linear-by-Linear Association | .041 | 1 | .840 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 2.000a | 6 | .920 |
| Likelihood Ratio | 2.715 | 6 | .844 |
| Linear-by-Linear Association | .033 | 1 | .855 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 2.000a | 6 | .920 |
| Likelihood Ratio | 2.715 | 6 | .844 |
| Linear-by-Linear Association | .115 | 1 | .734 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.464a | 4 | .833 |
| Likelihood Ratio | 2.035 | 4 | .729 |
| Linear-by-Linear Association | .385 | 1 | .535 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 2.500a | 6 | .868 |
| Likelihood Ratio | 3.220 | 6 | .781 |
| Linear-by-Linear Association | .360 | 1 | .549 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 5.833a | 12 | .924 |
| Likelihood Ratio | 6.672 | 12 | .878 |
| Linear-by-Linear Association | .267 | 1 | .606 |
| N of Valid Cases | 10 | | |

#### 5.3.4.2 Matric subject choices and performance in preferred teaching philosophy

The chi-square tests' results on Table 5.30, Table 5.31 and Table 5.32 indicate that no correlation was found between students' matric subjects' choices (for home language, first additional language and computing) and their academic performance in introductory computer programming when taught in their preferred teaching philosophy.

Table 5.30: Chi-square test results on matric home language choice and performance in introductory computer programming for Phase 3

| HOME LANGUAGE. CHOICE | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson chi-square | 1.837[a] | 2 | .399 |
| Likelihood Ratio | 2.657 | 2 | .265 |
| Linear-by-Linear Association | 1.134 | 1 | .287 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.111a | 3 | .774 |
| Likelihood Ratio | 1.668 | 3 | .644 |
| Linear-by-Linear Association | .202 | 1 | .653 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.111a | 3 | .774 |
| Likelihood Ratio | 1.668 | 3 | .644 |
| Linear-by-Linear Association | .357 | 1 | .550 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | .714a | 2 | .700 |
| Likelihood Ratio | .988 | 2 | .610 |
| Linear-by-Linear Association | .640 | 1 | .424 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 6.429a | 3 | .093 |
| Likelihood Ratio | 7.719 | 3 | .052 |
| Linear-by-Linear Association | .045 | 1 | .833 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 6.825a | 6 | .337 |
| Likelihood Ratio | 8.398 | 6 | .210 |
| Linear-by-Linear Association | .152 | 1 | .696 |
| N of Valid Cases | 10 | | |

Table 5.31: Chi-square test results on matric first additional language choice and performance in introductory computer programming for Phase 3

| First additional language choice | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson chi-square | 1.837[a] | 2 | .399 |
| Likelihood Ratio | 2.657 | 2 | .265 |
| Linear-by-Linear Association | 1.134 | 1 | .287 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.111a | 3 | .774 |
| Likelihood Ratio | 1.668 | 3 | .644 |
| Linear-by-Linear Association | .202 | 1 | .653 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.111a | 3 | .774 |
| Likelihood Ratio | 1.668 | 3 | .644 |
| Linear-by-Linear Association | .357 | 1 | .550 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | .714a | 2 | .700 |
| Likelihood Ratio | .988 | 2 | .610 |
| Linear-by-Linear Association | .640 | 1 | .424 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 6.429a | 3 | .093 |
| Likelihood Ratio | 7.719 | 3 | .052 |
| Linear-by-Linear Association | .045 | 1 | .833 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 6.825a | 6 | .337 |
| Likelihood Ratio | 8.398 | 6 | .210 |
| Linear-by-Linear Association | .152 | 1 | .696 |
| N of Valid Cases | 10 | | |

Table 5.32: Chi-square test results on matric computing subject choice and performance in introductory computer programming for Phase 3

| COMPUTING SUBJECT | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson chi-square | 4.444[a] | 2 | .108 |
| Likelihood Ratio | 3.729 | 2 | .155 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 2.593a | 3 | .459 |
| Likelihood Ratio | 2.683 | 3 | .443 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 2.593a | 3 | .459 |
| Likelihood Ratio | 2.683 | 3 | .443 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.667a | 2 | .435 |
| Likelihood Ratio | 2.003 | 2 | .367 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.667a | 3 | .644 |
| Likelihood Ratio | 2.003 | 3 | .572 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 4.444a | 6 | .617 |
| Likelihood Ratio | 3.729 | 6 | .713 |
| N of Valid Cases | 10 | | |

### 5.3.4.3 Matric subject scores and performance in preferred teaching philosophy

Table 5.33, Table 5.34, Table 5.35, and Table 5.36 are the results of the chi-square tests conducted by this study to find out whether students' academic performance in the compulsory matric subjects (mathematics, home language, first additional language) were related to their performance in introductory computer programming when taught in their preferred teaching philosophy. Readers are reminded that the programming concepts in question are on the understanding of the notion of comments, variables, input instructions, processing instructions and output instructions. Among these matric subjects and programming concepts, academic performance in the home language subject is the only factor that was found to correlate with academic performance in one of the introductory programming concepts, i.e., the concept of processing instructions.

Table 5.33: Chi-square test results on matric home language score and performance on processing instructions in Phase 3

| | | PROC | | | | Total |
|---|---|---|---|---|---|---|
| | | 10 | 20 | 70 | 150 | |
| HOLANGMRK | Level 3 | 0 | 0 | 1 | 0 | 1 |
| | Level 4 | 0 | 1 | 0 | 0 | 1 |
| | Level 5 | 0 | 0 | 0 | 1 | 1 |
| | Level 6 | 4 | 0 | 0 | 3 | 7 |
| Total | | 4 | 1 | 1 | 4 | 10 |

Table 5.34: Chi-square test results on matric home language score and performance in introductory computer programming in Phase 3

| | HOME LANGUAGE SCORE | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|---|
| COMMENTS | Pearson chi-square | 1.837[a] | 6 | .934 |
| | Likelihood Ratio | 2.657 | 6 | .851 |
| | Linear-by-Linear Association | .916 | 1 | .338 |
| | N of Valid Cases | 10 | | |
| VARIABLES | Pearson chi-square | 4.667a | 9 | .862 |
| | Likelihood Ratio | 5.487 | 9 | .790 |
| | Linear-by-Linear Association | .163 | 1 | .686 |
| | N of Valid Cases | 10 | | |
| INPUT INSTRUCTIONS | Pearson chi-square | 4.667a | 9 | .862 |
| | Likelihood Ratio | 5.487 | 9 | .790 |
| | Linear-by-Linear Association | .288 | 1 | .591 |
| | N of Valid Cases | 10 | | |
| OUTPUT INSTRUCTIONS | Pearson chi-square | 3.714a | 6 | .715 |
| | Likelihood Ratio | 4.808 | 6 | .569 |
| | Linear-by-Linear Association | .517 | 1 | .472 |
| | N of Valid Cases | 10 | | |
| PROCESSING INSTRUCTIONS COMMENTS | Pearson chi-square | 21.429a | 9 | .011 |
| | Likelihood Ratio | 14.310 | 9 | .112 |
| | Linear-by-Linear Association | .029 | 1 | .864 |
| | N of Valid Cases | 10 | | |
| TOTAL SCORE | Pearson chi-square | 22.381a | 18 | .216 |
| | Likelihood Ratio | 14.990 | 18 | .663 |
| | Linear-by-Linear Association | .012 | 1 | .913 |
| | N of Valid Cases | 10 | | |

Table 5.35: Chi-square test results on matric first additional language score and performance in introductory computer programming in Phase 3

| FIRST ADDITIONAL LANGUAGE SCORE | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson chi-square | 2.500[a] | 4 | .645 |
| Likelihood Ratio | 3.220 | 4 | .522 |
| Linear-by-Linear Association | 1.412 | 1 | .235 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 3.333a | 6 | .766 |
| Likelihood Ratio | 3.958 | 6 | .682 |
| Linear-by-Linear Association | .018 | 1 | .893 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 3.333a | 6 | .766 |
| Likelihood Ratio | 3.958 | 6 | .682 |
| Linear-by-Linear Association | .062 | 1 | .803 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 1.875a | 4 | .759 |
| Likelihood Ratio | 2.231 | 4 | .693 |
| Linear-by-Linear Association | .370 | 1 | .543 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 6.875a | 6 | .333 |
| Likelihood Ratio | 7.235 | 6 | .300 |
| Linear-by-Linear Association | .007 | 1 | .933 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 12.500a | 12 | .406 |
| Likelihood Ratio | 14.507 | 12 | .270 |
| Linear-by-Linear Association | .039 | 1 | .844 |
| N of Valid Cases | 10 | | |

Table 5.36: Chi-square test results on matric mathematics score and performance in introductory computer programming in Phase 3

| MATHEMATICS SCORE | Value | df | Asymptotic Significance (2-sided) |
|---|---|---|---|
| Pearson chi-square | 7.321[a] | 4 | .120 |
| Likelihood Ratio | 7.719 | 4 | .102 |
| Linear-by-Linear Association | .581 | 1 | .446 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 8.067a | 6 | .233 |
| Likelihood Ratio | 10.044 | 6 | .123 |
| Linear-by-Linear Association | .684 | 1 | .408 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 8.067a | 6 | .233 |
| Likelihood Ratio | 10.044 | 6 | .123 |
| Linear-by-Linear Association | .732 | 1 | .392 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 4.900a | 4 | .298 |
| Likelihood Ratio | 5.545 | 4 | .236 |
| Linear-by-Linear Association | .978 | 1 | .323 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 5.125a | 6 | .528 |
| Likelihood Ratio | 6.051 | 6 | .418 |
| Linear-by-Linear Association | .079 | 1 | .779 |
| N of Valid Cases | 10 | | |
| Pearson chi-square | 10.750a | 12 | .550 |
| Likelihood Ratio | 12.275 | 12 | .424 |
| Linear-by-Linear Association | .291 | 1 | .590 |
| N of Valid Cases | 10 | | |

Tables 5.33 and 5.34 show that high school home language subject high performances lead to a better understanding of the concept of processing instructions, except for cases where participants with an isiZulu indigenous high school home language choice decide to program in the modern English language.

#### 5.3.4.4 Teaching approach and philosophy factors

This section will present the results of the t-tests on the relationship between students' academic performance in introductory programming and the teaching approach and philosophy to which they were subjected. The two tested teaching approaches were the ethnoscience teaching approach in comparison to the conventional teaching approach. The t-test results in Table 5.37 and Table 5.38 show that there is a significant difference between the academic performance of the control group and the experimental group. In fact, the experimental group performed significantly ($p<0.05$) better than the control group with regards to the understanding of the concepts of: variables (mean score of 58.00 out of 60 for the experimental group, and mean score of 37.14 out of 60 for the control group); input instructions (mean score of 38.00 out of 40 for the experimental group, and mean score of 31.43 out of 40 for the control group); processing instructions (mean score of 122.00 out of 150 for the experimental group, and mean score of 24.00 out of 150 for the control group); and overall IPO (mean score of 267.00 out of 300 for the experimental group, and mean score of 111.00 out of 300 for the control group).

Table 5.37: Group statistics for Phase 3 t-test results on the impact of the ethnoscience teaching philosophy on academic performance in introductory programming

| | GRP | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| COMMENTS | CONV. | 5 | 20.00 | 6.124 | 2.739 |
| | EXP. | 5 | 25.00 | .000 | .000 |
| VARIABLES | CONV. | 5 | 26.00 | 19.494 | 8.718 |
| | EXP. | 5 | 58.00 | 4.472 | 2.000 |
| INPUT INSTRUCTIONS | CONV. | 5 | 22.00 | 10.954 | 4.899 |
| | EXP. | 5 | 38.00 | 4.472 | 2.000 |
| OUTPUT INSTRUCTIONS | CONV. | 5 | 19.00 | 5.477 | 2.449 |
| | EXP. | 5 | 24.00 | 2.236 | 1.000 |
| PROCESSING INSTRUCTIONS | CONV. | 5 | 24.00 | 26.077 | 11.662 |
| | EXP. | 5 | 122.00 | 62.610 | 28.000 |
| TOTAL SCORE | CONV. | 5 | 111.00 | 64.265 | 28.740 |
| | EXP. | 5 | 267.00 | 65.727 | 29.394 |

Table 5.38: Independent sample Phase 3 t-test results on the impact of the ethnoscience teaching philosophy on academic performance in introductory computer programming

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | Df | | | | Lower | Upper |
| COMMENTS | Equal variances assumed | 4.571 | .065 | -1.826 | 8 | .105 | -5.000 | 2.739 | -11.315 | 1.315 |
| | Equal variances not assumed | | | -1.826 | 4.000 | .142 | -5.000 | 2.739 | -12.604 | 2.604 |
| VARIABLES | Equal variances assumed | 3.467 | .100 | -3.578 | 8 | .007 | -32.000 | 8.944 | -52.626 | -11.374 |
| | Equal variances not assumed | | | -3.578 | 4.420 | .020 | -32.000 | 8.944 | -55.930 | -8.070 |
| INPUT INSTRUCTIONS | Equal variances assumed | 1.282 | .290 | -3.024 | 8 | .016 | -16.000 | 5.292 | -28.202 | -3.798 |
| | Equal variances not assumed | | | -3.024 | 5.297 | .027 | -16.000 | 5.292 | -29.376 | -2.624 |
| OUTPUT INSTRUCTIONS | Equal variances assumed | 1.282 | .290 | -1.890 | 8 | .095 | -5.000 | 2.646 | -11.101 | 1.101 |
| | Equal variances not assumed | | | -1.890 | 5.297 | .114 | -5.000 | 2.646 | -11.688 | 1.688 |
| PROCESSING INSTRUCTIONS | Equal variances assumed | 2.089 | .186 | -3.231 | 8 | .012 | -98.000 | 30.332 | -167.945 | -28.055 |
| | Equal variances not assumed | | | -3.231 | 5.347 | .021 | -98.000 | 30.332 | -174.471 | -21.529 |
| TOTAL SCORE | Equal variances assumed | .015 | .904 | -3.795 | 8 | .005 | -156.000 | 41.110 | -250.799 | -61.201 |
| | Equal variances not assumed | | | -3.795 | 7.996 | .005 | -156.000 | 41.110 | -250.807 | -61.193 |

## 5.4 Validated Model

The above presented findings are adding value to the existing body of knowledge as a piece of empirical evidence on the veracity of the ethnoscience theory and of Walberg's Theory of Educational Productivity (Figure 5.17 and Figure 5.18) through the partial validation of the following research hypotheses from those two theories:

H1: Students' academic performance is affected by their demographics (accepted for gender, and rejected for the other demographics) (Walberg's Theory of Educational Productivity);

H2: Students' academic performance is affected by their academic background (accepted for Computing and English Home language, and rejected for the other academic background subjects) (Walberg's Theory of Educational Productivity); and

H7: Students' academic performance is affected by the adoption of the ethnocomputing teaching approach (Hypothesis accepted) (Ethnoscience Theory and Walberg's Theory of Educational Productivity).

