MULTILEVEL ANALYSIS OF ACADEMIC PERFORMANCE IN GRADE 12 STEM SUBJECTS, IN SECONDARY SCHOOLS IN NAMIBIA.

A MINI THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN (APPLIED STATSISTICS AND DEMOGRAPHY)

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**ABSTRACT**

According to Francesco and Nicole (2015), the fourth goal of the United Nations Sustainable Development Goals (SDGs) aims “to ensure inclusive and quality education and promote lifelong learning for all learners to have access to education” by 2030 to facilitate literacy and numeracy equal opportunities. High-quality STEM education is a global prerequisite for individual development and participation in a technology-driven world, no wonder the need to focus on education programs on science and technology. Skills such as critical thinking, problem solving and the ability to innovate are increasingly important for openly embracing change and responsibly shaping the future.

The aim of the study was to examine the relationships between academic achievement and demographic variables and socio-economic variables and to what extent students’ factors; teacher’s factors and school factors affect the students’ academic performance in STEM subjects in secondary schools in Namibia. Using a hierarchically built data of 24407 students nested in 190 schools and a series of two-level multilevel model were explored to determine predictors of academic performance. The AIC established the balance between accuracy of model and its complexity. The model that had the lowest AIC was considered the best. The Intra Class Correlation (ICC =0.169) indicated remarkable clustering of the number of STEM subjects passed within centres. The findings indicated that, the school type were not significant to the study. Teachers with and without formal education were found with a negative significant toward STEM subjects The study further established that, number of classrooms, number of media or resource centres, students’ age and students’ sex, were found to be significantly related to students' STEM subjects passed. Based on findings, the study recommends that, there is a need for a comprehensive concept that addresses several dimensions of proper coordination and management school environments to ensure that students are equipped with the necessary resources in terms of large numbers of students in classroom, learning facilities and ensure qualified teachers are employed.

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## Abbreviations / Acronyms

| | |
|---|---|
| AIC | Akaike Information Criterion |
| AIDS | Acquired Immunodeficiency Syndrome |
| ANOVA | Analysis of variance |
| BIC | Bayesian Information Criterion |
| DNEA | Directorate of National Examinations and Assessment |
| ELL | English Language Learners |
| FML | Full Maximum Likelihood |
| HIV | Human Immunodeficiency Virus |
| ICC | Intra Class Correlation |
| MOE | Ministry of Education |
| MOEAC | Ministry Of Education, Arts and Culture |
| NQF | National Qualifications Framework |
| NRC | National Research Council |
| NSF | National Sanitation Foundation |
| NSSCAS | Namibian Senior Secondary Certificate Advanced Subsidiary |
| NSSCO | Namibia Senior Secondary Certificate Ordinary Level |

| | |
|---|---|
| OLS | Ordinary least squares |
| PCAST | President's Council of Advisors on Science and Technology |
| PISA | Program for International Student Assessment |
| REML | Restricted Maximum Likelihood |
| SCCT | Social Cognitive Career Theory |
| SDG4 | Sustainable Development Goal 4 |
| SES | Social Economic Status |
| SPSS | Statistical Package for the Social Sciences |
| STEM | Science, Technology, Engineering and Mathematics |
| TIMSS | Trends in International Mathematics and Science Study |
| UN | United Nations |
| USA | United States of America |
| WEF | World Economic Forum |

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## Dedications

This thesis is dedicated to Taimi Nelago Ndeutapo and my daughter Kristine Etuhole Tsenaye Makili and I hope it will serve a motivation to them to take their studies seriously.

**Declaration**

I, Ester Komotolo, hereby declare that this is my own work and is a true reflection of my research, and that this work has not been submitted for a degree at any other institution.



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# CHAPTER 1: INTRODUCTION

## 1.1. Background of the study

The Science education system has become an international topic of discussion over the past decade and a vital pillar of a country's development, which is driven by the changing global economy and workforce. Education is one of the most powerful tools to prepare a workforce that will improve national economies, reduce poverty and sustain leadership within the constantly ever-changing and expanding economy (Kelley and Knowles, 2016, p. 2).

Educated people will be able to accomplish their desired objectives and goals as well as render efficient contribution towards the community well-being by providing employment or other necessities which will enhance the economic growth of a country. Moreover, in the US, (President Obama's Council of Advisors on Science and Technology [PCAST], 2010) expressed the requirement for countries to advocate at all levels to transform Science, Technology, Engineering, and Mathematics (STEM) education and establish the framework for a nation progress. These deliberations consist of:

a) **STEM subjects tend to be highly cumulative and sequential** - if students are faced with difficulty in understanding the content at early stage my struggle down the road, especial in mathematics since each step is interdependent. However, the teachers need to play their roles to enhance students understanding and achievement. This means, teacher should have full background knowledge of the subject.

b) **STEM knowledge is specialized** - mastering of STEM subject can be challenging for the student and qualified teachers' at all level need to have a deep content knowledge to be able to elucidate the basic concept well.

c) **STEM knowledge is rapidly changing** - STEM fields are ever-widening and with the rapid change in technology present remarkable opportunities for engaging students by explorations and investigations.

Moloko, Mphale and Mhlauli (2014) believed that education is an advocate for human development and the transformer of today's society. Additionally, the ability to educate today's students in STEM will help to nurture the county's future. Lai (2018) urged the nations to focus on the STEM programs in order to guide students to develop their ability to assimilate interdisciplinary knowledge, inspiring their interest in STEM and help them to develop abilities needed for students to solve real-world problems and adapting into the ever-changing modern society as well as future employment.
Like other nations within the world, Namibia will operate a totally integrated, unified, flexible and top quality and training system, including advanced Science and technology (Stability, 2004).

"STEM is an integrated education that combines scientific inquiry, technology, engineering design, and mathematical analysis into a cohesive learning paradigm, including curriculum content, teaching activities, and educational policy" (Lai, 2018). According to Ministry of Education [MOE] (2009) STEM education in Namibia covers following subjects; Biology, Chemistry, Physics, Agricultural science, Design and technology, Mathematics, Computer studies and Geography.

Researchers have instigated the common policies of inclusive STEM colleges via working leadership to apprehend and synthesize the work they do. English (2016) added that, a lot of nations talk to STEM education jointly with the motive of their school, to lift science education from elementary to secondary curricula. Duarte, Jankowski, Tillotson and Wilson (2018), believed that, improving STEM education at the first level will change the balance in the future. Duarte et al (2018) argued that, in order to improve STEM education in Namibia, the standard of primary education must be improved by enhancing teacher's education and training. Continuous professional development should be essential for ensuring that teachers keep up with new information and course materials.

According to Emmanuel (2019), school is an institution established to provide learning spaces and environment for the teaching and learning with the aim of inculcating morals into the learners under the support of teachers. The secondary education, as specified in the national policy of education, is to prepare students for useful living in the society and a fundamental role in the development of human capital [MOE, 2009].

The Namibia basic education system is sub-divided into 4 phases, namely junior primary (Pre-Primary and grades 1-3), senior primary (4-7), junior secondary (8-9) and senior secondary phase (10-12). Phase 1 focused more on literacy, numerical and broad knowledge of the immediate environment. The second phase consolidated the foundation laid at phase one and develop it further. Grade 4 focused on the mathematics, natural and social science as well as the moral and physical education while the grade 5 -7 intensified HIV and AIDS as well as the entrepreneurial skills. The third phase provided learners with the opportunity to explore wider range of subjects to enable them to make an informed decision for future career choice and the last phase consolidated the absorbed decision so that learners continue in lifelong learning Ministry of Education, Arts and Culture, [MoEAC] (2016)

The senior secondary level is the final phase for basic education in Namibia ([MoE], 2010). This is a crucial stage for many Namibians, as it determines whether a student qualifies for university entry or not. Grade 12 prepares learners for higher education upon completion of the final examination. Furthermore, learners will have an internationally recognized certificate known as the Namibian Senior Secondary Certificate Advanced Subsidiary (NSSCAS) level which gave them access to higher education institutions with NQF level 4 entry requirements. For a learner to qualify for the NSSCO group, the learner must have a minimum of 6 subjects. Out of the 6 subjects, English and one additional language of the learners' choice as is compulsory.

Admission requirements for higher learning institutes differ and learners are required to perform exceptionally well, in order to secure a place. Furthermore, the learners must obtain good points in 5 subjects if they want to be accepted in their preferred programs due to demand in different courses requirements. In addition, students with high points are normally considered and students who want to pursue their career in science fields need to do exceptionally well in STEM subjects for them to be admitted.

A scale of $A^+$ to G is used for the Ordinary level, and grade 1 to grade 4 is used for Higher level, with ungraded (U) being used at both levels. The $A^+$ and Grade1 were the highest levels.

### 1.2. Statement of the problem

The academic performance among the grade 12 students in STEM subjects is a concern in Namibia. The general trend in the examination results for 2017, 2018 and 2019 has shown poor performance in STEM as cited in the annual release of the (NSSCO, 2020). There were high numbers of students obtaining the symbol between E and U in STEM subjects. For this reason, this study seeks to investigate the factors affecting academic performance in STEM subjects, which include school factors like teacher's qualification, learning resources and their influence on academic performance in STEM. According to new research (Hox, 2017) the multilevel linear model, provided a mathematical modeling environment in which researchers could investigate theories about relationships between variables at each level of the sampling hierarchy. By considering both levels simultaneously in the analysis, multilevel modeling allows researchers to avoid the aggregation or disaggregation problem. Methods used to access performance in STEM discipline includes descriptive summary, regression analyses (Howard, Howard, Busse & Hunt, 2019), longitudinal analysis (Joseph, Tyler, Howard, Akridge & Rugo, 2020) and the quantitative descriptive research design and explanation research. The most popular method used was multilevel modelling (Su & He, 2020; Akay & Karadağ 2019; Khan & Zubaidy, 2017; Eshetie, 2016; Flunger, Trautwein, Nagengast, Lüdtke, Niggli & Schnyder, 2019), hence the need to use multilevel model. In Namibia there are no studies that examine STEM performance, except the study by Duarte, Jankowski, Tillotson and Wilson (2018).

### 1.3. Objectives of the study

The purpose of this research was to conduct a multilevel analysis on the factors affecting academic achievement on grade 12 NSSCO STEM subjects in Namibia. The specific objectives were:

a) To examine, the relationships between academic achievement and demographic variables and socio-economic variables of students.
b) To examine to what extent students' factors, teacher's factors and school factors affect the students' academic performance in STEM subjects.