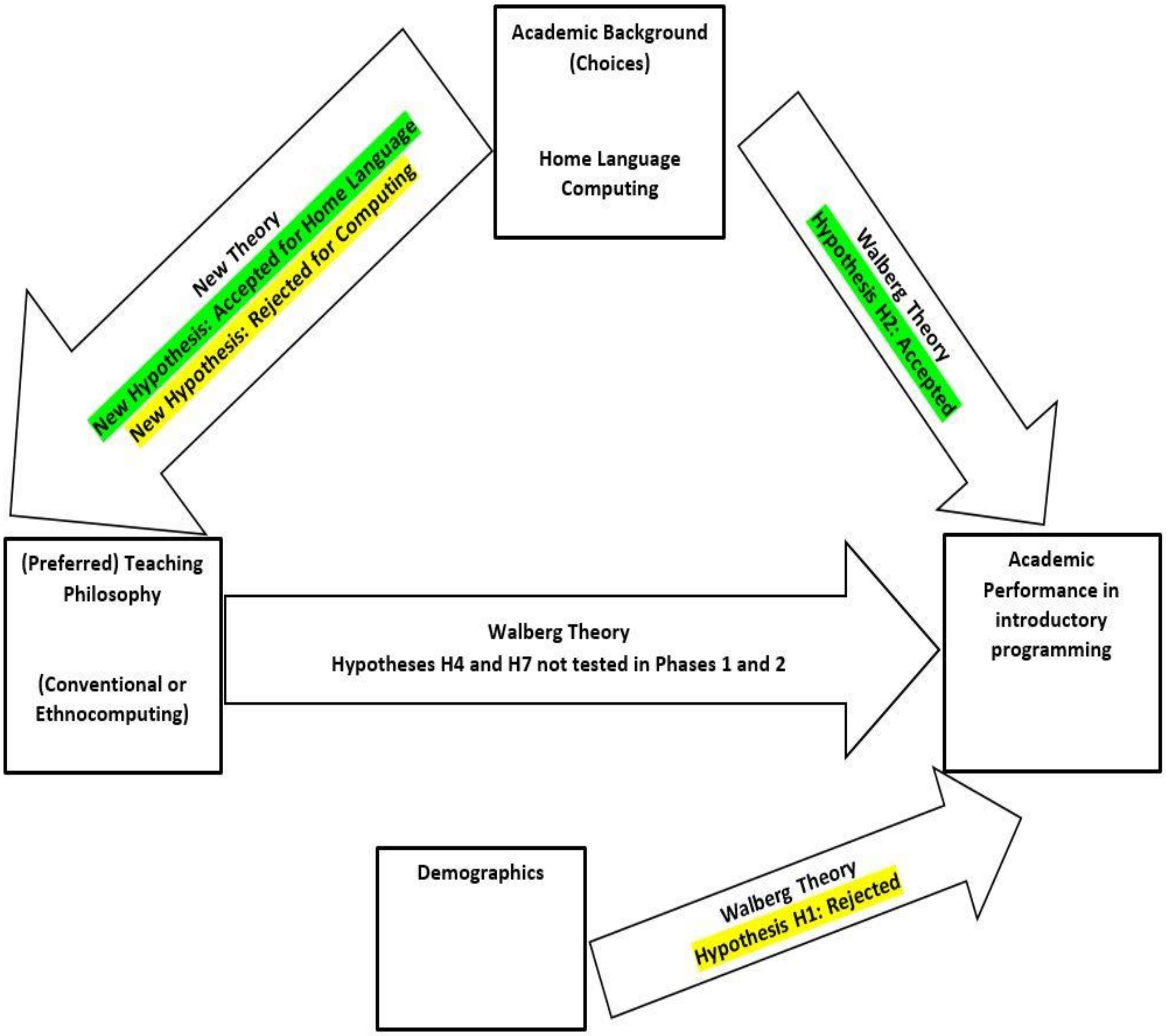


Figure 5.17: Validated Model for Phases 1 and 2

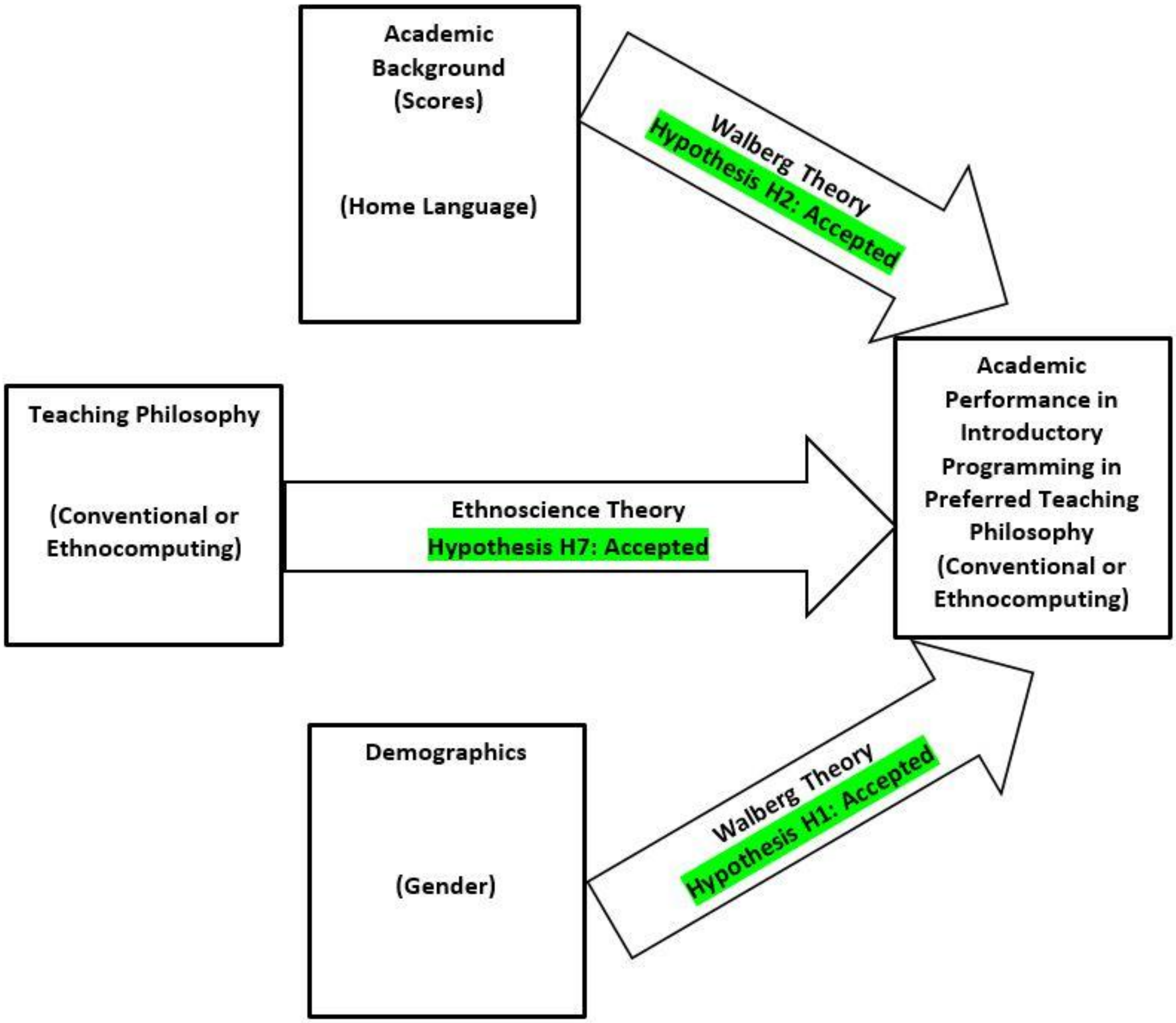


Figure 5.18: Validated Model for Phase 3

## 5.5 Conclusion

The empirical findings of this study can be summarized by the following four main points on the impact of the ethnoscience teaching philosophy on academic performance in introductory computer programming. Firstly, in culturally neutral introductory programming, students who take a computing subject in high school outperform the ones who do not; but the ones with a high school indigenous home language subject perform poorly compared to the ones with a high school English home language subject. Secondly, when the participants of this study were given the choice to program either in the isiZulu indigenous language or in the English modern language, they generally chose to program in the same language that they had for their national high school exit examination home language subject, except for isiXhosa high school home language participants who all chose English as their programming language, even though isiZulu and isiXhosa are two close and mutually understandable languages. Thirdly, after the participants chose to learn to program either in English or in their isiZulu indigenous language, the female gender became stronger than the male gender with regards to the understanding of the concept of output instructions, and students with high scores in their high school indigenous home language subjects also scored high for the understanding of the concept of processing instructions. Finally, after the participants chose to learn to program either in English or in their isiZulu indigenous language, the ethnoprogramming isiZulu group started to outperform the conventional English group on almost all the IPO aspects of introductory programming. A tabular version of this summary of the empirical findings of this study can be found on Table 5.39. The next chapter will discuss these findings in comparison with those from existing empirical studies on the impact of the ethnoscience teaching philosophy on students’ academic performance in introductory programming.

Table 5.39: Summary of the significant correlations empirically found by this study

| Independent Variables | | | Dependent Variable: Performance in introductory programming (IPO Concept) — Phase 1 Culturally Neutral Programming | Phase 2 Choice between Ethno and Culturally Neutral Programming | Phase 3 Ethnoprogramming Versus Culturally Neutral Programming |
|---|---|---|---|---|---|
| Demographics | | Gender | | | √ (Output) |
| | | Age | | | |
| | | Location | | | |
| | | Year | | | |
| Academic Background | Home Language | Choice | √ | √ | |
| | | Marks | | | √ (Proc.) |
| | First Additional Language | Choice | | | |
| | | Mark | | | |
| | Computing | Choice | √ | | |
| | | Mark | | | |
| | Maths Core | Mark | | | |
| Teaching approach | | | | | √ (Var., Inp., Proc., & Total) |

# CHAPTER SIX
# GENERAL CONCLUSION

This is the final chapter of this study on the examination of the influence of the ethnoscience teaching approach on academic performance in introductory programming. In this chapter, the author of this thesis intends to briefly describe how he has achieved the initially set research objectives, and to also briefly compare his study against the current state of the art of research in this field, in order to determine the main contribution of this research. It seems, however, important to start this chapter with a brief summary of the study in order to allow readers to have a general overview of this research without necessarily having to read all the previous chapters. This chapter also identifies the limitations of this study, as well as the list of possible areas for future research on academic performance in introductory programming and on the influence of the ethnoscience teaching approach on academic performance in that field.

## 6.1 Summary of the current study

This summary is brief description of the background, problem statement, research goal, objectives and questions, as well as the methodology and the findings of this study.

**Research background.** STEM fields, in general, and computer programming, in particular, are crucial in this emerging 4IR (Fourth Industrial Revolution) era. In fact, computer programming or coding is seen as one of the most important skills that one can acquire today in this 4IR era because it is the foundation and the key knowledge area for all the other five core “pillars” of the IT curriculum. Computer programming elicits different intrinsic excitement facets and rewards for practitioners, and it also attracts numerous job opportunities around the world despite the fact that it is reputed to be a difficult subject to teach and to learn, especially at the introductory level, due to the fact that it is a very challenging and complex intellectual activity, despite the use of various teaching and learning approaches.

**Research problem, questions and goal.** Failure rates in introductory computer programming are as high as sixty (60) percent or more in many countries all over the world. Countries such as Finland, Brazil, Germany, Portugal and South Africa have the highest failure rates in computer programming in the world. Existing teaching approaches, including the use of visual programming environments, such as Scratch and Alice, the use of media computation and gamification, and the use of a combination of other hybrid teaching interventions, are reported to only be able to improve overall worldwide average pass rates in introductory programming by 16%. The basket of theories on the examination of academic performance in introductory programming is also limited. Similarly, existing teaching approaches also disregard the culturally sensitive teaching methods of introductory computer programming and other STEM subjects. Moreover, students from the African continent are largely underrepresented in the research populations of the existing studies on this problem, and existing studies are also usually silent on types of time horizons, and on reliability and validity methods. Interestingly, culturally sensitive teaching approaches, such as the ethnoscience teaching method, have the proven ability to have improved academic performance in STEM subjects, such as mathematics, chemistry, biology, and even computer programming, for primary and secondary education. This study, therefore, examined the impact of an ethnocomputing teaching approach on the academic performance of higher education students for introductory computer programming with the hope of contributing towards improving academic performance in this difficult but very important subject, because of the crucial role that it is playing in the currently emerging fourth industrial revolution (4IR).

**Methodology.** The research population of this study was made up of the group of IT freshers enrolled in an introduction to programming course at the Durban University of Technology (South Africa) for the year 2018. This study was divided in three phases. In the first phase, volunteering participants were given an introduction to programming test after being instructed with the help of conventional teaching methods in order to examine the influence of their demographics and their academic background on their academic performance in introductory programming in culturally neutral education. In the second phase, volunteering participants were requested to choose their preferred teaching philosophy between the culturally neutral approach and the culturally sensitive one in order to examine the factors influencing their choices. In the third phase, a quasi-experiment was undertaken with the English language being used both as the medium of instruction and as the interface of the programming language for the control group (conventional teaching approach), and the isiZulu language being used as the medium of instruction and as the interface of the programming language for the experimental group (ethnoscience teaching approach). In each of the above described three phases, students' demographics and their academic background were collected from the secondary data of their results for their high school exit examination. The programming tests' results for the first phase and for the third phase constitute the primary data of this study, together with students' choices for a preferred teaching philosophy.

Students' demographics, and their academic background, as reflected by the secondary data on their high academic transcripts, were identified as the two independent variables of this study, even though there was no manipulation of these independent variables. Cronbach alpha coefficients were chosen as the method for the analysis of the reliability of the data of this study, Pearson correlation coefficients were chosen as the method for the analysis of the validity of the data of this study, and frequencies, percentages, and means for descriptive statistics, and chi-square and t-tests for inferential statistics. A post-test was conducted after teaching the control group with the conventional teaching approach and the experimental group with the ethnoscience teaching approach in order to assess the differences between the performances of the two groups.

An analysis of the differences in the academic performance of the two groups was conducted in order to compare and contrast them in the above described post-test, as well as to identify other possible factors that affect their academic performance in introductory programming.

**Main findings.** The current study can roughly be summarized by the following list of findings**.** Academic background (home language subject prior choices and computing subject prior choices) influences academic performance in introductory programming in culturally neutral education**.** Academic background (home language subject prior choices) also influences preferred teaching approaches for introductory programming either as conventional or as ethnoscientific. Finally, it was found that students' demographics (gender, in favour of female students), their academic background (positive influence of home language subject prior marks), and the teaching method (ethnoscience teaching approach significantly better than the conventional one) all have an influence on their academic performance within their preferred teaching philosophy.

## 6.2 Contribution, Discussion, and Future Research

This section is a discussion on the contribution of this study compared to the research gaps from the existing literature as reviewed in chapter 2. Consequently, this section borrows its structure from the one of chapter 2.

### 6.2.1 Prevalence and Contexts of the Reviewed Studies

The research gaps from the existing literature are hereby recalled with regards to the prevalence and the contexts of the reviewed studies as presented in chapter 2 so that the contribution of the current study can be discussed in comparison to the identified gaps.

**Prevalence of the studies.** The literature review conducted in chapter 2 pointed to a research gap on the need for more culturally sensitive research on academic performance in STEM subjects, and on the need for culturally sensitive studies on the factors that affect academic performance in introductory programming. This research has contributed to the decline of that research gap due to the fact that it is precisely a culturally sensitive study on academic performance in STEM subjects, and specifically on the factors that affect academic performance in introductory programming. The above identified research contribution is certainly important, but the literature review presented in chapter 2 highlights that there are still far too many culturally neutral studies on academic performance in STEM subjects, in general, and in introductory programming, in particular. This study has considered language as a cultural asset and it has examined its impact on academic performance in introductory programming. More culturally sensitive studies are also needed to explore introductory programming with regards to other cultural paradigms, such as songs, folktales, proverbs, riddles, figures of speech, oral literature, imitation, drums, gongs, oral narratives, stories, incantations, drama, body movement dances, games and expressive play activities (Plockey, 2015).

**Places and years of publications.** The literature review conducted in chapter 2 pointed to a research gap on the need for more culturally neutral studies on academic performance in introductory programming in Africa and for more recent ones in the world, in general, and on the need for more culturally sensitive studies on academic performance in STEM subjects outside of Africa. This research did not contribute to the decline of this research gap. Instead, it has confirmed that Africa is the place where most culturally sensitive studies on academic performance in STEM subjects are conducted. This is despite the fact that the Intangible Cultural Heritage list from UNESCO shows that the world has a very rich and diverse cultural heritage (UNESCO, 2020). That list describes cultural practices from the entire world, and having Africa as the context of most culturally sensitive studies on academic performance in STEM subjects is surprising, to say the least. In fact, the UNESCO Intangible Cultural Heritage list contains 549 elements corresponding to 127 countries from six world regions. Therefore, more culturally sensitive studies are needed to explore introductory programming with regards to the contexts of other cultural paradigms from other world regions beyond the African continent.

### 6.2.2 Reviewed Theories

The research gaps from the existing literature are hereby recalled with regards to the theories of the reviewed studies as presented in chapter 2 so that the contribution of the current study can be discussed compared to the identified gaps. According to the literature review conducted in chapter 2 on the theoretical backgrounds of the reviewed studies, there is a research gap on the need for culturally sensitive research to identify more theories on the factors that affect academic performance in STEM subjects. This research has contributed to the reduction of this research gap by identifying three theories, namely, ethnoscience theory, Walberg's theory of educational productivity, and self-regulated learning theories as culturally sensitive theories in support of the factors that affect academic performance in introductory programming.  According to Grant and Osanloo (2014), ground studies  on theoretical frameworks in relevant previous works help fit a proposed study into what is already known, and help researchers move from observation to explanation, and provide a blueprint by which all other components of a research study, from methodological design, to data collection plans and interpretation of results are influenced. Therefore, other theories, such as behaviourism theories, social cognitive theories, information processing theories, constructivism theories, cognitive learning processes theories, motivation theories, self-regulation theories and development theories, as reviewed by Bransford et al. (2006), can also be examined by future culturally sensitive research to assess their suitability to determine academic performance in STEM subjects. More culturally sensitive studies are also needed to identify other related theories that are suitable to explore academic performance in STEM subjects.

### 6.2.3 Reviewed Methodologies

The research gaps from the existing literature are hereby recalled with regards to the methodologies of the reviewed studies as presented in chapter 2 so that the contribution of the current study can be discussed compared to the identified gaps.

**Research designs.** The literature review conducted in chapter 2 pointed to a research gap on the need for more qualitative culturally sensitive research on academic performance in STEM subjects. This study did not contribute to the reduction of this research gap. Instead, it has confirmed the fact that most culturally sensitive research on academic performance in STEM subjects are quantitative, as shown by the literature review conducted in chapter 2. This preponderance of quantitative culturally sensitive research on academic performance in STEM subjects deserves to be probed by further research, for example, from the analysis of the advantages (recall features which aid problem-solving, non-numerical primary data, emergence of theory from data, etc.) of qualitative research, despite its disadvantages (generalization concerns, replicability problems, subjectivity, etc.) as presented by Eyisi (2016). The advantages and disadvantages of quantitative research are also contrasted against their qualitative counterparts in the same paper.

**Research strategies.** The literature conducted in chapter 2 pointed to a research gap on the need for more survey-based culturally sensitive research on academic performance in STEM subjects. This study did not contribute to the decrease of this research gap. On the contrary, it has reinforced the viewpoint according to which most culturally sensitive research on academic performance in STEM subjects are experiments, as shown by the literature review conducted in chapter 2. This preponderance of experiments in culturally sensitive research on academic performance in STEM subjects deserves to be probed by further research, for example, from the comparison of the appropriateness of surveys (broadly representative answers to a research question, possibility of short structured questions, high percentage of respondents, etc.) against experiments (focus on causal processes, manipulability of independent variables, controlled conditions, etc.), as presented by Vogt et al. (2012).

**Types of research data.** The literature review conducted in chapter 2 pointed to a research gap on the need for more culturally sensitive studies to analyze secondary data on academic performance in STEM subjects. This research has contributed to the decline of that research gap by analyzing secondary data obtained from students' transcripts consisting of their demographic data, their compulsory subject choices for their national high school exit examination and their grades for that examination. This predominance of primary data in culturally sensitive research on academic performance in STEM subjects deserves to be probed by further research, for example, from the comparison of the advantages of secondary data (large size datasets quickly available at a low cost) against the disadvantages of primary data (time, cost, small datasets, etc.), as presented by Gorard (2010).

**Data collection methods.** The literature conducted in chapter 2 pointed to a research gap on the need for more questionnaire-based culturally sensitive studies on academic performance in STEM subjects. This study did not contribute to the reduction of this research gap. Instead, it has confirmed the fact that most culturally sensitive research on academic performance in STEM subjects are standardized tests-based, as shown by the literature review conducted in chapter 2. This predominance of standardized tests in culturally sensitive research on academic performance in STEM subjects deserves to be probed by further research, for example, from the analysis of the advantages (low cost of administration, time-effectiveness, convenience for respondents; absence of bias, etc.) and disadvantages (poor design, doubts over respondents' competencies, low response rate, etc.) of questionnaire-based research, as presented by Douglas et. al. (2009).

**Types of time horizons.** The literature review conducted in chapter 2 pointed to a research gap on the need for academic performance studies to specify their type of time horizons, both for introductory programming and for STEM subjects. This study did not contribute to the reduction of this research gap. Instead, it has confirmed the fact that none of the reviewed culturally sensitive research on academic performance in STEM subjects specified their types of time horizons. This prevalence of none specification of time horizons' types in culturally sensitive research on academic performance in introductory programming and in STEM subjects deserves to be probed by further research, for example, from the analysis of the advantages (sequencing of events, detection of change over time, correction of the cohort effect, etc.) and disadvantages (non-completion and interruptions, increased temporal and financial demands, etc.) of longitudinal studies, as presented, for example, by Caruana et al. (2015) as well as the cross-sectional studies, as presented by Levin (2006).

**Research Populations.** The literature review conducted in chapter 2 pointed to a research gap on the need for culturally sensitive studies on the academic performance of introductory programming university students. This research has contributed to the decline of that research gap by examining the academic performance of introductory programming university students in the culturally sensitive context. This work can even be extended further by new studies, for example, on various research angles on students, such as the ones reviewed by Luxton-Reilly et al. (2018), which are students' subgroups, their sentiments and their interaction with the learning content. More culturally sensitive studies on the academic performance of introductory programming university students can also be done on students' motivation and engagement, performance and learning approaches, as reviewed by Szabo et al. (2019) for their K-12 counterparts.

**Sample sizes.** The literature review conducted in chapter 2 pointed to a research gap on the need for large sample size culturally sensitive studies on academic performance in STEM subjects. This study did not contribute to the reduction of this research gap. Instead, it has confirmed the fact that most culturally sensitive research on academic performance in STEM subjects have small sample sizes, as shown by the literature review conducted in chapter 2. This prevalence of small sample sizes culturally sensitive research on academic performance in STEM subjects deserves to be probed further, having in mind, for example, the evidence from Evans and Buehner (2011:792) that there is "unequivocal evidence that large samples result in greater accuracy" even though they are sometimes difficult to obtain; and small samples can avoid fatigue, overload and save costs.

**Sampling methods.** The literature review conducted in chapter 2 pointed to a research gap on the need for non-probability sampling culturally sensitive studies on academic performance in STEM subjects. This research has contributed to the decline of that research gap by examining the academic performance of a voluntary sample (a non-probability sampling method) of introductory programming university students in the culturally sensitive context. This predominance of probability sampling culturally sensitive studies on academic performance of introductory programming can be studied more with the following considerations on probability and non-probability sampling methods, as presented by Oribhabor and Anyanwu (undated): systematic errors; bias; representability; generalization; efforts; time consumption; and cost.