### 1.4. Significance of the study

This study will be vital to any or all stakeholders in education because, it provides a more robust understanding on the link between students', school and teacher factors and performance in STEM subjects in several ways. In addition, the study will benefit the Ministry of Education in Namibia by creating awareness of some challenges faced by students and teachers in STEM.

### 1.5. Organization of the study

The thesis is organized as follows: Chapter 1 introduced the background of the study, statement of the problem, objectives of the study, the significance of the study, limitations and delimitations of the study. Chapter 2 provided the literature review and theoretical framework of the study. Chapter 3 outlined the methodology and it involved research design, population and sample size, data analysis, and research ethical considerations. In Chapter 4 the results were analyzed and discussed. Chapter 5 summarized the findings of the study, conclusion and recommendations of the study.

### 1.6. Chapter Summary

This chapter discussed the background of the study, statement of the problem, objectives of the study, the significance of the study, limitations and delimitations of the study. The study results would help all the education stake holders to identify the challenges faced by the students and teachers in STEM.

# CHAPTER 2: LITERATURE REVIEW

## 2.1. Introduction

This chapter contains a comprehensive review of the literature, followed by the conceptual and theoretical framework and it further looks into different approaches of statistical models to measure academic performance.

The first stage of research focuses on demographic variables, socioeconomic variables, gender, and SES that influence student achievement at an individual level, followed by an examination of the roles of teachers, students, and school factors. The analysis of TIMSS data in South African data using multilevel models revealed that the school students attend accounts for approximately 55% of the variation in their mathematics achievement levels (Scherer & Gustafsson, 2015). They also stated that students' proficiency in the English language is an important determinant of their achievement in mathematics learning. Their multilevel analysis confirmed that students learn mathematics more effectively in schools where teachers have more time for work and lesson planning (Scherer & Gustafsson, 2015). The analysis of these data frequently necessitates complex statistical procedures known as multilevel models, which allow us to assess school effect—the extent to which schools influence students' academic success (Raudenbush & Bryk, 2002).

One method that has proven effective for modeling academic data such is multilevel structural equation modeling multilevel structural modeling is used for unbiased estimates for the relationship among variables. This method reduces bias in the estimation of direct and indirect effects and guarantees accuracy in confidence interval (CI) coverage (Preacher, Zhang & Zyphur, 2011).

The multilevel path analysis was used at the same time to test the hypothesized relationships between variables at different levels. Educational studies are frequently nested, with the student nested in the class and the class nested in the school. Because there are multilevel influences, multilevel modeling that considers the data's multilevel, hierarchical structure is appropriate.

Scheerens (2013, pp. 10–12) concluded his systematic review of the theoretical underpinnings of educational effectiveness research by stating "as it comes to furthering educational effectiveness research, the piecemeal improvement of conceptual maps and multilevel structural models may well reflect that, the complexity of educational 'production' may be such that different units and levels are addressed by different theories."

### 2.2. Student factors which contribute to academic performance

Parental expectations have a significant impact on children's academic performance in STEM subjects. However, parents' involvement in school work and checking their children's homework has little effect on STEM academic achievement (An, Wang, Yang & Du, 2018). Several researches isolate cognitive, behavioral, and emotional engagement and its impact on academic achievement in STEM subjects (An, Wang, Yang & Du, 2018; Bicer & Capraro, 2019).

Findings by Pleiss, Perry and Zastavker (2012), show that project-based learning affects the self-efficacy of engineering students, especially in the first year of college. Studies have shown that self-efficacy can have a significant effect in the academic achievement settings. Students with low self-efficacy for learning may avoid tasks and question their abilities when faced with difficult problems. (Lou, Liu & Shi, 2011), in the investigation of STEM self-efficacy and professional commitment to engineering among high school students, found that self-efficacy is an important factor for future job selection. Several studies asserted that, student's personal motivation plays an important role in academic achievements.

Pleiss, Perry and Zastavker (2012), extend to the four sources of Self-efficacy that was identified by Bandura (1997):

**a) Skilled experience** - this distinguishes between experiences with successful STEM outcomes due to a strong association with high self-efficacy and experiences with negative outcomes due to low self-efficacy.

**b) Surrogate experience** - STEM experience occurs when students observe others and compare themselves with them with respect to their work, forgetting that, they don't have the same understanding of the subject and it may result in different outcomes.

**c) Social belief** - is another person's verbal suggestion, often associated with a stereotype or prejudice. There is risks and challenged faced by minority students, however students from traditionally underrepresented groups show positive academic results.

**d) Physiological state -** investigated that, students in STEM field are associated with lower psychological well-being (i.e anxiety or stress and lower self-esteem) and poorer academic perceptions.

One of the most important factors influencing interest in STEM for American and Turkish students' is self-motivation and motherhood. Children's career choices are influenced by families, teachers, and career counselors (Wellcome Trust, 2013a). Similarly, self-motivation rated by Turkish students as a second factor, is one of the major influencing factors in almost all related studies with the same or derived name, such as belief in one's abilities (Edzie, 2014). Traditionally, profession and competitions have given gifted and capable students the opportunity to test their skills; therefore, this encourages student involvement in STEM-related career and to encourage awareness in STEM-related profession (Sahin, Ayar & Adiguzel, 2014).

## 2.3. Age and academic performance

Many studies had shown that, student age has a significant impact on academic performance of the student. According to Abadoo (2018), a study on factors contributing to academic performance, found age to have a positive significant relationship with academic performance. In contrast, Voyles (2011) found that, age is not a contributing factor to student's performance. Similarly, a study by, Amuda, Bulus and Joseph (2016) indicated that, age had no significant effect on academic performance. Naderi, Abdullah, Aizan, Sharir and Kumar (2009) recommended that other studies should be conducted to include other factors that determine academic performance, because they found that age has a weak positive effect on academic performance.

**2.4. Gender and academic achievement**

Researchers conducted numerous studies on performance disparities correlated with socioeconomic status and the topic of gender is surely a social category which is equally important as socio-economic status. Girls and boys learn differently and gender gaps in academic success remain one of the most difficult topics in educational research. Meanwhile, studies on the sciences and gender have indicated that, females tend to dislike STEM subjects (Makarova, Aeschlimann & Herzog, 2019).

Recent research showed that, girls tend to be more interested in other field of studies while boys were more likely to expressed interest in STEM (Chachashvili-Bolotin, Milner-Bolotin & Lissitsa, 2016; BlaŽev, Karabegovic, Buruši & Selimbegovi, 2017). In agreement, (Legewie & DiPrete, 2014) there is evidence that boys in South Korea increase the level of interest in STEM and no corresponding effect on the girls. By Contrast, the National Assessment of Academic ability was reintroduced in 2007 and the outcomes showed that, little attention have been given to gender disparities and currently there is no evident concerning gender disparity in academic performance in Japan (Isa & Chinen, 2016). In contrast, the research by (Great Britain. Department for Education, 2019), gender differences in STEM interests were noticeable among KS4 students, with girls showing more than twice as much interest in biology as boys while being less likely to like chemistry.

Additionally, a meta-analysis of two major international data sets, the International Trends in Mathematics and Science Research (TIMMS), confirmed that gender equality in education is not just important for girls, but the self-confidence and value of mathematics in girls as well as in their mathematical achievements (Else-Quest, Hyde & Linn, 2010). Students' gender-related perceptions of various science subjects could have different effect on their STEM subject preferences at school.

According to Gonzalez and Kuenzi (2012), the scientific and technological enterprise in the United States has historically relied primarily on white male labour (especial in the fields of engineering and mathematics). Despite overall improvements in the standardized score, gender differences also exit with male scoring more compare to female.

A study by Hand, Rice and Greenlee (2017) exploring the gender roles of teachers and students found that high school students girls reported to have lower self-efficacy in mathematics and science compared with boys. Namibia and South Africa, is among the top 20 nations that have narrowed the gender gap by 78% to 76%, however it is important to note that gender parity is often critical to the success of economies and communities (World Economic Forum's [WEF], 2017, p. 23).

According to a recent report by the United Nations Educational Scientific Cultural Organization (2017), the higher the level of education, the more pronounced the gender gap and elective courses are available. However, the gender gap in earning a STEM bachelor's degree after four years of college has narrowed since 1977, of which 25% of STEM degrees were awarded to women in 2000 and 40% of STEM degrees are earned by women particularly in the fields of biology and agricultural sciences and gender parity has been achieved since the 1990s, while gender gaps remain noticeable in engineering, physical sciences and mathematics (National Science Board [NSB], 2014).

Women tend to receive equally many degrees in biology and agriculture; women prefer non-STEM degrees (Mann & DiPrete, 2013). According to Lubinski, Benbow, Shea, Eftekhari-Sanjani and Halvorson (2001), girls have equal opportunities for STEM careers, but they have more career choices and choose careers that apply their interpersonal skills and language skills

The Social Role Theory (Eagly & Wood, 2012) stated that, gender roles and their inhabitants are very prominent in everyday situations, depending on the observations of women and men in various social roles, and professional choices. Women receive 57% of bachelor's degrees in the United States today, and 50% of bachelor's degrees in STEM fields National Sanitation Foundation (NSF, 2018). Gender-related problems are no longer about women's talent in STEM fields, but the cost of STEM that would be higher if all eligible and competent applicants, including women, did not participate, despite the fact that there are more women in STEM fields, awards for research in STEM were still mostly male-dominated (Charlesworth & Banaji, 2019).

The explanations for gender discrimination in STEM have been debated by academics. Prejudices such as self-efficacy, institutional culture, discrimination, family formation and child upbringing, gender expectations, lifestyle choices, career preferences, and personal choices were some of the limiting factors toward women in STEM (Amogne, 2015). A study conducted by Jones, Ruff and Paretti (2013) on the impact of engineering identification and stereotypes of first-year college students found that negative stereotypes about female engineering and mathematical abilities were more strongly endorsed by male students, while female students more likely to report a higher perception of their technical abilities.

When developing policies and strategies to improve educational outcomes, gender disparities in academic achievement must be considered .According to ([WEF], 2017, p31) latest global gender gaps study, which reports that on average, men were underrepresented in the fields of education, health, and welfare, while women were underrepresented in STEM fields, highlights the persistence of gendered paths in career choices.

Knight (2016) stated that, job opportunities play an important role when choosing a field of study, in addition to personal interests and characteristics. Many of the problems associated with educating female students in STEM courses can be explained through many aspects of society, involving the macro level of large-scale institutions and cultural beliefs, as well as the micro level of the interactive environment and personal experience (Risman, 2004). Most parents, educators and girls themselves consider future career opportunities when making educational decisions and investments (Riegle-Crumb & Moore, 2014).

Previous researches have shown that women report a threat of social identity in STEM. Generally speaking, women expect to perform worse in STEM fields than their male peers. According to Crato (2020, p. 217) the Taiwanese government had made it a priority to develop female scientists and technologists, in order to address gender disparities in STEM fields and encourage more young women to pursue careers in science, technology, engineering, and mathematics (STEM).

Furthermore, a meta-analysis of two major international data sets "Trends in International Mathematics and Scientific Research" (TIMSS) and "Program for International Student Assessment" (PISA) confirms that, gender equality in education is not only relevant but can also increase girls' academic performance. Mathematical achievements will boost girls' self-esteem and perceptions of mathematics

According to (Kapur, 2018) home environment should be friendly in order to generate appropriate academic outcomes. The schools and home environment can influence the role of gender in academic achievements. Individual disciplines could be a major attribute, since there is a great complexity and much need to be understood and accounted for, on how student acquire knowledge and skill (Honey, Pearson & Schweingruber, 2014, p. 141).

(Muchunku, 2014) opined that, in most countries, educational achievements were related to social background of the student.

## 2.5. Classroom Environment

The physical facilities in the classroom play a vital role, and the classroom environment will seriously affect students' academic performance. It is important to ensure that, schools have sufficient facilities in the classroom before participating in the learning process to achieve an effective and successful teaching and learning process. It was pointed out that, the influences of schools and classrooms were some of the factors leading to changes in STEM performance and by helping students to participate in learning-related activities such as developing plans, improving communication and co-ordination in the classroom is critical (Hanımoğlu, 2018).

Technology is an ever-changing and as time pass by, the achievement gap in STEM fields is getting bigger and bigger (Good, Bourne & Drake, 2020). Studies have shown that, student background plays a major role towards STEM achievement. Brew, Nketiah and Koranteng (2021) opined that an unfavorable classroom environment and insufficient school facilities can have negative impact on teacher efficiency and student performance.

According to research, the classroom atmospheres have a huge effect on student engagement and learning. Effective classroom management lays the groundwork for this students' growth. In poorly organized and turbulent classrooms, very little learning occurred. Establishing classroom rules will assist teachers in developing effective and efficient rules to promote a conducive environment for student. Teachers who use effective classroom strategies can expect their students to achieve higher levels of success as a result of their instruction.

According to Struyf, De Loof, Boeve-de Pauw and Van Petegem, (2019), student engagement should be a core principle in the STEM learning environment, because it will help the instructor to implement the student-centered approach in the classroom. In agreement, Skinner, Saxton, Currie, and Shusterman (2017), there is urgent need for students to participate in STEM and the learning environment should be able to promote and encourage student participation in STEM.

According to some research reports, meaningful activities should include all STEM subjects as well as real-world applications so that students can see the connection between what they are learning and their daily lives. It is very important for the teachers to integrate characteristics of several cultures through the classroom activities which include books discuss of various cultures' languages, values and ceremonies. There is a need to clarify the theoretical framework of integrated STEM and fully understand the curricular and classroom practices. Classroom policy encourages learning and provided an environment in which all students can thrive.

According to Lin and Bates (2014), some teachers' lack true understanding of diversity and regardless of the type of diversity that teachers face, there is a need for the teachers to be willing to learn about the diversity in the classroom. Teachers must be provided with opportunities to learn about diversity and the integration of diversity and diversity curriculum into their classrooms. Teachers should integrate diversity throughout all content course and they should go beyond offering one diversity class.

STEM integration is a curriculum strategy that combines STEM concepts in interdisciplinary teaching methods (Wang, Moore, Roehrig & Park, 2011). One of the most significant educational challenges for K-12 STEM education is the lack of general guidelines for teachers to follow when teaching using STEM integration approaches in their classroom as a result, research into teachers' understandings and implementation of STEM integration is required.

The curriculum development and design should pay attention to the planning of assessment as it might have a significant impact on the student’s approaches of learning and academic performance (Zohrabi, 2011: Baeten, Dochy & Struyven, 2013) stressed that, the constructivist learning theory has been receiving extensive attention in educational research in the past few decades and it has inspired the student-centered learning environments. (NRC, 2014) suggested that, STEM education should be able to foster the “cognitive skills, understanding and appreciation of the process of scientific investigation”.

According to Stohlmann et al. (2012) provided criteria for what constitutes effective STEM instruction in the classroom and students in a STEM integration classroom should be able to perform as, problem solvers, innovators, inventors, logical thinkers, as well as understand and develop the skills required. The incorporation of STEM activities should cultivate student thinking skills, which can help students to form the ability to analyze, evaluate, and draw correct rational conclusions and arguments about difficulties to be solved. Students must have valuable innovation and creativity skills in order to solve world related problem. Some scholars believed that, in a small classroom, teaching can increase teacher attention and student participation, reduce classroom problems and improve morale (Abun, 2018; Blazar & Kraft, 2016).

Rosli, Siregar, Maat and Capraro (2019) suggest that, cooperation and exchange of ideas should be prioritized in the classroom and students in STEM classrooms should accustomed to collaborative learning and discussion, learning through questioning, exploration and investigating various activities.

According to Ajayi and Adeyemi (2011), in order to achieve standard education in Nigeria, the Nigerian education system needs adequate facilities such as classrooms, furniture, laboratories, teaching materials, libraries and other equipment. Classroom is the primary environment in which students can influence the behavior of others and classroom had become one of the factors that disturb the students' academic success. This should be a standard for each country in order for them to have effective integrated STEM. Science subjects are very practical in nature and students need to visualize, hence the physical arrangement plays an important role in appropriateness teaching process and learning.

The government of Kenya had provided teachers with the in-services training on STEM on how and where to use the teaching aids in the classroom and interact with learners (Musau, Migos & Muola, 2013; Mushtaq & Khan, 2012) found that school environment, school facilities and professional development are essential for student learning and it could have a significant impact on academic performance in STEM. It was argued that student's achievement was associated with many variables.

A supportive learning environment is important to facilitate teaching and learning, since successful interpersonal abilities are established in good classroom. The availability of practical lessons clarified and reinforced scientific concepts and the effective teaching approaches promote a productive relationship that is essential for students to make connection and classroom provide students with setting on how can express their ideas (Ngema, 2017; Wang, 2012). They further state that, integrating engineering and mathematics in the classrooms can benefit the student's learning and classroom observation can help students to understand the whole concept.

Classroom environment is the fundamental component that includes spatial components and it might influence learners' well-being, hence it should be promising to ensure effective learning (Kausar, Kiyani & Suleman, 2017).

In agreement, Marks (2017) showed that, the classroom environment can be frustrating to students' and performance can be affected. Furthermore, lack of accomplishment and frustration level could increase in female students compared to the male students.

**2.6. School factors which contribute to academic performance**

Lack of resources in schools is a worldwide challenge and it could lead to a failure. Textbooks are useful for further reading, for preparing lesson plans, diagrams, illustrations, exercises and even for instructions to be given to students. Teachers determined for the improvement of student's education respect that, enhancing teaching books would positively result in the adjustment of instruction (Pelton, 2010). Additionally, lack of student's affordability to buy textbooks is one of the factors contributing to academic achievement is STEM (Sun, Flores & Tanguma, 2012).

Research on partnerships between schools and professional institutions such as businesses, universities, and foundations had found benefits to schools by increasing access to resources and knowledge ( Gross, Haines, Hill, Francis, Blue-Banning and Turnbull, 2015). According to Holmlund, Lesseig and Slavit (2018), connections between schools and communities can provide new opportunities for students to learn in a variety of settings, such as church congregations, community organizations, and afterschool programs

According to Ejiwale (2013), many schools were not equipped with the required resources to facilitate the STEM. He further stated that, teachers should learn to improvise when there was a shortage of resources at the school in order to improve academic achievement.

According to Bonney, Amoah, Micah, Ahiamenyo and Lemaire (2015), the emphases on success or failure of any educational program depends primarily on the adequate availability of qualified (professional) personnel, competent and dedicated teacher. Moloko, Mphale and Mhlauli (2014) stressed that, the world needs a generation of professional who aimed to develop learners and help them to become independent and provide them with the interest for life-long learning.

According to Tjihenuna (2016), due to the shortage of qualified teachers and large inflow of learners and shortage of classrooms, some tent classes has been erected to accommodate all the learners. Studies affirm that the classroom size can result in outstanding outcomes. Furthermore, classrooms are filled with unqualified and under-prepared individual.

Concerns about not having sufficient Science, Technology, Engineering, and Mathematics (STEM) professionals were linked to underperformance of American students on science and mathematics examinations, mostly women and ethnic minorities, who were underrepresented in STEM degree achievement (Nguyen & Redding, 2018). Another problem in establishing a team of qualified STEM teachers is the retention of these teachers, especially keeping the most qualified teachers. The general model of teacher quality and ability research suggests that, the least effective teachers might leave teaching, then the more effective teachers (Goldhaber, Gross & Player, 2011).

The curriculum should be extended to expose the STEM teachers to the nitty-gritty of the subject content. In addition, STEM teachers should be motivated to participate in professional development because, the world of science is changing every day and they should be ready to change as technology changes and the emphasis should be given to the "T" is STEM (Ejiwale, 2013).

In ([PCAST], 2010) stated that, Nations need to accept common baseline and they need to employ STEM teachers that are flexible and be able to adapt to the changes in technology and rewards them for preparing and inspiring students in STEM through learning opportunities inside and beyond.

The significance of academic achievement for people pursuing STEM occupations (Riegle- Crumb, King, Grodsky, & Muller, 2012) emphasized the crucial role of instructors in shaping students' mathematics and scientific abilities.

The role of academic staff is an ultimate aspect of teaching and learning and the academic staff could be reasonably expected to have a cultural understanding of the schools. The teacher’s interest in the subject is very important and the teachers should be very informative, engaging and the content should be well defined for the student to understand.

**2.7. Parent factors which contribute to academic performance**

Recent studies have shown that parental involvement has a positive impact on children's academic performance. In a meta-analysis, Jaynes (2013) concluded that, the two components of parental engagement were significantly associated with higher academic achievement. The two components are:

a) **Parental involvement as a time investment** - spending time with the children will have them to achieve positive results and enable them to meet their educational need. Some parents believed that knowledge is power and by investing time, money and energy into communicating their children’s dream is the biggest achievement.

b) **Parental involvement related to parenting styles and expectations -** Parents outline their children’s expectations and that cultural variations need to be examined. Prominently, parental expectations improve the children’s self-efficacy and achievement in STEM subjects.