**Methods of data analysis.** The literature review conducted in chapter 2 pointed to a research gap on the need for non-parametric culturally sensitive studies on academic performance in STEM subjects. This research has contributed to the decline of that research gap by analyzing data on the academic performance of introductory programming university students using a non-parametric data analysis method. This call for more non-parametric culturally sensitive studies on academic performance in STEM subjects should be considered in line with the following advantages and disadvantages of non-parametric analysis, as presented by Buis (2006). The main advantage of this form of analysis is that many assumptions are not needed, and it is really the data that matters. Its main disadvantage is that it can only compare a limited number of groups, such as males and females, rural versus urban, etc., without the possibility of testing the influence of one variable while controlling others (Buis, 2006).

**Data validity and reliability testing methods.** The literature review conducted in chapter 2 pointed to a research gap on the need for academic performance studies to specify their data validity and reliability testing methods, both for introductory programming and for STEM subjects. This research has contributed to the decline of that research gap by precisely specifying its data validity and reliability testing methods. This research gap can even be reduced further, having in mind that the "importance of validity and reliability is more desired in quantitative than in qualitative research" (Shahi, 2014:96).

### 6.2.4 Academic performance factors

The research gaps from the existing literature are hereby recalled with regards to the academic performance factors of the reviewed studies, as presented in chapter 2 so that the contribution of the current study can be compared to the identified gaps.

**Demographics.** The literature review conducted in chapter 2 pointed to a research gap on the need for academic performance studies on the influence of gender on academic performance, both for introductory programming and for STEM subjects. This research has contributed to the decline of that research gap by examining the influence of gender on academic performance in introductory programming. The literature review conducted in chapter 2 also pointed to a research gap on the need for academic performance studies on the relationship between students' and learners' demographics (beyond the gender factor) and their academic performance in introductory programming and in STEM subjects, in general. This research has also contributed to the reduction of that research gap by examining the influence of other demographic factors, such as age, school location and matriculation exam year on academic performance in introductory programming with none of these factors having any influence on academic performance. This call for more research on the relationship between demographics and academic performance is further supported by Connelly (2013:269) who recommends that demographic data, such as age, gender, ethnicity, and level of education, are an important part of studies that should be examined carefully. Their importance is, for example, visible when assessing the representativeness of a sample by comparing its presented demographics against "what is known from the larger population" (Connelly, 2013:269).

**Academic Background.** The literature review conducted in chapter 2 pointed to a research gap on the need for academic performance studies on the influence of academic background on academic performance in STEM subjects within the culturally sensitive context. This research has contributed to the decline of that research gap by examining the influence of academic background on academic performance in introductory programming. The literature review conducted in chapter 2 also pointed to a research gap on the need for academic performance studies beyond the high school mathematics grades' academic background factor. This research has also contributed to the reduction of that research gap by examining the influence of other academic background factors beyond mathematics, precisely, home language, additional language and computing subjects. Further research on the relationship between academic background and academic performance in STEM subjects, such as introductory programming, can be undertaken within the broader concept of students' background knowledge, as explained by Fisher et al. (2012:23), who assert that "by starting with what students already know, teachers can be more precise in their teaching". According to the same authors, educators first have to identify the core background knowledge that will be needed by students, and attempt to activate it in them. In cases where such knowledge is missing, educators must develop it by using strategies, such as “wide reading, direct experiences, virtual experiences, anticipating misconceptions, […] assessing background knowledge”, and systematic vocabulary instruction (Fisher et al., 2012:24).

**Intellectual Abilities.** The literature review conducted in chapter 2 pointed to a research gap on the need for more research on the influence of intellectual abilities on academic performance in STEM subjects within the culturally sensitive context. This research did not contribute to the reduction of this research gap that can further be examined within the context of the following definition of intelligence by Gottfredson (2004): “the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, earn quickly and learn from experience”. Singh et al. (2017:71) also posit that there are “nine known intelligences at present, including (i) linguistic, (ii) spatial, (iii) logical, (iv) interpersonal, (v) intrapersonal, (vi) naturalistic, (vii) kinesthetic, (viii) musical and (ix) existential”

**Learning Style and Behaviour.** The literature review conducted in chapter 2 pointed to a research gap on the need for research on the influence of learning style on academic performance in STEM subjects within the culturally sensitive context. This research did not contribute to the reduction of this research gap that can be examined by further studies on the effect of learning style on academic performance in introductory programming based on the following nine learning styles from the fourth version of Kolb Learning Style Inventory version 4.0 (KLSI 4.0): The initiating style, The experiencing style, The imagining style, The reflecting style, The analyzing style, The thinking style, The deciding style, The acting style and The balancing style (Kolb and Kolb, 2017).

**Teaching Approach and Philosophy.** The literature review conducted in chapter 2 pointed to a research gap on the need for academic performance studies on the influence of the ethnoscience teaching approach of academic performance beyond mathematics, chemistry, and biology. This research has contributed to the decline of that research gap by examining the influence of the ethnoscience teaching approach on academic performance in introductory programming. The literature review conducted in chapter 2 also pointed to a research gap on the need for more research on other teaching approaches and philosophies beyond the ethnoscience teaching approach for introductory programming and for STEM subjects, in general. However, this study did not contribute to the reduction of this research gap. Instead, it has confirmed the fact that most culturally sensitive research on academic performance in STEM subjects, such has mathematics, chemistry, and biology, only examined the influence of the ethnoscience teaching approach on academic performance, as shown by the literature review conducted in chapter 2. Many more teaching approaches and philosophies can also be researched to determine their influence both in the culturally sensitive and neutral computer programming education, including the following ones identified by Sarpong et al., (2013): Lectures; Explicit teaching; Laboratory practice; Command style teaching; Projects; Teaching by task; e-learning; Problem solving teaching; Seminars and tutorials; Pre-recorded lectures; Field trips; Puzzled-based learning; Continuous assessment and examinations; Pair/group programming; Problem based teaching; and Peer tutoring. Similarly, Jarošová et al., (2017) identified some relevant teaching approaches for MBA courses and lifelong learning programs, such as small group discussion, large group discussion, feedback, interactive lectures, simulations, model situations, case studies, lectures, role-playing, self-assessment questionnaires, oral presentation, reflective methods, exams, knowledge test, short written exercise, and research projects. Other types of teaching methods that can also be researched include the ones identified by Owoc and Hołowińska (2018), namely, lectures, presentations, discussions, group work, cooperative/ collaborative learning, the use of case study method and brainstorming.

**Psychological Strength.** The literature review conducted in chapter 2 pointed to a research gap on the need for research on the influence of psychological strength on academic performance in STEM subjects within the culturally sensitive context. This research did not contribute to the reduction of this research gap that can further be examined in the context of educational psychology research which is defined by Szulevicz and Tanggaard (2017:3) “as a sub-discipline of psychology with a particular focus on the meaning of psychological aspects in pedagogical practices as these are undertaken both within and outside the education system”. The same authors have highlighted supervision, counselling, special needs students, early response and prevention, as some of the key issues to address for the reinforcement of the psychological strength of students.

## 6.3 Verification of research objectives of this study

It seems appropriate to recall the main objectives of this study, as initially presented by chapter one, in order to assess to what extent these objectives have been achieved:

a. To identify the theories that can support the ethnocomputing teaching method as an effective teaching approach for introductory computer programming in higher education;
b. To examine the factors that can affect the influence of the ethnocomputing teaching method on academic performance in introductory programming for a group of African students, and test these factors with a suitable research methodology and design; and
c. To make recommendations on how to improve the use of the ethnocomputing method as a solution to the stubborn problem of academic failure in introductory computer programming in higher education.

The ethnocomputing theoretical model mentioned by the above stated first objective can be found at the end of chapter 3, and a summary of its constructs and theories is available in the first section of this chapter. Similarly, the findings of the empirical test of part of that model are presented in chapter 5 and their summary is presented in the preceding sections.

Overall, the design of a theoretically supported model of the factors affecting students' performance in introductory programming is the main outcome of the literature review conducted by this study on these factors. It is important to note that this model is mainly supported by three theories, namely, Walberg's theory of educational productivity, the self-regulated learning theory and the ethnoscience theory. According to that model, it can be hypothesized that students' performance in introductory programming is influenced by their demographics, academic background, intellectual abilities, learning styles and behaviour, psychological strength and by the teaching approaches and philosophies of their instructors.

## 6.4 Limitations of the current study

This section will highlight the limitations of this study on the influence of the ethnoscience teaching approach on academic performance in introductory computer programming.

- Even though this study has added value to the body of research on the impact of the ethnoscience teaching philosophy on academic performance, the fact that its scope is restricted to the context of introductory computer programming can be seen as a limitation in the sense that similar studies could also be undertaken for other computing subjects, such as databases, networks, algorithm and data structures, etc. Similarly, the fact that the research population of this study is limited to DUT first-year IT freshers enrolled in an introduction to programming course in the 2018 academic year can also be seen as a limitation in the sense that further research can be undertaken not only for freshers, but also for higher level students, including other national and international institutions of higher learning.
- One of the limitations of this study is the volunteering aspect of the assignment of participants to the control group and to the experimental group of the quasi-experiment. Possible future research can, therefore, be undertaken with a

random assignment of participants to these two groups. This is also true for the sample size of the quasi-experiment which is small, and future research can be undertaken with bigger sample sizes.

- Another limitation of this study relates to the fact that the design of its quasi-experiment did not completely rename all the C# keywords from English to isiZulu. Future research can, therefore, be undertaken on how to fully rewrite the interface of a programming language into an indigenous language so that the resulting interface can improve the programming abilities of the natives of that indigenous language.
- Another limitation of the current study relates to the fact that this study was not able to empirically examine the influence of intellectual abilities, learning style and behaviour, and psychological strength on students' academic performance in introductory programming.

## 6.5 Closing remarks

This thesis is concluded by recalling its research problem and by summarizing its research contribution prior to a brief presentation of its challenges.

The problem of academic failure in introductory programming has not yet found a satisfactory answer from the existing literature where several research gaps exists from a theoretical, contextual and methodological perspective, as presented in chapter 1 and recalled at the beginning of the current chapter. From that current state of research, this study made the following summarized contribution to the existing body of research.

This study used a mix of primary and secondary data, and it also used first-year undergraduate students as its research population, as opposed to almost all the reviewed studies on the influence of ethnoscience on academic performance in STEM subjects which used only primary data and secondary school students as their research population. Finally, the literature review conducted in this study found that none of the reviewed studies on the influence of ethnoscience teaching approach on academic performance in STEM subjects focused on programming, and the same literature also found that none of the reviewed studies on the factors affecting academic performance in introductory programming made use of the ethnoscience teaching approach. Therefore, the fact that the current study focuses both on academic performance in introductory programming and on the use of the ethnoscience teaching approach makes it novel compared to the existing body of knowledge on the understanding of academic performance in introductory programming and on the influence of the ethnoscience teaching approach.

This thesis has revealed how the ethnoscience teaching approach can be applied for the purpose of improving students' academic performance in introductory computer programming. Even though this was a very demanding task, it is important to highlight some of the less demanding as well as the more challenging aspects of the development and empirical testing of this teaching approach. Some of the less demanding tasks carried out during the course of this study include the selection of the database (s) for the literature review, the selection of the research population for the experiment, the selection of a sampling method for the assignment of subjects to the control and to the experimental group, the identification of the control group and the experimental group for the quasi-experiment, the selection of data collection method and data sources for the experiment, selection of methods for the analysis of the data of the experiment, choosing the language for the ethnoscience teaching approach, and the exclusion of students with prior programming experience and high academic strength.

However, some of the more challenging tasks include the selection of the studies included in the literature review, estimating the sample size for the control group and for the experimental group, ensuring non-contamination between experimental and control groups, designing the treatment, i.e., the ethnoscience teaching approach which involved translating C# programs written in English into isiZulu, recording the screencasts of digital footages on how to code basic IPO programming patterns for both groups, and analyzing the differences in the academic performance of the experimental and control groups.

# BIBLIOGRAPHY


Abiam, P. O., Abonyi, O. S., Ugama, J. and Okafor, G. 2016. Effects of ethnomathematics-based instructional approach on primary school pupils' achievement in geometry. *Journal of Scientific Research and Reports*: 1-15

Abonyi, O.S., 1999. Effects of an Ethnoscience-based instructional package on students' conception of scientific phenomena and interest in science. Unpublished Ph. D Thesis, University of Nigeria.

Abonyi, O.S., 2002. Effects of ethnoscience-based instructional package on students' interest in science. *Journal of the Science Teachers Association of Nigeria*, *37*(2): 60-68.

Ajayi, V.O., Agamber, T. and Angura, T., 2017. Effect of Gender on Students' Interest in Standard Mixture Separation Techniques Using Ethnochemistry Teaching Approach. *Sky Journal of Educational Research*, *5*(5): 27-33.

Anderl, R. 2014. Industrie 4.0-advanced engineering of smart products and smart production. In: Proceedings of *Proceedings of International Seminar on High Technology*.

Asgari, S. and Baptista Nunes, J. 2011. *Experimental and quasi-experimental research in information systems*. In: IADIS International Workshop Information Systems Research Trends: approaches and methodologies (ISRTAM 2011), 20-26 July, Italy.

Atkinson, R.C. and Shiffrin, R.M., 1968. Some speculations on storage and retrieval processes in long term memory.

Auge, M. 1999. *The War of Dreams: Exercises in Ethno-fiction*. London: Pluto Press.