A study by Lee and Nie (2015) on the “Why/’ and “How” of the engaging parents on their children’s science learning in formal context has found 3 major factors that influence the parental engagement with their child’s STEM learning, namely:

a) **Time and commitment** - parents are too busy to check their children’s book or to talk to them and understand the challenges their children are facing in academic progress.

b) **Self-efficacy -** parents believed in their own ability to contribute positively to their children`s education. Parents lose confidence when children’s curriculum advances beyond their intellectual and will not be able to understand the subject content.

c) **Resources** - parents with no STEM experience may lack the resources to identify STEM and believe it, to be costly if they have to invest in the necessary equipment.

In contrast, (Epstein, 2005; Jeynes, 2007) have found other two distinct characteristics of parental involvement of prominent in the literature to be parental participation in schools, Parental communication and home educational activities. Parental involvement in their children’s education can potentially contribute to academic achievement by: a) supporting children's growing self-awareness of cognitive abilities and b) working with teachers and schools to develop meaningful student-teacher relationships (Bakker, Denessen, & Brus-Laeven, 2007).

Ochoa (2021) on the other hand asserted that, parental involvement methods are mechanisms by which parental-level factors, including parental self-efficacy, predict student learning outcomes, including students' self-study effectiveness. A study by Amponsah, Milledzi, Ampofo and Gyambrah (2018) showed that, parental involvement at home had a significantly positive relationship with academic performance in their neighborhood school, but there was a negative relationship between parental involvement parents at school and academic performance at school. Similarly, Howard, Howard, Busse and Hunt (2019) found that, parental involvement in conversation is an important predictor of mathematics achievement for girls, but not for Hispanics and Asians.

Study has revealed links between teacher enthusiasm, Parents’ involvement in children’s education and student outcomes. Parents can have an impact on their children's educational outcomes by actively participating in school engagement, such as attending school meetings and events, talking with teachers and volunteering at school. Despite a growing number of studies of high school girls and the impact of parental involvement on academic achievement, previous studies have shown that girls of black color lack parental involvement and have a negative impact on academic achievement, or that their parents are less engaged than their own appeared colleague (Howard, 2015).

Teachers who are aware of their students' conceptions and learning processes may be able to focus on students' comprehension during instruction by connecting course materials to students' thinking. Learner-centered strategies Collaboration, according to Lee and Hannafin (2016), can improve teacher-student relationships by fostering students' voices, thinking, and learning, as well as increasing their sense of ownership in their own learning process. Furthermore, instructional support for learning can predict student achievement. Effective use of classroom time by teachers, explicit instruction, modeling, scaffolding, and providing adequate feedback throughout the learning process can all help students learn more effectively.

Another aspect to consider is the impact of parental involvement patterns is by introducing incentives or reinforcement may have more specific socialization aspects, the opportunities and values communicated to students in relation to both the short and long term for career aspiration (Wang & Sheikh-Khalil, 2014). Through empirical observation, it was found that parental participation had a significant positive (+) effect on the academic achievement of the ward, but the degree and level of parental participation varied, and it was found to have an indirect effect on the children's academic achievement.

### 2.8. Conceptual and Theoretical framework

Different researchers have used several theories to study the factors that affect academic performance. In evaluating the factors that affect the grade 12 STEM academic performance of the Namibian secondary school, the Social Cognitive Career Theory (SCCT) by Yusoff, Mahfa and Saud, (2019) have been used. Self-efficacy, goal orientation and outcome expectations were some of the attributes that can shape career interests (Falco and Summers1, 2017). According to the SCCT, their thoughts, beliefs, personal factors and environmental factors have effects on career interest, choices and educational (Petersen, 2014).

The SCCT focused on explaining the manner in which people decide and revise their vocational educational plans, developing basic academic and career interest as well as achieving the performance of different quality in their career pursuits (Lent, 2013). Furthermore, the SCCT focused more on constructing self-efficacy, outcome expectations, and choice goal and how these constructs interact with environmental factors to predict the choice of educational and vocational plans, academic and performances.

The cognitive category have identified other factors that can be considered under the STEM studies, such as students' perception about science, teacher's influence on this perception, students' expectations, student's background, culture and personal beliefs (Huelskamp, 2010). Kennedy and Odell (2014) added that, students should do investigation before engaging in STEM careers.

Preceding studies had identified a number of important factors that prejudiced students' interest in STEM careers. For example, Christensen, Knezek and Tyler-Wood (2015) found that, student's own self-motivation, student interest in STEM, high quality of motivating teacher and family member or parents are some of the factors that influence student's performance. Although self-concept is an important predictor of student academic choice and long-term engagement

(Nagengast & Marsh, 2011), the findings from the TIMSS results are concerning for the educational authorities and teachers in East Asian countries, who may need to reconsider the relationship between student achievement and self-concept.

Teachers use instruction approaches to help students become self-sufficient (Mushome & Monobe, 2015). When students choose and apply appropriate approaches on their own, they become learning strategies. This is where instructional approaches can help by providing a concrete framework for learning opportunities, classroom interaction, and academic performance. According to research on students' social and cognitive development, their perceptions of the student-teacher relationship influence their school performance and academic success (McGrath & Bergen, 2015; Mikk, Krips, Sääl, & Kalk 2016; Stronge, 2018). Teachers can influence the social and intellectual experiences of their students.

The environmental and social impacts could be the driving factors of STEM education around the globe. Teachers can foster a learning environment in the classroom by acting as a regulator for the development of emotional, behavioral, and academic skills (Roorda, Koomen, Spilt & Oort, 2011; Stronge, 2018). Teachers who are sensitive to the needs of their students can help them learn more academically and socially. Teachers' mediation of peer relationships, as well as students' emotional closeness, conflict, and dependency, can all be linked to students' perceptions of teacher-student interactions and their academic and social growth (Allen, Gregory, Mikami, Lun, Hamre & Pianta, 2013; Wubbels, Brekelmans, Mainhard, denBrok& van Tartwijk, 2016). Kelley and Knowles (2016) indicated that, STEM educators might lack cohesive understanding of STEM and might struggle to make connection across the STEM disciplines. The last two decades, USA government experienced a massive STEM reform and they could benefit from the conceptual framework of STEM education ([NRC], 2012). The STEM education had been contemplated in the USA since the 1990s, but only after several decades when few teachers were able to teach STEM education (Kennedy and Odell, 2014).

Students can learn in more relevant and stimulating experience if they are provided with well-integrated instruction and this can encourage the use of higher critical thinking skills, improve problem solving skills and increase the level of retention (Stohlmann, Moore & Roehrig, 2012).

The conceptual framework for academic performance in STEM disciplines required a deep understanding of the complexities of teaching and understanding STEM content. However, research in integrated STEM had a better understanding of STEM background and the level of complexities; hence they could inform the STEM educators and stakeholders on the identified barriers and be able to determine the best practice around it. The conceptual framework could help the educators to realize the full potential of the integrated STEM education. An integrated approach seeks to discover the connections between STEM subjects and provide a relevant context for learning the content. Teachers need to have sufficient content knowledge and pedagogical knowledge in order to improve the STEM education (Nadelson, Seifert, Moll & Coats, 2012). STEM education can be grounded within the cognition theory. Figure 1 shows several factors that affect academic performance in STEM.

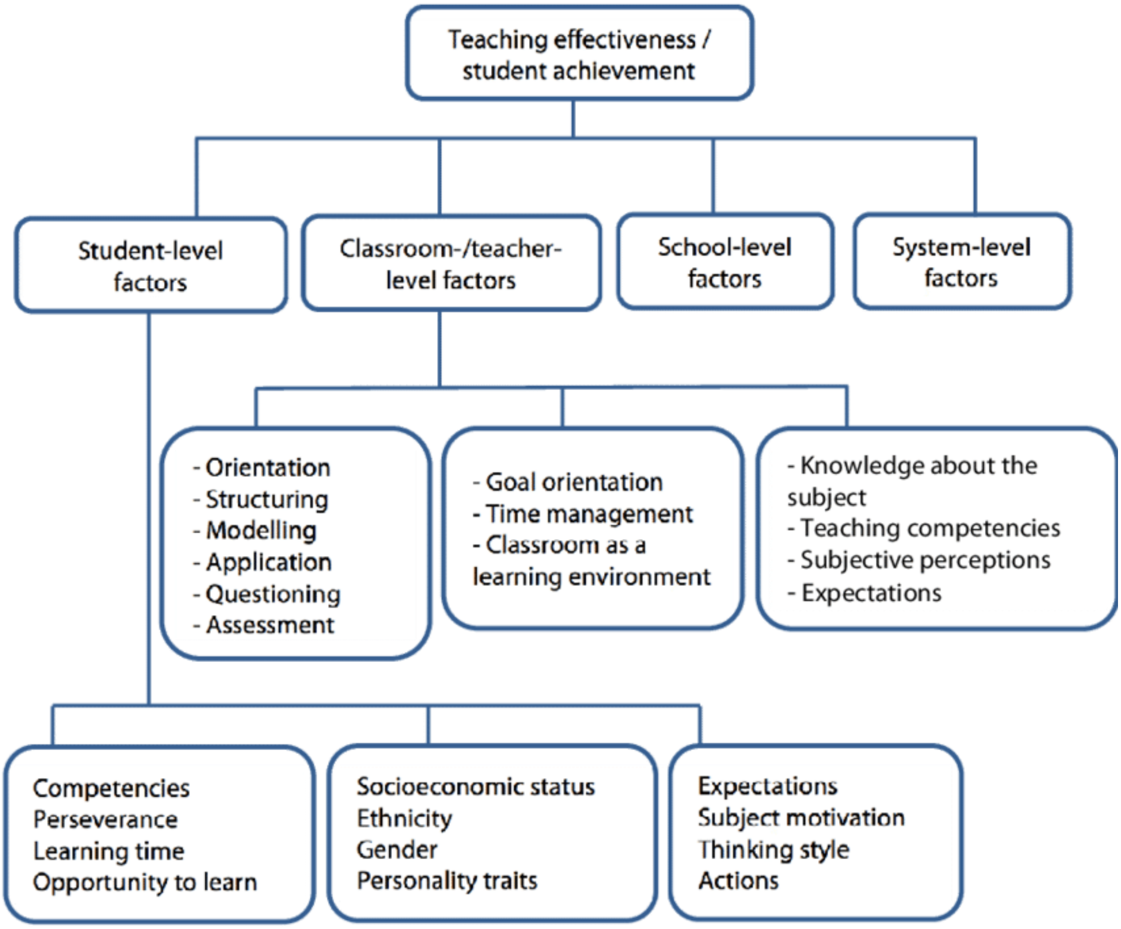


**Figure 1. Dynamic model of educational effectiveness upgrade of the Creemers and Kyriakides model (Creemers, Kyriakides and Antoniou, 2013)**

The old saying of "the parent is the children's teacher" couldn't be truer. Parents played an important role in their children's learning and development and there is an ever-collective mindfulness of the importance of the parent's role in the progress and development of the children.

Parents of different professional have different styles of child rearing, different ways of disciplining their children and different ways of reacting to their children. According to (Webb-Williams, 2021), ability-grouping can lead to greater academic success than mixed ability-grouping. Thus, using the predictive model, the instructor can determine a student's academic ability.

Provision of quality education can be a top priority of each country and it needs to incorporate amongst the national goals of education (Moloko, Mphale & Mhlauli, 2014). According to Mekonnen (2014), science is regarded as the body of knowledge that have been accumulated and a foundation of the modern-day technological advance. Kelley and Knowles (2016) added that, “building a strategic approach for integrating STEM concepts necessitates strong conceptual and foundational understanding of how students learn and apply STEM content”.

John, Sibuma, Wunnava, Anggoro and Dubosarsky (2018) found that, high quality early childhood programs is important for every child, because it is associated with long-term outcomes. Meeting the children’s cognitive, emotional and development needs is an effective way to foster children’s learning. (NRC, 2014), in agreement, the STEM disciplines extend beyond workplace and advocates of more integrated approaches to K-12 STEM and the education claims that, it had advantaged for learning and development and motivation, in the K–12 Curriculum.

The ([NRC], 2011) showed that, many education system and policy maker around the world were anxious with advancing competencies in STEM domains, as the study of STEM practices can provide a better understanding of each domain and help teachers identify key learning outcomes necessary to achieve STEM learning. The ([NRC], 2014), recommended that science teaching and curriculum should include the following:

a) Understand the nature and development of scientific knowledge, generate and evaluate scientific evidence and explanations.
b) Empowering students to become innovators and technologically proficient problem solvers
c) Increasing student's 21st century skills and STEM literacy
d) Enriching community understanding of STEM education and its importance in building capacity to prepare students for work and life in the 21st century

In the, ([PCAST], 2010) interest and achievement gap in STEM subjects among racial, ethnic and gender group need to be closed if the United States want to remain at the forefront of Science and Technology. He further stated that, majority of its students in the field of Science and Technology is underrepresented in the STEM fields, especially women.

The System level factor of Dynamic model of educational effectiveness upgrade of the Creemers and Kyriakides model was not discussed in the study, because there is no available data to measure the performance on system.

### 2.9. Statistical Modelling Methods

#### 2.9.1. Linear Models

The linear model is the core of the field of statistics, and it may also be the most commonly used set of statistical techniques in practice (Maravelakis, 2019).

In simple linear regression, we try to model the relationship between two variables (dependent variable Y and one predictor). Many of the most frequent statistical approaches used in applied statistics are unified by linear models. For a simple linear regression, we can use a model of the form

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \quad i = 1,2,\dots,n \qquad \text{Eq. (1)}$$

where; $y_i$ is the dependent or response variable

$x_i$ is the independent or predictor variable

$\beta_0$ *and* $\beta_1$ are the regression coefficients

$\varepsilon_i$ is the error term in the model

Model (2.6.1.) is associated with four assumptions:

a) **Linearity**: The relationship between $x$ and the mean of $y$ is linear.
b) **Homoscedasticity**: The variance of residual is the same for any value of $x$.
c) **Independence**: Observations are independent of each other.
d) **Normality**: For any fixed value of $x, y$ is normally distribute

A linear model relating the response y to several predictors has the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \qquad \text{Eq. (2)}$$

Only the mean of the dependent variable is considered in Linear Regression. The link between the mean of the dependent variable and the independent variables is studied using linear regression. When the assumption of normality is met and no outliers are present in the sample, MLMs using restricted maximum likelihood estimation (REML) provide researchers with accurate estimates of parameters and standard errors at all levels of the data (Śpiewak, 2018).

### 2.9.2. The Generalized linear models

A generalized linear model (GLM) consists of three components:

**a) A random component**

Refers to the probability distribution of the response variable $y$, with individual observations ($y_1$,..., $y_n$) from a distribution having probability density or mass function for $y_i$ .

The exponential family can be generalized by including a (constant) scale parameters, say$\emptyset$ in the distribution, such that

$$f(y_i;\theta_i,\emptyset) = \exp \left[\frac{y_i\theta_i - b(\theta_i)}{a(\emptyset)} + c(y_i,\emptyset)\right] \quad \text{Eq. (3)}$$

where; $\theta_i$ is still the canonical form of the location parameter, some function of the mean $\mu_i$

$a(\cdot)$, $b(\cdot)$, and $c(\cdot)$ are known functions that vary from one exponential family to another.

$$c(y_i,\emptyset) = -1/2(\log(2\pi\sigma 2)) - y\, 2/(2\sigma\, 2).$$

$\theta = g_c(\mu)$, the canonical parameter for the exponential family in question, is a function of the expectation $\mu = E(Y)$ of Y ; moreover, the canonical link function $g_c((\cdot)$ does not depend on $\emptyset$.

$\emptyset > 0$ is a dispersion parameter, which, in some families, takes on a fixed, known value, while in other families it is an unknown parameter to be estimated from the data along with θ.

The natural exponential family of the form $f(y_i;\theta_i) = h(y_i)\exp\,[y_i\theta_i - b(\theta_i)]$

$$h_n(y_i) = \Pi h(y_i).$$

The member of exponential family included in the $y_i$ distribution is such as the Gaussian (normal), binomial, Poisson, gamma, or inverse-Gaussian families of distributions.

**b) A linear predictor $\eta_i$ that is a linear function of regressors**

$$\eta_i = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} , \qquad i = 1,2, \ldots, n \qquad \text{Eq. (4)}$$

As in the linear model and in the logit and probit model, the regressors $x_{ij}$ are specified functions of the explanatory variables.

**c) Link function**

The *link function* of a GLM connects the random component and the linear predictor (Wiley, 2015). The link $g(.)$ transforms the expectation of the response variable, $\mu_i = E(y_i)$ to the linear predictor**:**

$$g(\mu_i) = \eta_i = \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \qquad \text{Eq. (5)}$$

Because the link function is invertible, we can also write

$$\mu_i = g^{-1}(\eta_i) = g^{-1}( \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} ) \qquad \text{Eq. (6)}$$

The inverse link $g^{-1}(.)$ is also called the *mean function.*

The Poisson regression and negative binomial models are commonly used to handle count data. Alghamdi, Aslam and Khan (2021) indicated that, in statistical techniques such as OLS regression or logistic regression on educational related variables are used, but they discovered very few studies using Poisson regression for modeling class participation or educational performance during their literature search. Although general linear models are not appropriate for analyzing discrete count data, linear regression analysis is still used in educational research for count data despite violations of fundamental general linear model assumptions. When the OLS regression model is applied to count data, it may produce negative predicted values that are inappropriate and incompatible with the observed values.

### 2.9.3. Poisson Model of counts data

According to Dobson and Barnett (2018) the Poisson distribution provided a plausible way of modelling these data as they were count data and within each group the sample mean and variance are similar.

According to Rodríguez (2007), a random variable Y is said to have a Poisson distribution with parameter $\mu$ if it takes integer values $y = 0,1,2,\ldots$ with probability

$$Pr\{Y = y\} = \frac{e^{-\mu}\mu^{y}}{y!} \qquad \text{Eq. (7)}$$

for $\mu > 0$. The mean and variance of this distribution can be shown to be

$$E(Y) = var(Y) = \mu$$

A useful property of the Poisson distribution was that the sum of independent Poisson random variables was also Poisson. Specially, $Y_1$ and $Y_2$ were dependent variables with $Y_i \sim P(\mu_i)$, then

$$Y_1 + Y_2 \sim P(\mu_1 + \mu_2) \qquad for\ i = 1,2$$

Suppose that we have a sample of n observations $y_1, y_2, \ldots, y_n$ which can be treated as realizations of independent Poisson random variables, with $Y_i \sim P(\mu_i)$, and suppose that we want to let the mean $\mu_i$ depend on a vector of explanatory variables$x_i$.We could entertain a simple linear model of the form

$$\mu_i = x'_i\beta \qquad \text{Eq. (8)}$$

For normally distributed data, the basic link function is the identity link function, which requires no transformation of before constructing the matrix of $\beta$s. In general, the distribution of a dependent variable restricts the user's options in relation to the link function used (Agresti, 2015). For binary dependent variables, the logit link is the standard linking function.

We can transform equation Eq (8) by taking the logarithm of $log(\mu_i) = \eta_i$

$$log(\mu_i) = x'_i\beta \qquad \text{Eq. (9)}$$

The likelihood function for $n$ independent Poisson observations is a product of probabilities given by equation 7. Taking logs and ignoring a constant involving log ($y_i$!), we find that the log-likelihood function is

$$logL(\beta) = \sum\{y_i \log(\mu_i) - \mu_i\} \qquad \text{Eq. (10)}$$

where $\mu_i$depends on the covariates $x_i$ and a vector of p parameters β of equation 9.

In the association analysis the MLM, it takes into consideration population structure and association. Due to relatedness and population structure, it decreases Type I error. The varying-coefficients approach allows each subgroup to have a distinct mean outcome level while still predicting the global mean outcome level, which is an important feature (Gelman & Hill, 2007).

**2.10. Multilevel linear models**

Gelman (2006) defined multilevel modelling as a generalization of regression methods that might be used for a wide range of applications, including prediction, data reduction, and causal inference from experiments and observational research. Multilevel regression models had grown increasingly relevant in a variety of disciplines of study (Goldstein, 2011), and articles containing estimations based on these models were becoming more common.

Generalized modelling support nonlinear multilevel modelling. Multilevel modeling is one of various methods for evaluating clustered data. Multilevel modeling has a wide range of applications in educational research; the models are also known as hierarchical linear models, mixed models, and random effects models (Ker, 2014). Multilevel modeling is a popular method for dealing with correlated errors.