Babbitt, W., Lachney, M., Bulley, E. and Eglash, R. 2015. Adinkra mathematics: A study of ethnocomputing in Ghana. *Multidisciplinary Journal of Educational Research*, *5*(2): 110-135.

Babbitt, W. E. 2014. Ethnocomputing: The design and assessment of culture-based learning software for math and computing education. Rensselaer Polytechnic Institute.

Banister, E.M., 1999. Women's midlife experience of their changing bodies. *Qualitative Health Research*, *9*(4): 520-537.

Belvedere, V., Chiarini, A. and Grando, A. 2018. The synergic effect of Industry 4.0 technologies on the operations performance. Evidence from Italy. In:

Proceedings of *European, Operations Management Association, Proceedings of the 25th Annual EurOMA Conference. To Serve, To Produce and to Servitize in the Era of Networks, Big Data and Analytics, EurOMA European Operations Management Association, Brussels, Belgium*. 1-7.

Benioff, M. (2016). The AI revolution is coming fast. But without a revolution in trust, it will fail. [online] World Economic Forum. Available at: https://www.weforum.org/agenda/2016/08/thedigital-revolution-is-here-but-without-a- revolution-intrust-it-will-fail/ [Accessed 19 May 2019].

Białoń, L. and Werner, K. 2018. Fourth industrial revolution and managers' cognitive competences. *Marketing Instytucji Naukowych i Badawczych*, 27(1): 81-106.

Bills, D. P. and Biles, J. A. 2005. The role of programming in IT. In: Proceedings of
*Proceedings of the 6th conference on Information technology education*. ACM, 43-49.

Borkowski, J.G., Weyhing, R.S. and Turner, L.A., 1986. Attributional retraining and the teaching of strategies. *Exceptional children*, *53*(2): 130-137.

Bransford, J., Stevens, R., Schwartz, D., Meltzoff, A., Pea, R., Roschelle, J., Vye, N., Kuhl, P., Bell, P., Barron, B. and Reeves, B., 2006. Learning theories and education: Toward a decade of synergy. Handbook of Educational Psychology (2nd Edition)

Brooks, F. 1975. Thy Mythical Man Month, Essays on Software Engineering. *Addison- Wesley, Reading*: 42.

Bryman, A. 2016. *Social research methods*. Oxford university press.

Buis, M.L., 2006. An introduction to survival analysis. *Department of Social Research Methodology Vrije Universiteit Amsterdam*.

Carlson, A., 2020. The Market at the End of History: Literary Structuralism and Canadian Infrastructural Aesthetics.

Caruana, E.J., Roman, M., Hernández-Sánchez, J. and Solli, P., 2015. Longitudinal studies. *Journal of thoracic disease*, *7*(11): 37-40.

Chahine, I.C., 2013. Towards an engaged pedagogy: bell hooks manifesto and the teaching and learning of mathematics. *Global Journal of Human Social Science Linguistics and Education*, 13(10): 23-27.

Chandler, A. D. 1992. Organizational capabilities and the economic history of the industrial enterprise. *Journal of economic perspectives*, 6 (3): 79-100.

Chaparro, E. A., Yuksel, A., Romero, P. and Bryant, S. 2005. Factors Affecting the Perceived Effectiveness of Pair Programming in Higher Education. In: Proceedings of PPIG 2005 Sussex University.

Chaves-Barboza, E., Trujillo-Torres, J.M. and López-Núñez, J.A., 2015. Accomplishments in learning self-regulation in personal environments. *Creative Education*, 6(11): 1108.

Clancey, W.J., 1995. A tutorial on situated learning.

Cohen, L., Manion, L. and Morrison, K. 2013. Approaches to qualitative data analysis. In *Research Methods in Education*. London: Routledge.

Connelly, L.M., 2013. Limitation section. *Medsurg Nursing*, *22*(5): 325.

Considine, R., Tynan, R., James, C., Wiggers, J., Lewin, T., Inder, K., Perkins, D., Handley, T. and Kelly, B. 2017. The contribution of individual, social and work characteristics to employee mental health in a coal mining industry population. *PLoS One*, 12 (1): 16-44.

D'Ambrosio, U., 1977. Science and Technology in Latin-America during Its Discovery. *Impact of Science on Society*, 27(3): 267-274.

D'Ambrosio, U., 1985. A methodology for ethnoscience: The need for alternative epistemologies. Theoria. Revista de Teoria, Historia y Fundamentos de la Ciencia, 1(2): 397-409

D'Ambrosio, U. 1998. Mathematics and peace: Our responsibilities. *ZDM*, 30 (3): 67.

D'Ambrosio, U., 2001. Ethnoscience and ethnomathematics: A historiographical proposal for non-Western science. *Science and Cultural Diversity. Filling a Gap in the History of Science*, 4(1): 37-50.

Dabbagh, N. and Blijd, C.W., 2009. Case designs for ill-structured problems: Analysis and implications for practice. *Journal of Educational Multimedia and Hypermedia*, 18(2): 141-170.

Dehnadi, S., Bornat, R. and Adams, R. 2009. Meta-analysis of the effect of consistency on success in early learning of programming. In *21st Annual Workshop of the Psychology of Programming Interest Group (PPIG). 1-13*.

Dewi, C.A., Khery, Y. and Erna, M., 2019. An ethnoscience study in chemistry learning to develop scientific literacy. *Jurnal Pendidikan IPA Indonesia*, *8*(2): 279-287.

Douglas, K.H., Ayres, K.M., Langone, J., Bell, V. and Meade, C., 2009. Expanding literacy for learners with intellectual disabilities: The role of supported eText. *Journal of Special Education Technology*, *24*(3): 35-44.

Eglash, R., Gilbert, J.E. and Foster, E. 2013. Toward culturally responsive computing education. *Communications of the ACM*, *56*(7): 33-36.

Eglash, R., Krishnamoorthy, M., Sanchez, J. and Woodbridge, A. 2011. Fractal simulations of African design in pre-college computing education. *ACM Transactions on Computing Education (TOCE)*, 11 (3): 17-25.

Eglash, R., Bennett, A., O'donnell, C., Jennings, S. and Cintorino, M. 2006. Culturally situated design tools: Ethnocomputing from field site to classroom. *American anthropologist*, *108*(2): 347-362.

Eggen, P. D., and Kauchak, D. P. 2007. Strategies for teachers: Teaching content and thinking skills (7th ed.). Needham Heights.

Elo, S., Kääriäinen, M., Kanste, O., Pölkki, T., Utriainen, K. and Kyngäs, H., 2014. Qualitative content analysis: A focus on trustworthiness. *SAGE open*, *4*(1): 21-33.

Evans, L. and Buehner, M.J., 2011. Small samples do not cause greater accuracy—but clear data may cause small samples: Comment on Fiedler and Kareev (2006).

Eyisi, D., 2016. The usefulness of qualitative and quantitative approaches and methods in researching problem-solving ability in science education curriculum. *Journal of Education and Practice*, *7*(15): 91-100.

Falkner, N., Sooriamurthi, R. and Michalewicz, Z. 2010. Puzzle-based learning for engineering and computer science. *Computer*, 43 (4): 20-28.

Feigelman, S., 2011. Growth, development, and behavior. *Nelson Textbook of Pediatrics. 19th ed. Philadelphia: Saunders*, 19(1): 48-54.

Fisher, D., Frey, N. and Lapp, D., 2012. Building and activating students' background knowledge: It's what they already know that counts: Teachers must assess and build on the background knowledge students possess. *Middle School Journal*, *43*(3): 22-31.

Forte, A. 2003. Programming for communication: overcoming motivational barriers to computation for all. In: Proceedings of *IEEE Symposium on Human Centric Computing Languages and Environments, 2003. Proceedings. 2003*. IEEE, 285-286.

Gantt, B.J., 2019. Academic Advising Methods and First-Year Full-Time Community College Student Achievement. *Doctoral thesis,* Walden University, Minneapolis, Minnesota.

Gaotlhobogwe, M., Major, T.E., Koloi-Keaikitse, S. and Chilisa, B., 2018. Conceptualizing evaluation in African contexts. *New Directions for Evaluation*, 159: 47-62.

Gaur, A. and Kumar, M. 2018. A systematic approach to conducting review studies: An assessment of content analysis in 25 years of IB research. *Journal of World Business*, *53*(2): 280-289.

Grant, C. and Osanloo, A., 2014. Understanding, selecting, and integrating a theoretical framework in dissertation research: Developing a “blueprint” for your house. *Administrative Issues Journal Education Practice and Research*, 4(2): 12–26.

Gorard, S., 2010. Research design, as independent of methods. *Handbook of mixed methods in social and behavioral research*, 237-252.

Gottfredson, L.S., 2004. Intelligence: is it the epidemiologists' elusive" fundamental cause" of social class inequalities in health?. *Journal of personality and social psychology*, *86*(1): 174-199.
Hariharasudan, A. and Kot, S. 2018. A scoping review on Digital English and Education 4.0 for Industry 4.0. *Social sciences*, 7 (11): 227.

Hess, T.M., 2000. Aging-related constraints and adaptations in social information processing. In *Generative Mental Processes and Cognitive Resources*. Springer, Dordrecht, 129-155.

Hiwatig, A.D.F. 2008. Ethno-Scientific Teaching Approach, Student Proficiency, and Attitude Toward Science and Ethnic Culture*. Education Quarterly*, 66 (1): 3-21.

Hung, D. and Nichani, M.R., 2002. Bringing communities of practice into schools: Implications for instructional technologies from Vygotskian perspectives. *International Journal of Instructional Media*, *29*(2): 171.

Imenda, G.M. 2018. *Exploring foundation phase learners’ understanding of a healthy environment through conceptual change and collateral learning strategies*. *Doctoral dissertation*. University of Zululand.

Jarošová, E., Lorencová, H., Půbalová, K. and Šedivý, L., 2017. Teaching methods in MBA and lifelong learning programmes for managers. *Journal on Efficiency and Responsibility in Education and Science*, 10(3): 86-92.

John-Steiner, V. and Mahn, H., 1996. Sociocultural approaches to learning and development: A Vygotskian framework. *Educational psychologist*, 31(4): 191-206.

Jensen, M. C. 1993. The modern industrial revolution, exit, and the failure of internal control systems. *The Journal of Finance*, 48 (3): 831-880.

Karacay, G. 2018. Talent development for Industry 4.0. In: *Industry 4.0: Managing the Digital Transformation*. Springer, 123-136

Kolb, A.Y. and Kolb, D.A., 2017. Experiential learning theory as a guide for experiential educators in higher education. *Experiential Learning and Teaching in Higher Education*, *1*(1): 7-44.

Kwon, S. and Schroderus, K. 2017. Coding in schools: Comparing integration of programming into basic education curricula of Finland and South Korea. *Finnish Society on Media Education,* Helsinki, Finland.

Laiti, O., 2016. The ethnoprogramming model. In: *Proceedings of the 16th Koli Calling International Conference on Computing Education Research*. ACM, 150-154.

Lantolf, J.P., Thorne, S.L. and Poehner, M.E., 2015. Sociocultural theory and second language development. *Theories in second language acquisition: An introduction*, 1: 207-226.

Lave, J. and Wenger, E., 1991. *Situated learning: Legitimate peripheral participation*. Cambridge university press.

Lerman, S., 2001. Cultural, discursive psychology: A sociocultural approach to studying the teaching and learning of mathematics. *Educational studies in mathematics*, 46(1): 87-113.

Levin, K.A., 2006. Study design III: Cross-sectional studies. *Evidence-based dentistry*, *7*(1): 24-25.

Liesener, K.L., 2017. Cultural competence education in undergraduate athletic training programs. *Theses and Dissertations*. 1658.

Livingston, M. 2016. Qugax̂: An Ethnoscience Analysis of Ancient Unangax̂. *Arctic Anthropology*, 53(2): 81-92.

Lutz, S., and Huitt, W. 2003. Information processing and memory: Theory and applications. *Educational Psychology Interactive*. Valdosta, GA: Valdosta State University.

Luxton-Reilly, A., Albluwi, I., Becker, B.A., Giannakos, M., Kumar, A.N., Ott, L., Paterson, J., Scott, M.J., Sheard, J. and Szabo, C., 2018, July. Introductory programming: a systematic literature review. In *Proceedings Companion of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education*, ITiCSE ’18 Companion, July 2–4, 2018, Larnaca, Cyprus, 55-106.

Malatji, K.J. 2017. *Students' perceptions of the role of the library in their studies at Tshwane University of Technology, Polokwane Campus*. *Doctoral dissertation*. Tshwane University of Technology.

Marion, L. 2001. Digital librarian, cybrarian, or librarian with specialized skills: Who will staff digital libraries? In: *Proceedings of Crossing the Divide: Proceedings of the Tenth National Conference of the Association of College and Research Libraries. Chicago, IL: American Library Association*: 143-149

McCracken, M., Almstrum, V., Diaz, D., Guzdial, M., Hagan, D., Kolikant, Y. B.-D., Laxer, C., Thomas, L., Utting, I. and Wilusz, T. 2001. A multi-national, multi-institutional study of assessment of programming skills of first-year CS students. In: *Proceedings* of *Working group reports from ITiCSE on Innovation and technology in computer science education*. ACM, 125-180.