Gelman and Hill (2007) highlight three main reasons as to why they prefer using MLM. To begin, not all multilevel models are strictly hierarchical, as we will see when we discuss cross-classified models. Second, the clustering variable does not have to be at the same organizational level as the classroom is with respect to the students. Rather, any categorical variable could be a clustering variable. Third, there is some ambiguity in linear modelling terminology regarding the term level, which may refer to the clustering variables.

The general purpose of multilevel modeling is the same as traditional regression is to determine whether a predictor for which you made a prediction contributes to explaining differences in the value of your outcome between and/or within cluster (O'Dwyer & Parker, 2014). Statistical models are developed for each level of the data hierarchy and grouped characteristics can be incorporated into models of individual outcomes, improving estimates of effects within groups and allowing testing of hypotheses about cross-level effects (Goldstein, 2013).

According to new research Hox (2017) the multilevel linear model, provided a mathematical modeling environment in which researchers could investigate theories about relationships between variables at each level of the sampling hierarchy. By considering both levels simultaneously in the analysis, multilevel modeling allows researchers to avoid the aggregation or disaggregation problem. According to O'Dwyer and Parker (2014) when studying nested data, multilevel modeling techniques were created to help analysts avoid erroneous findings caused by improper analytic procedures, such as employing OLS regression with unadjusted standard errors. Multilevel data frequently violates the OLS regression assumption of data independence, as dependent variables at level 1 may cluster within groups defining level 2.
The relationships between the dependent variable and the independent variables are expressed as regression in a multilevel model. Multilevel analysis allows you to divide an outcome's variation into distinct components (e.g., within and across units) and assign explanatory variables to different organizational levels within the analysis. The researcher would integrate data from people and subunits within each organization to establish an organizational-level set of measures, and then study between-organizational variation in the aggregated measures using the aggregation approach (Hox, 2017).

Because individuals are nested in the same group, the assumption of uncorrelated mistakes is difficult to meet when there is statistical dependency in the data. If the link is truly zero in the population, the predicted probability of finding a relationship of the size observed or larger in the sample is artificially reduced (Hox, 2017).

In multilevel modeling approaches it is necessary to have adequate sample sizes at each level in order to obtain accurate estimates of the regression coefficients and their standard errors, as well as the variance components and their standard errors (Lee & Hong, 2021). When the multilevel model assumptions are met, the bias in the standard errors of the regression coefficients is reduced, the estimated probability that researchers use to assess statistical significance is no longer artificially reduced, and the incidence of Type I, false-positive errors is reduced (O'Dwyer and Parker ,2014).

When compared to an OLS model, multilevel regression modeling does not correct bias in regression coefficient estimates; however, when the data is nested, it produces unbiased estimates of the standard errors associated with the regression coefficients and easily allows group characteristics to be included in models of individual outcomes (Hox, 2010). Because of its flexible treatment of the time predictor, MLM has the advantage of being able to use all available data in the estimation of model parameters.

To predict the outcome variable, we would consider simple regressions developed for each individual *i*:

$$Y_{ij} = \beta_{0j} + \beta_1 x_{ij} + e_{ij} \qquad \text{Eq. (11)}$$

where:

$Y_{ij}$ = the response variable

$x_{ij}$ =level 1 predictor

$\beta_{0j}$=the refers to the intercept of the dependent variable in group $j$ (level 2)

$\beta_{1j}$= regression coefficient associated with $X_{ji}$ for the $j$th level-2 unit, and the dependent variables

$e_{ij}$ = random error associated with the $i$th level-1 unit nested within the $j$th level-2 unit.

$E(e_{ij}) = 0, var(e_{ij}) = \sigma^2$

In the level-2 models, the level-1 regression coefficients ($\beta_{0j}$ and$\beta_{1j}$) are used as outcome variables and are related to each of the level-2 predictors.

We will consider the case of a single level-2 predictor that, the relationship between dependent and explanatory variables will be measured at this level.

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j} \qquad \text{Eq. (12)}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}X_j + u_{1j} \qquad \text{Eq. (13)}$$

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}Z_j + \gamma_{11}X_{IJ}Z_J + U_{1j}X_{ij} + U_{oj} + e_{ij} \qquad \text{Eq. (14)}$$

where:

$z_j$=value on the level-2 predictor;

$\gamma_{00}$ =refers to the overall regression coefficient, or the slope, between the dependent variable and the level 2 predictor

$\gamma_{10}$=estimates the average effect of the level 1 predictor

$\gamma_{01}$ = regression coefficient associated with $Z_{ij}$

$\beta_{1j}$=indicates that the effect for the student-level predictor is fixed

$\gamma_{11}$=regression coefficient associated with Z relative to level-1 slope;

$u_{0j}$ =error term representing a unique effect associated with school $j$

$u_{1j}$ =random effects of the school level-2 unit adjusted for Z on the slope.

There are three models to be considered, we using the multilevel modelling, namely; null model, random intercept model and random intercepts and slopes model.

GLMs are a type of regression model that extends traditional linear regression to a family of regression models in which the dependent variable is either normally distributed or follows an exponential distribution (Rabe-Hesketh, Skrondal and Zheng, 2012). Currently, there is a trend in higher education research to recognize the limitations of linear regression in explaining the relationships between categorical criterion variables of interest (success / failure, dropping out / remaining) and a set of continuous and categorical predictors (Alnahdi and Aftab, 2020).

**The Null model (intercept-only model)**

According to Hox (2010), the first model of multilevel model is an intercept-only model, which allows the research to see if the group mean is significant, by computing the interclass correlation. Hox (2002) asserted that, the intercept only model is a model with no explanatory variables. The model contains only random groups and random variation within the group,

$$Y_{ij} = \beta_{0\mathrm{j}} + e_{ij} \qquad \text{Eq. (15)}$$

**Random Intercept Model:** The random intercept includes the random effect of the cluster variable. This means, the model allows the intercepts to vary and assumes that the slope is fixed. We add all the level 1 predictor to the null model and examine the deviation in each.

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + U_{oj} + e_{ij} \qquad \text{Eq. (16)}$$

$X_{ij}$ =Level 1 explanatory variable

**Random intercepts and Slopes Model:** All the explanatory variables from level 1 to level 2 are entered in the model. This model allows the slopes to vary. Some of the group level variables may be random slopes from level 1 model, but other group level variables may be variables defined only at level 2, such as group size (Hox, 2010)

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}Z_j + \gamma_{11}X_{IJ}Z_J + U_{1j}X_{ij} + U_{oj} + e_{ij} \quad \text{Eq. (17)}$$

$Z_J$ =Level 2 explanatory variables.

The multilevel make the same assumptions as the Simple linear regression (Hox, 2010).

The multilevel regression analysis assumes the followings:

a) Perfectly measured predictor variables

b) Linearity of relationships,

c) Normal residual errors

d) Homoscedasticity and independence conditional on the grouping variables in the model.

It further assumes that, residual errors at the separate levels are independent. When data has a nested structure, multilevel logistic regression analysis is more useful than typical single-level regression modeling in research investigations. Using several levels in modeling allows researchers to look at the effects of group and individual level variables on individual level outcomes at the same time, while accounting for the interdependence of observations within groups. MLMs also allow for the investigation of both between group and within group variability, as well as the relationship between group and individual level variables and variability at both levels.

According to McNeish (2014), Small group sizes at the lowest level are problematic with moderate or small sample sizes at the higher level, though such issues can be mitigated if the sample at the higher level is large enough. The most common estimation method for multilevel models and data is maximum likelihood. Two advancements in estimation and testing have resulted in the ability to obtain accurate estimates and standard errors with few clusters. The first improvement is to replace Full ML (FML) estimation with Restricted Maximum Likelihood (REML), FML estimates the model's variance components while assuming that the fixed effects (the regression coefficients) are known (Hox & McNeish, 2020). The multilevel approach to determining individual and school factors and a Linear Modeling, level-1 intercepts and coefficients were the outcomes in the level-2 model; thus, student outcomes were predicted not only by level-1 predictor variables but also by level-2 predictor variables. We used multilevel linear regression because the response or outcome variable is continuous.

**Parameter estimation under the multilevel Model**

a). **Restricted maximum likelihood estimation**: The first step of the analysis is to obtain an estimate of the unknown fixed effects $\beta$, as well as the estimates of the unknown variance components (El-Horbaty and Hanaf, 2018).

**b). Intraclass Correlation Coefficient**

The intraclass correlation coefficient (ICC) identifies the proportion of total variance that is between Level 2 units. ICC can be calculated using an intercept-only model (Eq. (15). The ICC is then calculated based on the following formula:

$$\rho = \frac{\sigma_{u_0}^2}{\sigma_{u_0}^2 + \sigma_e^2} \qquad \text{Eq. (18)}$$

According to Finch, Bolin and Kelley (2019), the $\rho$ is a measure of the proportion of the variation in the outcome variable that occurs between the groups compared to the overall variation that exists. It varies from 0 (no variance between groups) to 1 (variance between groups, but no intra-group relationship between the results for people from the same group.

Higher values ρ indicate that a greater proportion of the total variation in the outcome measure is related to group membership; i.e., there is a reasonably strong association between the outcomes for individuals in the same cluster.

There are two statistical approaches to estimating how well a given model fits a dataset and how complex the model is. They are:

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Akaike information criterion (AIC) and the Bayesian information criterion (BIC) in model selection and the appraisal of psychological theory.

The AIC and BIC statistics are defined for logistic regression as

a) $AIC = -\frac{2}{N} * LL + 2 * \frac{k}{N}$

b) $BIC = -2 * LL + log(N) * k$

where; $LL$ is the log-likelihood of the model, k is the model degrees of freedom calculated as the rank of variance–covariance matrix of the parameters and N is the number of observations

According to Vrieze (2012), the AIC had a minimax property compared to the BIC. To use AIC for model selection, we simply choose the model giving smallest AIC over the set of models considered because the AIC penalizes complex models less.

### 2.11. Chapter Summary

In this chapter, the conceptual framework of the study was also provided. A review of factors that affect academic performance was outlined and all other literatures related to this study were extensively reviewed. The chapter further outlines the statistical model that could be used.

# CHAPTER 3: RESEARCH METHODS

## 3.1. Introduction

This chapter outlines the approach on how the objective and specific objectives of the study was achieved. It describes the research design, population and sample size, sampling technique, instrument used, data analysis and the ethical consideration of the study.

## 3.2. Research Design

The study was quantitative and followed a cross-sectional design by comparing the STEM performance in Namibia. The analysis was based on secondary data obtained from the Directorate of National Examinations and Assessment (DNEA) and Ministry of Education's database for the year 2019.