McCraw, T. K. and Keller, M. 1981. *Regulation in perspective: historical essays*. Boston: Harvard Business School Press.

McClelland, J.L., St. John, M. and Taraban, R., 1989. Sentence comprehension: A parallel distributed processing approach. *Language and cognitive processes*, *4*(3-4): 287-335.

Melyasari, N.S., Sutoyo, S. and Widodo, W., 2018, September. Scientific Literacy Skill of Junior High School Student Using Ethnoscience Based Learning. *Advances in Engineering Research*, 171: 125-128

Merrick, K. E. 2010. An empirical evaluation of puzzle-based learning as an interest approach for teaching introductory computer science. *IEEE Transactions on Education*, 53 (4): 677-680.

Mohorovičić, S. and Strčić, V. 2011. An overview of computer programming teaching methods. In: *Proceedings of XXII Central European Conference on Information and Intelligent Systems*. 1-6.

Muhammad, S.A. 2011. *Effects of inquiry teaching method on academic achievement, retention and attitudes towards chemistry among diploma students of Kano State polytech*nic. *Master’s thesis*, Department of Science Education, Ahmadu Bello University, Zaria.

Murai, S. 2016. “Computer programming seen as key to Japan’s place in ‘fourth industrial revolution’”. *The Japan Times,* [Online]. Available: https://www.japantimes.co.jp/news/2016/06/10/business/tech/computer-programming- industry-seen-key-japans-place-fourth-industrial-revolution/ [Accessed: 15-Jan-2019]

Nuutila, E., Törmä, S. and Malmi, L. 2005. PBL and computer programming—the seven steps method with adaptations. *Computer Science Education*, 15 (2): 123-142.

Onyeneke, A.O., 1996. *Doing sociology: An introduction to sociological perspectives for Africa*. Institute of African Studies, University of Nigeria, Nsukka.

Oribhabor, C.B. and Anyanwu, C.A., Research Sampling and Sample Size Determination: A practical Application.

Ortiz, M. 2012. “Culturally responsive multicultural education”. Education Masters. Paper 289.

Owoc, M. and Hołowińska, K., 2018. Differentiation of supporting methods of business informatics teaching offered by selected educational portals. *Informatyka Ekonomiczna*, 48(2): 54-66.

Park, H. A. 2016. Are we ready for the fourth industrial revolution? *Yearbook of medical informatics*, 25 (1): 1-3.

Peni, H. Y. 2011. Impact of ethnoscience-enriched-instruction on attitude, retention, and performance in basic science among rural and urban students in Kano state, Nigeria. *PhD thesis*, Department of Science Education, Ahmadu Bello University, Zaria.

Plaut, D.C. and Shallice, T., 1994. *Connectionist modelling in cognitive neuropsychology: A case study*. Psychology Press.

Dedzoe-Dzokoto Plockey, F., 2015. Indigenous Knowledge Production, Digital Media and Academic Libraries in Ghana. *Journal of Pan African Studies*, *8*(4).

Potter, W.J. and Levine-Donnerstein, D., 1999. Rethinking validity and reliability in content analysis.

Pressley, M. and Ghatala, E.S., 1990. Self-regulated learning: Monitoring learning from text. *Educational psychologist*, 25(1): 19-33.

Reynolds, A.J. and Walberg, H.J., 1992. A process model of mathematics achievement and attitude. *Journal for research in mathematics education*, 23(4): 306-328.

Rhoads, C. H. 2011. The implications of “contamination” for experimental design in education. *Journal of Educational and Behavioral Statistics*, 36 (1): 76-104.

Rogers, T.T. and McClelland, J.L., 2008. Précis of semantic cognition: A parallel distributed processing approach. *Behavioral and Brain Sciences*, 31(6): 689.

Rosa, M. and Orey, D., 2011. Ethnomathematics: the cultural aspects of mathematics. *Revista Latinoamericana de Etnomatemática: Perspectivas Socioculturales de la Educación Matemática*, 4(2): 32-54.

Sarpong, K.A.M., Arthur, J.K. and Amoako, P.Y.O., 2013. Causes of failure of students in computer programming courses: The teacher-learner Perspective. *International Journal of Computer Applications*, *77*(12): 27-32
Schwab, K. 2016. The fourth industrial revolution (Geneva, World Economic Forum). 4. *Innovation in firms and labour market outcomes*, 145.

Shahi, S., 2014. An experimental investigation of settling velocity of spherical and industrial sand particles in Newtonian and non-Newtonian fluids using particle image shadowgraph.

Shume, T.J. and Blatt, E., 2019. A sociocultural investigation of pre-service teachers’ outdoor experiences and perceived obstacles to outdoor learning. *Environmental Education Research*, 25(9):1347-1367.

Singh, H., 2017. Relationship between leisure-time physical activity and emotional intelligence in female university students: a correlational study. *European Journal of Physical Education and Sport Science*.

Smith, G. and Fidge, C. 2008. On the efficacy of prerecorded lectures for teaching introductory programming. In: Proceedings of *Computing Education 2008. Proc. Tenth Australasian Computing Education Conference (ACE 2008)*. Australian Computer Society, 129-136.

Smith, C.P., 2000. Content analysis and narrative analysis. In Harry T. Reis and Charles M. Judd (Eds): *Handbook of research methods in social and personality psychology*. Cambridge: Cambridge University Press. 313-335.

Snow, A.J., 1972. American Indian Ethno-Science; A Study of the Many Farms Science Project. *Journal of American Indian Education*, 12(1): 5-11.

Sung, K., Hillyard, C., Angotti, R. L., Panitz, M. W., Goldstein, D. S. and Nordlinger, J. 2010. Game-themed programming assignment modules: A pathway for gradual

Szabo, C., Sheard, J., Luxton-Reilly, A., Becker, B.A. and Ott, L., 2019, November. Fifteen years of introductory programming in schools: a global overview of K-12 initiatives. In *Proceedings of the 19th Koli Calling International Conference on Computing Education Research*, 1-9.

Szulevicz, T. and Tanggaard, L., 2017. Approaches and Methods Used in Educational Psychology Practice. In *Educational Psychology Practice*. Springer, Cham. 15-34.

Tedre, M., 2002, May. A Multicultural View on Computer Science. In *IEEE conference ICALT*. 1-5.

UNESCO. 2020. World Heritage Information Kit. Paris: UNESCO.

Varughese, V.K., 2007. Students' Approaches to Learning: A Case Study of Learning Biology in Foundation Studies at the Royal Melbourne Institute of Technology University. RMIT University.

Vihavainen, A., Airaksinen, J. and Watson, C. 2014. A systematic review of approaches for teaching introductory programming and their influence on success. In: Proceedings of *Proceedings of the tenth annual conference on International computing education research*. 7(2):19-26.

Vogt, W.P., Gardner, D.C. and Haeffele, L.M., 2012. *When to use what research design*. Guilford Press.

Vygotsky, L.S., 1978. Socio-cultural theory. *Mind in society*, (6): 52-58.

Walberg, H.J., 1980. A psychological theory of educational productivity.

Watson, C. and Li, F. W. 2014. Failure rates in introductory programming revisited. In: *Proceedings of the 2014 conference on Innovation & technology in computer science education*. ACM, 39-44.

White, D. W. 2014. What is STEM education and why is it important. *Florida Association of Teacher Educators Journal*, 1 (14): 1-9.

Wu, C. T. 2006. *An Introduction to object-oriented programming with Java TM*. New York: McGraw-Hill Incorporated.

Yahaya, A. 2010. Information processing and its implications to teaching and learning. *Unpublished*. Faculty of education: University Technology, Malaysia.

Yoneyama, Y., Matsushita, K., Mackin, K. J., Ohshiro, M., Yamasaki, K. and Nunohiro, E. 2008. Puzzle based programming learning support system with learning history management. In: *Proceedings of the 16th International conference on Computers in Education*: 623-627.

Zimmerman, B.J., 2002. Becoming a self-regulated learner: An overview. *Theory into practice*, 41(2): 64-70.

Zimmerman, B.J. and Martinez-Pons, M., 1990. Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. *Journal of educational Psychology*, *82*(1): 51.

Zimmerman, B.J., 1986. Becoming a self-regulated learner: Which are the key subprocesses?. *Contemporary educational psychology*, *11*(4): 307-313.

# APPENDICES

## APPENDIX A

## CODING SCHEME TABLES FOR THE CONTENT ANALYSIS PRESENTED BY CHAPTER 4

Table A2.1: Coding scheme of the reviewed culturally neutral studies

| Study code | Study | Study code | Study |
|---|---|---|---|
| 1 | Allert 2004 | 21 | Jegede 2009 |
| 2 | Alturki 2016 | 22 | Jones and Burnett 2008 |
| 3 | Ambrosio *et al.* 2014 | 23 | Katz *et al*. 2003 |
| 4 | Bennedsen and Caspersen 2006 | 24 | Katz *et al.* 2006 |
| 5 | Bennedsen and Caspersen 2005 | 25 | Kinnunen and Malmi 2006 |
| 6 | Bergin and Reilly 2005 | 26 | Law *et al.* 2011 |
| 7 | Bergin and Reilly 2006 | 27 | Longi 2016 |
| 8 | Byrne and Lyons 2001 | 28 | McDowell *et al*. 2003 |
| 9 | Buerck *et al.* 2003 | 29 | Norwawi *et al*. 2009 |
| 10 | Campbell and Johnstone 2010 | 30 | Amoako *et al*. 2013 |
| 11 | Cakiroglu 2014 | 31 | Pillay and Jugoo 2005 |
| 12 | Caspersen *et al.* 2007 | 32 | Ranjeet 2011 |
| 13 | Chamillard and Braun 2000 | 33 | Ranjeet 2008 |
| 14 | Cutts *et al.* 2006 | 34 | Rodrigo *et al.* 2009 |
| 15 | Duran 2016 | 35 | Rountree et al. 2002 |
| 16 | Fincher *et al.* 2006 | 36 | Shaw 2012 |
| 17 | Golding *et al.* 2006 | 37 | Sheard *et al.* 2008 |
| 18 | Golding et al. 2009 | 38 | Simon *et al*. 2006 |
| 19 | Goold and Rimmer 2000 | 39 | Su 2008 |
| 20 | Hall *et al.* 2006 | 40 | Bennedsen and Caspersen 2008 |

Table A2.2: Coding scheme of the reviewed culturally sensitive studies.

| Study code | Study |
|---|---|
| 41 | Abiam *et al.* 2016 |
| 42 | Abonyi 1999 |
| 43 | Ajayi *et al.* 2017 |
| 44 | Aktuna 2013 |
| 45 | Achor *et al.* 2009 |
| 46 | Babbitt 2014 |
| 47 | Eglash *et al.* 2013 |

| Study code | Study |
|---|---|
| 48 | Eglash *et al.* 2011 |
| 49 | Ibe and Nwosu 2017 |
| 50 | Odili and Okpobiri 2011 |
| 51 | Okwara and Upu 2017 |
| 52 | Ugwanyi 2015 |
| 53 | Ugwu and Diovu 2016 |
| 54 | Unodiaku 2013 |

Table A2.3: Coding scheme for the theories of the reviewed studies

| Code | Theory |
|---|---|
| 1 | Kolb learning style Theory |
| 2 | Piaget theory of cognitive development |
| 3 | Human cognitive Theory |
| 4 | Davis's theory on knowledge acquisition |
| 5 | Frame theory |

| Code | Theory | Code | Theory |
|---|---|---|---|
| 6 | Self-regulated learning theory | 11 | Constructivism |
| 7 | Motivation theory | 12 | Cognitive evaluation theory |
| 8 | Creativity theory | 13 | Ausubel's subsumption theory |
| 9 | Problem solving theory | 14 | Situated learning theory |
| 10 | Adult learning theory | 15 | Ethnomathematics |
| | | 0 | No theory |

Table A2.4: Coding scheme of the theories for the reviewed culturally neutral studies (V3)

| Code | Theory | Study code |
|---|---|---|
| 0 | No theory | 2,3,6,7,12,13,14,15,17,18,20,21,22,23,24,25,26,27,28,34,35,37,38 |
| 1 | Kolb learning style theory | 1,8,9,10,11,16,19,29,30,31,32 |
| 2 | Piaget theory of cognitive development | 4,5,33,40 |
| 3 | Human cognitive theory | 33 |
| 4 | Davis's theory on knowledge acquisition | 33 |
| 5 | Frame theory | 33 |

| | | |
|---|---|---|
| 6 | Self-regulated learning theory | 36 |
| 7 | Motivation theory | 39 |
| 8 | Creativity theory | 39 |
| 9 | Problem solving theory | 39 |
| 10 | Adult learning theory | 39 |

Table A2.5: Coding scheme of the theories of the reviewed culturally sensitive studies (V3)

| **Code** | **Theory** | **Study code** |
|---|---|---|
| 0 | No theory | 43, 48, 51 |
| 2 | Piaget theory of cognitive development | 42, 49 |
| 11 | Constructivism | 46 |
| 12 | Cognitive evaluation theory | 45 |
| 13 | Ausubel's meaningful learning theory | 47, 52, 53 |
| 14 | Situated learning theory | 47 |
| 15 | Ethnomathematics | 41, 44, 45, 50, 54 |

Table A2.6: Coding scheme for the research designs of the reviewed studies (V4)

| **Code** | **Research design** | **Study code** |
|---|---|---|
| 1 | Quantitative | 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,12, 13, 15, 17, 18, 19, 20, 21, 22, 23, 24, 26, 27, 28, 29, 30, 31, 34, 35, 36, 37, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54 |
| 2 | Mixed (Quantitative and qualitative) | 14, 16, 25,32, 33, 38 |

Table A2.7: Coding scheme for the research strategies of the reviewed studies (V5)

| **Code** | **Research strategies** | **Study code** |
|---|---|---|
| 1 | Survey | 1, 2, 5, 6, 7, 8, 10, 11, 12, 18, 19, 21, 24, 26, 27, 29, 30, 31, 32, 35, 37 |
| 2 | Experiment | 3, 4, 20, 23, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54 |
| 3 | Survey and Experiment | 9, 15, 17, 22, 28, 34, 36 |
| 4 | Survey and Case study | 25 |
| 5 | Experiment and Case study | 13, 33 |
| 6 | Survey, Experiment and Case study | 14, 16, 38 |

Table A2.8: Coding scheme for the types of research data of the reviewed studies (V6)

| **Code** | **Research data** | **Study code** |
|---|---|---|
| 1 | Primary data | 1, 6, 9, 11, 12, 17, 20, 23, 25 ,26, 30, 39, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54 |
| 2 | Secondary data | 3, 13, 24, 40 |
| 3 | Mixed of primary and secondary data | 2, 4, 5, 7, 8, 10, 14, 15, 16, 18, 19, 21, 22, 27, 28, 29, 31, 32, 33, 34, 35, 36, 37, 38 |

Table A2.9: Coding scheme for the data collection methods of the reviewed studies (V7)

| Code | Data collection methods | Study code |
|---|---|---|
| 1 | Questionnaires | 11, 12, 25, 26, 30 |
| 2 | Standardized tests | 3, 13, 23, 20, 24, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54 |
| 3 | Questionnaires and standardized tests | 1, 2, 4, 5, 6, 7, 8, 9, 10, 15, 17, 18, 19, 21, 22, 27, 28, 29, 31, 35, 36, 37, 38, 39 |
| 4 | Questionnaires, standardized tests and interviews | 14, 16 |
| 5 | Interviews and standardized tests | 32, 33 |
| 6 | Observations and standardized tests | 34 |

Table A2.10: Coding scheme for the types of time horizons of the reviewed studies (V8)

| **Code** | **Time horizon** | Study code |
|---|---|---|
| 0 | Not specified | 1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54 |
| 1 | Longitudinal study | 7, 40 |

Table A2.11: Coding scheme for the place of publications of the reviewed culturally neutral studies (V9)

| **Code** | **Place of publication** | **Study code** |
|---|---|---|
| 1 | North America | 1, 9, 13, 17, 18, 20, 23, 24, 28 |
| 2 | Europe | 3, 4, 5, 6, 7, 8, 11, 12, 22, 25, 27, 40 |
| 3 | Asia | 2, 15, 26, 29, 34, 36, 39 |
| 4 | Australia | 10, 14, 16, 19, 35, 37, 38 |
| 5 | Africa | 21, 30, 31, 32, 33 |

Table A2.12: Coding scheme for the place of publications of the reviewed culturally sensitive studies (V9)

| Code | Place of publication | Study code |
|---|---|---|
| 1 | North America | 46, 47, 48 |
| 2 | Europe | 44 |
| 5 | Africa | 41,42, 43, 45, 49, 50, 51, 52, 53, 54 |

Table A2.13: Coding scheme for the years of publication of the reviewed culturally neutral studies (V10)

| Code | Year of publication | Study code |
|---|---|---|
| 1 | 1998-2002 | 8, 13, 19, 35, 27, 30 |
| 2 | 2003-2007 | 1, 4, 5, 6, 7, 9, 12, 14, 16, 17, 20, 23, 24, 25, 28, 31, 38 |
| 3 | 2008-2012 | 10, 18, 21, 22, 26, 29, 32, 33, 34, 36, 37, 39, 40 |
| 4 | 2013-2017 | 2, 3, 11, 15 |

Table A2.14: Coding scheme for the years of publication of the reviewed culturally sensitive studies (V10)

| Code | Year of Publication | Study code |
|---|---|---|
| 1 | 1998-2002 | 42 |
| 3 | 2008-2012 | 45, 48, 50 |
| 4 | 2013-2017 | 41, 43, 44, 46, 47, 49, 51, 52, 53, 54 |

Table A2.15: Coding scheme for the research populations of the reviewed culturally neutral studies (V11)

| Code | Research population | Study Code |
|---|---|---|
| 1 | First year undergraduate students | 3, 4, 5, 6, 7, 8, 9, 10, 12, 13, 14, 16, 17, 18, 19, 21, 22, 23, 24, 28, 29, 30, 31, 32, 33, 34, 38, 39, 40 |
| 2 | Undergraduate students from all levels | 1, 2, 11, 15, 20, 25, 26, 27, 35, 36, 37 |

Table A2.16: Coding scheme for the research populations of the reviewed culturally sensitive studies (V11)

| Code | Research population | Study code |
|---|---|---|
| 3 | Junior secondary school students | 41, 47, 50 |
| 4 | Senior secondary school students | 42, 43, 44, 45, 46, 48, 49, 51, 52, 53, 54 |

Table A2.17: Coding scheme for the sample and sample sizes of the reviewed culturally neutral studies (V12)

| Code | Sample and sample size | Study code |
|---|---|---|
| 1 | Less than 30 students | 3 |
| 2 | 30 – 100 students | 6, 9, 10, 11, 15, 17, 19,22, 23, 29, 30, 31, 32,33 |
| 3 | 101 – 300 students | 1, 2,4,5, 7, 8, 12,14,16,18, 20, 21, 24, 25, 27, 34, 36, 37, 38,39, 40 |
| 4 | 301- 500 students | 26, 35 |
| 5 | 500 – 1500 students | 28 |
| 6 | Above 1500 students | 13 |

Table A2.18: Coding scheme for the sample and sample sizes of the reviewed culturally sensitive studies (V12)

| Code | Sample and sample size | Study code |
|---|---|---|
| 1 | Less than 30 learners | 44, 46, 47, 50 |
| 2 | 30 – 100 learners | 48 |
| 3 | 101 – 300 learners | 42, 43, 45, 49, 52, 53, 54 |
| 4 | 301- 500 learners | 41, 51 |

Table A2.19: Coding scheme for the sampling methods of the reviewed culturally neutral studies (V13)

| Code | Sampling method | Study code |
|---|---|---|
| 0 | Not specified | 1, 2, 3, 4, 5, 6, 7,8, 9,10, 11, 12, 13, 14, 16, 17, 19, 20, 21, 22, 24, 25, 26, 28, 29, 31, 34, 36, 37, 38,39, 40 |
| 1 | Convenience sampling | 18 |
| 2 | Purposive sampling | 30 |
| 3 | Random sampling | 23 |
| 4 | Gibbs sampling | 27 |
| 5 | Self-selected sampling | 35 |
| 6 | Stratified sampling | 15, 32,33 |

Table A2.20: Coding scheme for the sampling methods of the reviewed culturally sensitive studies (V13)

| Code | Sampling method | Study code |
|---|---|---|
| 0 | Not specified | 42, 44, 47, 48, 50, 51, 43, 49 |
| 2 | Purposive sampling | - |
| 3 | Random sampling | 41, 53 |
| 6 | Stratified sampling | 46, 52, 54 |
| 7 | Multi-stage sampling | 45 |

Table A2.21: Coding scheme for the research variables of the reviewed culturally neutral studies (V14)

| Code | Research variable | Study code |
|---|---|---|
| 1 | Demographics | 5, 6, 8, 9, 19, 22, 23, 27, 28, 30 ,31, 35, 37, 40 |
| 2 | Academic background | 1, 2, 4, 5, 6, 7, 8, 13, 15, 19, 21, 22, 23, 24, 27, 30, 31, 35, 37 |
| 3 | Intellectual abilities | 2, 3, 4, 5, 6, 7, 8, 13, 15, 19, 21, 22, 23, 24, 27, 30, 31, 35, 37, 38 |
| 4 | Learning style and behaviour | 1, 7, 8, 9, 10, 11, 16, 19, 23, 25, 29, 32, 34, 36, 38 |
| 5 | Teaching approach and philosophy | 1, 9, 12, 17, 18, 21, 24, 26, 28, 30, 39 |
| 6 | Psychological strength | 2, 7, 17, 18, 19, 20, 21, 22, 24, 25, 26, 27, 35, 37, 39 |

Table A2.22: Coding scheme for the research variables of the reviewed culturally sensitive studies (V14)

| Code | Research variables | Study code |
|---|---|---|
| 1 | Demographics | 42, 43, 49, 52, 53, 54 |
| 3 | Intellectual abilities | 43, 45 |
| 5 | Teaching approach and philosophy | 41, 42, 43, 44, 45, 46, 47, 48, 49 ,50, 51, 52, 53, 54 |
| 6 | Psychological strength | 44, 51 |

Table A2.23: Coding scheme for the methods of data analysis for the reviewed studies (V15)

| Code | Method of data analysis | Study code |
|---|---|---|
| 1 | Non-parametric | 5, 9, 25, 29, 35, 38 |
| 2 | Parametric | 1,2, 3, 4, 6, 7, 8,10, 11,12, 13, 14, 15,16, 17, 18,19, 20,21, 23, 26, 27, 28,30, 31,32,33,34,39,40, 41, 42, 43, 44, 45, 46, 47, 48, 49 ,50, 51, 52, 53, 54 |
| 3 | Parametric and non-parametric | 22, 24,36, 37 |

Table A2.24: Coding scheme for the data validity test methods of the reviewed culturally neutral studies (V16)

| Code | Validity test method | Study code |
|---|---|---|
| 0 | None | 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 21, 22, 23, 24, 25, 28, 29, 30, 31, 32, 33, 34, 35, 37, 38, 39 |
| 1 | Pearson's correlation coefficients | 12, 20, 27, 40 |
| 2 | Exploratory factor analysis | 26, 36 |

Table A2.25: Coding scheme for the data validity test methods of the reviewed culturally sensitive studies (V16)

| Code | Validity Test method | Study code |
|---|---|---|
| 0 | None | 41, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54 |
| 2 | Exploratory factor analysis | 42 |

Table A2.26: Coding scheme for the reliability tests methods of the reviewed culturally neutral studies (V17)

| Code | Reliability test | Study |
|---|---|---|
| 0 | None | 2, 3, 4, 5, 6, 8, 9, 12, 13,14,15,16, 17, 19, 20, 21, 22, 24, 25, 27, 28, 29,30, 31, 32, 33, 34,35, 37, 38,39, 40 |
| 1 | Cohen's kappa coefficient | 23 |
| 2 | Cronbach’s alpha coefficient | 7, 11, 18, 26, 36 |
| 3 | Test/re-test approach | 1, 10 |

Table A2.27: Coding scheme for the reliability tests methods of the reviewed culturally sensitive studies (V17)

| Code | Reliability test | Study code |
|---|---|---|
| 0 | None | 44, 46, 47, 48, 49 ,50 |
| 1 | Cohen's kappa coefficient | 45, 51, 54 |
| 2 | Cronbach’s alpha coefficient | 52, 53 |
| 3 | Test/re-test approach | 41, 43, 42 |

Table A2.28: Coding scheme for the research findings of the reviewed studies both for culturally neutral and culturally sensitive studies (V18)

| Code | Key research findings |
|---|---|
| 1 | No correlation |
| 2 | Negative correlation |
| 3 | Positive correlation |
| 4 | Inconclusive |

Table A2.29: Coding scheme for the research findings of the reviewed neutral studies on the relationship between academic background (V14: 2) and performance (V18)

| Code | Key research findings | Study code |
|---|---|---|
| 1 | No correlation | 6,7,8,22,27,31,35,37 |
| 2 | Negative correlation | - |
| 3 | Positive correlation | 4,5,6,7,8,13,15,19,21,24,30,31,35,37,38 |
| 4 | Inconclusive | 1, 2 |

Table A2.30: Coding scheme for the research findings of the reviewed neutral studies on the relationship between intellectual abilities (V14: 3) and academic performance (V18)

| Code | Key research findings | Study code |
|---|---|---|
| 1 | No correlation | 4,20,25, 39,40 |
| 2 | Negative correlation | 1, 23 |
| 3 | Positive correlation | 6,14,16,19,22,23,30,31,38,39 |
| 4 | Inconclusive | 2,3,33 |

Table A2.31: Coding scheme for the research findings of the reviewed neutral studies on the relationship between learning style and behaviour (V14: 4), and academic performance (V18)

| Code | Key research findings | Study code |
|---|---|---|
| 1 | No correlation | 7,9,19,25,30 |
| 2 | Negative correlation | 23 |
| 3 | Positive correlation | 23,30,31,35 |
| 4 | Inconclusive | 8,10,11,16,29,32,34,36,38 |

Table A2.32: Coding scheme for the research findings of the reviewed neutral studies on the relationship between teaching approach/philosophy (V14: 5) and academic performance (V18)

| Code | Key research findings | Study code |
|---|---|---|
| 1 | No correlation | 9,12,18 |
| 2 | Negative correlation | - |
| 3 | Positive correlation | 17,21,24,26,30,39 |
| 4 | Inconclusive | - |

Table A2.33: Coding scheme for the research findings of the reviewed neutral studies on the relationship between psychological strength (V14: 6) and academic performance (V18)

| Code | Key research findings | Study code |
|---|---|---|
| 1 | No correlation | 7,17,18,24,25,27,37 |
| 2 | Negative correlation | 19 |
| 3 | Positive correlation | 2,7,17,20,21,22,24,26,27,35,39 |
| 4 | Inconclusive | 3,27 |

The meaning of the variables V1, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13, V14, V15, V16, V17, and V18 can be found on Table A2.30.