## 3.3. Population

The population of this study consisted of all Grade 12 learners who wrote National examination for the year 2019

## 3.4. Sample

The study focused on the STEM subjects, hence only students that did science will be considered in the study. No sampling was done since all eligible students were considered.

## 3.5. Procedure

Data for this research was obtained from the 2019 DNEA data file and would be merged to the data from MOE to allow for multilevel modelling.

### 3.6. Variables

The dependent will be the number of subjects passed and the independent variables will be learner's sex, age, school type, resources, classroom and teachers' qualification

**Table 1: Explanatory variables**

| **Variable** | **Description** |
|---|---|
| **Level1 Variables** | |
| Candidate Age | Age of the Students (in years). The age ranges between 15 - 40. |
| Ownership | The types of school were students attended and wrote the final exams in 2019 (Private= 0, State=1) |
| Candidate Sex | Female = 0, Male=0 |
| **Level 2 Variables** | |
| Computer room per region | Computer room per region |
| Libraries centers per region | Resource Centre per region that students can use |
| Specialist teaching rooms | Number of special teaching classrooms in the school per region |
| Classrooms per region | Number of classrooms in the school per region |
| Teacher without formal teaching training per region | Teachers that are teaching grade 12 without formal education training |
| Teachers with formal teaching training per region | Teachers that are teaching grade 12 with formal education training |

### 3.7. Data analysis: Multilevel Linear Model

Data was edited, classified and coded into a Excel sheet and analysed using a computerized data analysis package known as Statistical Package for Social Science (SPSS) and RStudio. The data from Directorate of National Examinations and Assessment (DNEA) and Ministry of Education (MoE), were combined because the data from Directorate of National Examinations and Assessment (DNEA) did not have all the variables that were considered in the study.

The traditional multilevel model was employed in the study with a two-level multilevel data structure. To predict the outcome variable, we will consider a simple regressions developed for each individual $i$ :

$$Y_{ij} = \beta_{0j} + \beta_1 x_{ij} + e_{ij} \qquad \text{Eq. (19)}$$

Where:

$Y_{ij}$ = the response variable (achievement for student $i$ in school $j$)

$x_{ij}$ = student-level predictor for student $i$ in school $j$

$\beta_{0j}$= the average achievement for school $j$

$\beta_{1j}$= regression coefficient associated with $X_{ji}$ for the $j$th level-2 unit, and

$e_{ij}$ = random error associated with the $i$th level-1 unit nested within the $j$th level-2 unit.

$$E(e_{ij}) = 0, var(e_{ij}) = \sigma^2 \qquad \text{Eq. (20)}$$

In the level-2 models, the level-1 regression coefficients ($\beta_{0j}$ and$\beta_{1j}$) are used as outcome variables and are related to each of the level-2 predictors.

We will consider the case of a single level-2 predictor that, the relationship between dependent and explanatory variables will be measured at this level.

We will be modelled using Equations 3 and 4:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j} \qquad \text{Eq. (21)}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}X_j + u_{1j} \qquad \text{Eq. (22)}$$

$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}Z_j + \gamma_{11}X_{IJ}Z_J + U_{1j}X_{ij} + U_{oj} + e_{ij} \qquad \text{Eq. (23)}$$

where:

$z_j$=value on the level-2 predictor;

$\gamma_{00}$ =Intercept for (the grand mean achievement across students and across schools)

$\gamma_{10}$=Estimates the average effect of the student-level predictor

$\gamma_{01}$ = Regression coefficient associated with $Z_{ij}$

$\beta_{1j}$=Indicates that the effect for the student-level predictor is fixed

$\gamma_{11}$=Regression coefficient associated with Z relative to level-1 slope;

$u_{0j}$ =Error term representing a unique effect associated with school $j$

$u_{1j}$ =Random effects of the school level-2 unit adjusted for Z on the slope.

### 3.8. Research Ethics

Ethical clearance and permission to conduct research was obtained from the University of Namibia, Research Ethics Committee and Centre for Postgraduate Studies. The data was collected with the permission of the Director of DNEA. A formal letter requesting permission to collect and use the data for the 2019

NSSCO examination results for the purpose of this study was submitted to the Director of Education.

### 3.9. Chapter summary

The purpose of this chapter was to present the methodological approaches that were adopted. The chapter further outlined the research designed, study population and research instruments used. Finally, the researcher presented the ethical considerations made in this study. Chapter 4 presents the results and discussion while chapter 5 the conclusion and recommendation of the study.

# CHAPTER 4: RESULTS AND DISCUSSIONS

## 4.1. Introduction

This chapter outlined and interpreted the results carried out using the statistical method discussed in chapter 3

## 4.2. Descriptive Statistics

Distribution of some response variables are summarized in Table 2. From the analysis, the total number of STEM students who wrote the national exams in 2019 was 24407. Majorities (94.1%) of students that wrote the national examination attended the state and only 5.9% of the students were at private school. Despite the fact that, only few (1432) students that attended grade 12 at private students, 617 students did not pass a single STEM subjects. In addition, the numbers of female STEM students were high compared to the male that wrote the national examination.

The results showed that, some regions had fewer numbers of students, namely; Omaheke, Kunene, Hardap, //Kharas and Kavango West which is only representing less than 3% of the total population, while Oshikoto, Oshana, Khomas, Ohangwena, and Omusati were having a greater number of students which was above 10% of the entire population. Omaheke, Kunene and Kavango West, found to be having more teachers with formal educational while Oshana found to be the least region employing teachers with formal education. Similarly, Ohangwena region found to be having the high number of teachers without the formal education. Majority of students that wrote National examination are in age group 18 years

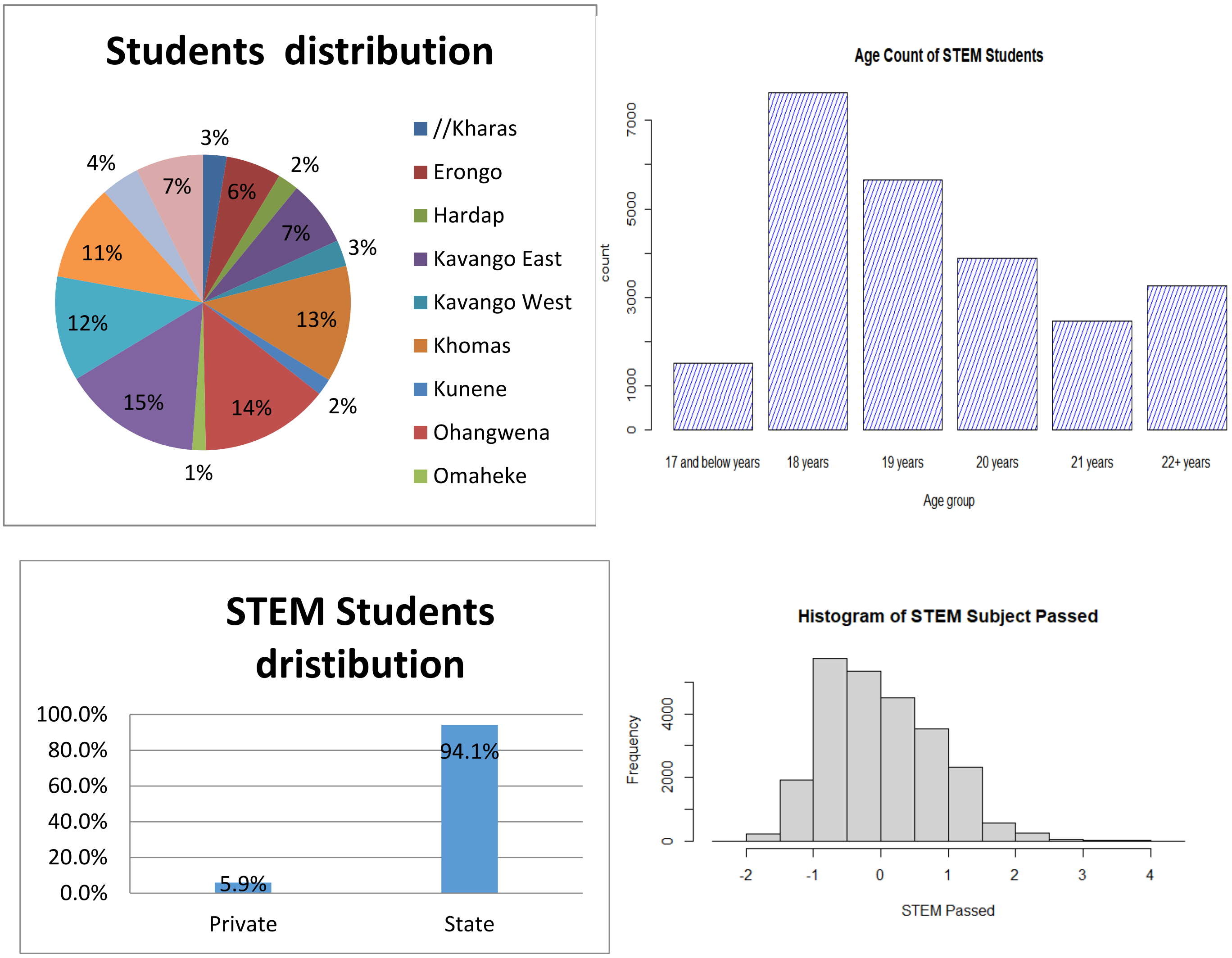


**Figure 2: Show the distribution of STEM subjects by Age group as well as regional distribution and Ownership.**

**Table 2: Summary measures for predictor variables on academic performance.**

| Level1 Variables | | |
|---|---|---|
| ***Candidate Age*** | | |
| | Count | Frequency |
| 17 and below years | 1519 | 6.2% |
| 18 years | 7623 | 31.2% |
| 19 years | 5666 | 23.2% |
| 20 years | 3879 | 15.9% |
| 21 years | 2468 | 10.1% |

| | | |
|---|---|---|
| 22 and above years | 3252 | 13.3% |
| ***Ownership*** | | |
| Private | 1432 | 5.9% |
| State | 22975 | 94.1% |
| ***Candidate Sex*** | | |
| Female | 13205 | 54.1% |
| Male | 11202 | 45.9% |