Table A2.34: Coding of the entire studies under review

| V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 | V9 | V10 | V11 | V12 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 1 | 3 | 0 | 1 | 2 | 2 | 3 |
| 2 | 2 | 0 | 1 | 1 | 3 | 3 | 0 | 3 | 4 | 2 | 2 |
| 3 | 3 | 0 | 1 | 2 | 2 | 2 | 0 | 2 | 4 | 1 | 1 |
| 4 | 4,5 | 2 | 1 | 2 | 3 | 3 | 0 | 2 | 2 | 1 | 2 |
| 5 | 4,5 | 2 | 1 | 1 | 3 | 3 | 0 | 2 | 2 | 1 | 2 |
| 6 | 6,7 | 0 | 1 | 1 | 1 | 3 | 0 | 2 | 2 | 1 | 2 |
| 7 | 6,7 | 0 | 1 | 1 | 3 | 3 | 1 | 2 | 2 | 1 | 3 |
| 8 | 8,9 | 1 | 1 | 1 | 3 | 3 | 0 | 2 | 1 | 1 | 3 |
| 9 | 10 | 1 | 1 | 3 | 1 | 3 | 0 | 1 | 2 | 1 | 2 |
| 10 | 11,12 | 1 | 1 | 1 | 3 | 3 | 0 | 4 | 3 | 1 | 2 |
| 11 | 13 | 1 | 1 | 1 | 1 | 3 | 0 | 2 | 4 | 2 | 2 |
| 12 | 14 | 0 | 1 | 1 | 1 | 1 | 0 | 2 | 2 | 1 | 3 |
| 13 | 15,16 | 0 | 1 | 5 | 2 | 2 | 0 | 1 | 1 | 1 | 6 |
| 14 | 17 | 0 | 2 | 6 | 3 | 4 | 0 | 4 | 2 | 1 | 3 |
| 15 | 18 | 0 | 1 | 3 | 3 | 3 | 0 | 3 | 4 | 2 | 2 |
| 16 | 19 | 1 | 2 | 6 | 3 | 4 | 0 | 4 | 2 | 1 | 3 |
| 17 | 20 | 0 | 1 | 3 | 1 | 3 | 0 | 1 | 2 | 1 | 2 |
| 18 | 20 | 0 | 1 | 1 | 3 | 3 | 0 | 1 | 3 | 1 | 3 |
| 19 | 32, 33 | 1 | 1 | 1 | 3 | 3 | 0 | 4 | 1 | 1 | 2 |
| 20 | 34 | 0 | 1 | 2 | 1 | 2 | 0 | 1 | 2 | 2 | 3 |
| 21 | 21 | 0 | 1 | 1 | 3 | 3 | 0 | 5 | 3 | 1 | 3 |
| 22 | 22,23 | 0 | 1 | 3 | 3 | 3 | 0 | 2 | 3 | 1 | 2 |
| 23 | 24 | 0 | 1 | 2 | 1 | 2 | 0 | 1 | 2 | 1 | 2 |
| 24 | 24 | 0 | 1 | 1 | 2 | 2 | 0 | 1 | 2 | 1 | 3 |
| 25 | 25,26 | 0 | 2 | 4 | 1 | 1 | 0 | 2 | 2 | 2 | 3 |
| 26 | 27 | 0 | 1 | 1 | 1 | 1 | 0 | 3 | 3 | 2 | 4 |
| 27 | 28 | 0 | 1 | 1 | 3 | 3 | 0 | 2 | 1 | 2 | 3 |
| 28 | 29 | 0 | 1 | 3 | 3 | 3 | 0 | 1 | 2 | 1 | 5 |
| 29 | 30 | 1 | 1 | 1 | 3 | 3 | 0 | 3 | 3 | 1 | 2 |
| 30 | 31 | 1 | 1 | 1 | 1 | 1 | 0 | 5 | 1 | 1 | 2 |
| 31 | 35,36 | 1 | 1 | 1 | 3 | 3 | 0 | 5 | 2 | 1 | 2 |
| 32 | 37 | 1 | 2 | 1 | 3 | 5 | 0 | 5 | 3 | 1 | 2 |
| 33 | 37 | 2 | 2 | 5 | 3 | 5 | 0 | 5 | 3 | 1 | 2 |
| 34 | 38 | 0 | 1 | 3 | 3 | 6 | 0 | 3 | 3 | 1 | 3 |
| 35 | 39 | 0 | 1 | 1 | 3 | 3 | 0 | 4 | 1 | 2 | 4 |
| 36 | 40 | 6 | 1 | 3 | 3 | 3 | 0 | 3 | 3 | 2 | 3 |
| 37 | 41 | 0 | 1 | 1 | 3 | 3 | 0 | 4 | 3 | 2 | 3 |
| 38 | 42 | 0 | 2 | 6 | 3 | 3 | 0 | 4 | 2 | 1 | 3 |
| 39 | 43 | 7,8,9,10 | 1 | 2 | 1 | 3 | 0 | 3 | 3 | 1 | 3 |
| 40 | 4,5 | 2 | 1 | 2 | 2 | 2 | 1 | 2 | 3 | 1 | 3 |

Table A2.35: Coding of the entire studies under review (Continued)

| V1 | V13 | V14 | V15 | V16 | V17 | V18 |
|---|---|---|---|---|---|---|
| 1 | 0 | 2, 3, 4 | 2 | 0 | 3 | 4, 2, 4 |
| 2 | 0 | 2, 3, 6 | 2 | 0 | 0 | 4, 4, 3 |
| 3 | 0 | 3, 3, 6, 3 | 2 | 0 | 0 | 4, 4, 4, 4 |
| 4 | 0 | 3,2 | 2 | 0 | 0 | 1,3 |
| 5 | 0 | 2,1 | 1 | 0 | 0 | 3,1 |
| 6 | 0 | 3,2,3,1,3,2,2,2 | 2 | 0 | 0 | 3,3,3,1,3,3,1,3 |
| 7 | 0 | 2,6,6,4,2 | 2 | 0 | 2 | 3,3,1,1,1 |
| 8 | 0 | 1,4,2,2 | 2 | 0 | 0 | 4,4,3,1 |
| 9 | 0 | 4,5,1 | 1 | 0 | 0 | 1,1,1 |
| 10 | 0 | 4 | 2 | 0 | 3 | 4 |
| 11 | 0 | 4 | 2 | 0 | 2 | 4 |
| 12 | 0 | 5 | 2 | 1 | 0 | 1 |
| 13 | 0 | 2,2,2 | 2 | 0 | 0 | 3,3,3 |
| 14 | 0 | 3 | 2 | 0 | 0 | 3 |
| 15 | 6 | 2 | 2 | 0 | 0 | 3 |
| 16 | 0 | 4,3,3,3,3 | 2 | 0 | 0 | 4,3,3,3,3 |
| 17 | 0 | 5,6,6,6,6,6 | 2 | 0 | 0 | 3,1,3,3,3,1 |
| 18 | 1 | 5,6,5 | 2 | 0 | 2 | 1,1,3 |
| 19 | 0 | 4,3,1,6,2,3,2,3,2 | 2 | 0 | 0 | 1,3,3,2,3,3,3,3,1 |
| 20 | 0 | 3,6,6 | 2 | 1 | 0 | 1,3,3 |
| 21 | 0 | 6,2,2,5 | 2 | 0 | 0 | 3,3,3,3 |
| 22 | 0 | 3,6,6,6,1,2,3 | 3 | 0 | 0 | 3,3,3,3,1,1,2 |
| 23 | 3 | 4,4,4,3,3,2,1,1 | 2 | 0 | 1 | 3,2,2,2,3,3,3,3 |
| 24 | 0 | 2,2,5,6,6,6,6,6,6 | 3 | 0 | 0 | 3,3,3,1,1,3,3,3,3 |
| 25 | 0 | 4,6,3 | 1 | 0 | 0 | 1,1,1 |
| 26 | 0 | 6,5 | 2 | 2 | 2 | 3,3 |
| 27 | 4 | 1,1,2,6,6,6,6,6,6 | 2 | 1 | 0 | 1,1,1,1,3,4,3,3,1 |
| 28 | 0 | 1,5 | 2 | 0 | 0 | 1,3 |
| 29 | 0 | 4 | 1 | 0 | 0 | 4 |
| 30 | 2 | 1,4,3,5,5,4,4,2 | 2 | 0 | 0 | 3,3,3,3,3,1,1,3 |
| 31 | 0 | 1,2,2,4,3 | 2 | 0 | 0 | 3,3,1,4,3 |
| 32 | 6 | 4 | 2 | 0 | 0 | 4 |
| 33 | 6 | 3 | 2 | 0 | 0 | 4 |
| 34 | 0 | 4 | 2 | 0 | 0 | 4 |
| 35 | 5 | 2,2,1,1,6,2,4 | 1 | 0 | 0 | 1,3,2,2,3,4,3 |
| 36 | 0 | 4,4 | 3 | 2 | 2 | 4,4 |
| 37 | 0 | 1,1,2,2,2,6,6,1 | 3 | 0 | 0 | 2,3,1,1,3,1,1,3 |
| 38 | 0 | 3,2,4,,3,3 | 1 | 0 | 0 | 3,3,4,3,3 |
| 39 | 0 | 1,1,6,3,3,5 | 2 | 0 | 0 | 4,3,3,1,3,3 |
| 40 | 0 | 3 | 2 | 1 | 0 | 1 |

Table A2.36: Coding of the entire studies under review (Continued and end)

| V1 | V2 | V3 | V9 | V10 | V11 | V12 | V13 | V14 | V17 | V18 |
|---|---|---|---|---|---|---|---|---|---|---|
| 41 | 44 | 15 | 5 | 4 | 3 | 4 | 3 | 5 | 3 | 3 |
| 42 | 45 | 2 | 5 | 1 | 4 | 3 | 0 | 1,5 | 3 | 1,3 |
| 43 | 46 | 0 | 5 | 4 | 4 | 3 | 2 | 1,3,5 | 3 | 1,3,3 |
| 44 | 47 | 15 | 2 | 4 | 4 | 1 | 0 | 5,6 | 0 | 3,3 |
| 45 | 48 | 12,15 | 5 | 3 | 4 | 3 | 7 | 5 | 3 | 3 |
| 46 | 49 | 11 | 1 | 4 | 4 | 1 | 6 | 5 | 0 | 3 |
| 47 | 50 | 13,14 | 1 | 4 | 3 | 1 | 0 | 5 | 0 | 3 |
| 48 | 50 | 0 | 1 | 3 | 4 | 2 | 0 | 5 | 0 | 3 |
| 49 | 51,52 | 2 | 5 | 4 | 4 | 3 | 2 | 1,5 | 0 | 1,3 |
| 50 | 53,54 | 15 | 5 | 3 | 3 | 2 | 0 | 5 | 0 | 3 |
| 51 | 55,56 | 0 | 5 | 4 | 4 | 4 | 0 | 5,6 | 2 | 3,3 |
| 52 | 57 | 13 | 5 | 4 | 4 | 3 | 6 | 1,5 | 2 | 1,3 |
| 53 | 58,59 | 0 | 5 | 4 | 4 | 3 | 3 | 1,5 | 2 | 1,3 |
| 54 | 60 | 15 | 5 | 4 | 4 | 3 | 6 | 1,5 | 0 | 3,3 |

V4=1; V5=2; V6=1; V7=3; V8=0; V15=2; V16=0 except for study no 42 whose value is 2 for V16

Table A2.37: Meanings of the variables V1, V2, V3, V4, V5, V6, V7, V8, V9, V10, V11, V12, V13, V14, V15, V16, V17, and V18.

| Variable | Meaning |
|---|---|
| V1 | Studies' codes |
| V2 | Authors' codes |
| V3 | Theories' codes |
| V4 | Research designs' codes |
| V5 | Research strategies' codes |
| V6 | Types of research data codes |
| V7 | Data collection methods codes |
| V8 | Types of times horizons' codes |
| V9 | Places of publication's codes |
| V10 | Years of publication's codes |
| V11 | Research populations' codes |
| V12 | Samples and Samples sizes' codes |
| V13 | Sampling methods' codes |
| V14 | Research variables' codes |
| V15 | Codes of the data analysis methods |
| V16 | Validity testing methods' codes |
| V17 | Reliability testing methods' codes |
| V18 | Inferential findings' codes |