**Level 2 Variables**

| | Number of STEM students per region | Computer room per region (Count) | Frequency | Libraries centers per region (Count) | Frequency | Specialist teaching rooms (Count) | Frequency | Classrooms per region (Count) | Frequency | Teacher without formal teaching training per region (Count) | Frequency | Teachers with formal teaching training per region (Count) | Frequency |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| //Kharas | 633 | 30 | 7.7% | 18 | 3.0% | 30 | 7.7% | 888 | 3.4% | 31 | 8.8% | 256 | 2.9% |
| Erongo | 1474 | 42 | 10.8% | 53 | 8.8% | 42 | 10.8% | 1480 | 5.7% | 19 | 5.4% | 544 | 6.1% |
| Hardap | 560 | 21 | 5.4% | 34 | 5.7% | 21 | 5.4% | 913 | 3.5% | 39 | 11.0% | 256 | 2.9% |
| Kavango East | 1759 | 24 | 6.2% | 33 | 5.5% | 24 | 6.2% | 1704 | 6.5% | 26 | 7.4% | 625 | 7.0% |
| Kavango West | 702 | 12 | 3.1% | 18 | 3.0% | 12 | 3.1% | 1335 | 5.1% | 15 | 4.2% | 373 | 4.2% |
| Khomas | 3116 | 90 | 23.1% | 112 | 18.6% | 90 | 23.1% | 2996 | 11.5% | 35 | 9.9% | 1261 | 14.0% |
| Kunene | 444 | 19 | 4.9% | 14 | 2.3% | 19 | 4.9% | 912 | 3.5% | 11 | 3.1% | 244 | 2.7% |
| Ohangwena | 3440 | 25 | 6.4% | 55 | 9.2% | 25 | 6.4% | 3752 | 14.4% | 46 | 13.0% | 1185 | 13.2% |
| Omaheke | 362 | 15 | 3.8% | 18 | 3.0% | 15 | 3.8% | 756 | 2.9% | 30 | 8.5% | 207 | 2.3% |
| Omusati | 3703 | 36 | 9.2% | 82 | 13.6% | 36 | 9.2% | 3782 | 14.5% | 16 | 4.5% | 1297 | 14.4% |
| Oshana | 2805 | 22 | 5.6% | 48 | 8.0% | 22 | 5.6% | 2151 | 8.2% | 11 | 3.1% | 826 | 9.2% |
| Oshikoto | 2579 | 21 | 5.4% | 56 | 9.3% | 21 | 5.4% | 2718 | 10.4% | 42 | 11.9% | 839 | 9.3% |
| Otjozondjupa | 1033 | 23 | 5.9% | 41 | 6.8% | 23 | 5.9% | 1443 | 5.5% | 16 | 4.5% | 499 | 5.6% |
| Zambezi | 1797 | 10 | 2.6% | 19 | 3.2% | 10 | 2.6% | 1260 | 4.8% | 16 | 4.5% | 567 | 6.3% |

## 4.3. Inferential Analysis (Multilevel modelling)

Several hierarchical regressions models were fitted to analyze the effect of the explanatory variables on the pass rate of grade 12 students in Namibian. The study first considered a random intercept-only model, to determine the number of STEM subjects passed in the absence of any predictors. Three (4) model were considered in order to determine whether other explanatory variables at individual and school levels resulted in the best fitting model. Firstly, random intercept-only model was used to determine the number of STEM subjects passed in the absence of any predictors, to better show these predictors' effect on the response variable in the proceeding model. Thereafter, the researcher then fitted various random intercepts, random slopes and fixed effects. A multilevel regression model, with different predictors at different level is presented in table 3.

**Table 3: Descriptions multilevel models**

| **Model name** | **Model description** |
|---|---|
| Model1 | Random intercept only and no explanatory variables |
| Model2 | Random intercept model with fixed level1 predictors. ***Level 1 predictors***: *Candidate sex, Candidate age and ownership.* |
| Model3 | Random intercept model with fixed level2 predictors. ***Level 2 predictors***: *Computer room per region, Libraries centers per region, Specialist teaching rooms Classrooms per region, Teacher without formal teaching training per region, Teachers with formal teaching training per region* |
| Model4 | Random intercept model with fixed level 1 and level 2 predictors and a random slope of selected Level1 predictors varying by Centre name)**Predictors:** *Candidate sex, Candidate age, ownership, Computer room per region, Libraries centers per region, Specialist teaching rooms* |

| | |
|---|---|
| | *Classrooms per region, Teacher without formal teaching training per region, Teachers with formal teaching training per region* |

According to Eshetie (2016), given two or more models that are both suitable for the same data, the model with the lower information criterion value is preferred. The AIC and BIC are two common methods for comparing maximum likelihood models. Table 4 shows the obtained AIC and log-likelihood values for these fitted. From Table 4 the lowest AIC value (**59879**).is observed in model4. Model 4 was the best option for explaining the variability in STEM subjects passed.

**Table4: Selection of best fitting multilevel model based on AIC**

| | AIC | BIC | logLik | ICC |
|---|---|---|---|---|
| Model1 | 61535 | 61559 | -30765 | 5.8% |
| Model3 | 61524 | 61597 | -30753 | 5.6% |
| Model2 | 59898 | 59979 | -29939 | 5.1% |
| Model4 | **59879** | 60009 | -29924 | **4.6%** |

### 4.3.1. Intercept only

The intercept only model was used as a baseline model. We used the intercept only model to see if the number of STEM subjects passes at level cluster by the center name. This would help us to determine if there was a school effect, and if the school effects exist, we will continue with the multilevel modelling.

**Table 5: Fixed effects of the Intercept-only model**

| | Estimate | Std. Error | P - value |
|---|---|---|---|
| Intercept ($\gamma_{00}$) | 0.93971 | 0.02892 | 0.0000*** |
| $Residual\ (e_{ij})$) | 0.712 | 0.8438 | |
| $ntercept(u_{oj}$ | 0.1452 | 0.381 | |

The intercept of 0.93971 was the estimate of the mean of number of STEM subjects passed and there was a variation within the Centre name (0.712 than among the different Centre name (0.1452).

$$\rho = \frac{\sigma^2{}_{u0}}{\sigma^2{}_{u0} + \sigma^2{}_e},$$

The ICC= $\frac{0.1452}{(0.1452+0.712\ )} = 0.16939$

where $\sigma^2{}_{u0} = 0.1452$ is the variance of the level-2 residuals and $\sigma^2{}_e = 0.712$ is the variance of the level-1 residuals. Here, we have evidence of substantial clustering, where 17% of the variation in achievement occurs between schools and the Ccntre name random effect component is significant. In an empty model, an ICC near to 0 may hide significant variability that would only be visible in more complicated models. Furthermore, a low ICC did not rule out the existence of meaningful connections between numbers of STEM subjects passed and Centre name.

**Table 6: Results of best fitting multilevel model**

| | Estimate | Std. Error | t value | P |
|---|---|---|---|---|
| (Intercept) | 1.3220 | 0.1051 | 12.581 | 0.0000*** |

| | | | | |
|---|---|---|---|---|
| **Level1 Predictors** | | | | |
| ***Candidate Sex*** | | | | |
| Candidate Sex: M | 0.1879 | 0.0107 | 17.568 | 0.0000*** |
| Candidate Sex: F **(Ref)** | | | | |
| ***Ownership*** | | | | |
| State | 0.0230 | 0.0708 | 0.325 | 0.7455 |
| Private (Ref) | | | | |
| ***Candidate Age*** | | | | |
| agegroup 17 years and below (Ref) | | | | |
| agegroup 18 years | -0.0597 | 0.0235 | -2.543 | 0.0110*** |
| agegroup 19 years | -0.2836 | 0.0244 | -11.632 | 0.0000*** |
| agegroup 20 years | -0.4615 | 0.0258 | -17.914 | 0.0000*** |
| agegroup 21 years | -0.5456 | 0.0279 | -19.554 | 0.0000*** |
| agegroup 22 years and above | -0.7229 | 0.0272 | -26.628 | 0.0000 |
| **Level2 Predictors** | | | | |
| Computer Room: Per Region | 0.0089 | 0.0034 | 2.582 | 0.01062** |
| Libraries, Media Or Resource Centres: Per Region | -0.0098 | 0.0032 | -3.012 | 0.0030* |
| Specialist Teaching Rooms | 0.0006 | 0.0047 | 0.137 | 0.8910 |
| Classrooms Per Region | 0.0011 | 0.0002 | 4.636 | 0.0000*** |
| Teachers Without Formal Teacher Training Per Region | -0.0217 | 0.0049 | -4.446 | 0.0000*** |

| | | | | |
|---|---|---|---|---|
| Teachers With Formal Teacher Training Per Region | -0.0022 | 0.0005 | -4.304 | 0.0000* |

**Significant. codes:**

0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

On the basis of alpha=0.05, the results henceforth are interpreted at the 95%. The results of the examination of combined effects of Level1 and Level2 variables indicated that the overall STEM subject passed for the grade 12 was 1.3220 (P<0.0000).

Table 7 shows that the variables that significantly determined the number of STEM subjects passed were; candidate age, candidate sex, teachers without formal teacher training, teachers with formal teacher training per region, classrooms, libraries, media or resource Centre’s and computer room per region

The results from Table 7, shows that the odds estimate for a one unit increase in an individual’s age on the expected intensity category given the other variables were held constant in the model is -0.0597 (Age group 18). This implies that, if an individual’s age was to increase by one year, their chances to pass STEM subjects will decrease by 0.0597 with all other variables in the model held constant. As the number of student’s age increases, their chances of passing STEM subjects decrease drastically. The students in the age group 22 and above were not significant at all. There appears to be some contradiction in research findings with regard to age, with some studies finding no significant difference in age and student performance (Kausar et al., 2017). Other studies have found that a significant linear relationship exists between age and performance and that over-age students perform better than grade-age appropriate students (Bitrus et al., 2016).

The results further reveal that, the number of STEM subject passed for male student was 0.1879 higher than the female students. The number of STEM subject passed for state/public school was 0.0230 higher than the students in private school, but this was not significant associated with the number of STEM subject passed

The number of computer room in the region was expected to increase the number of STEM subjects passed by 0.0089 points for each unit increase with all other variables in the model held constant, whereas the number of classrooms was expected to increase the number of STEM subjects passed by 0.0011 points for each unit increase with all other variables in the model held constant. In addition, the number of teachers with and without formal education were negative coefficient in the study, was significantly related to the number of STEM subjects passed, but there was a negative relationship.

### 4.4. Discussion

This study was developed to obtain the outline of discrepancy and factors associated with academic performance in secondary schools in Namibia. The development of an effective education system that provides opportunities for all students to be successful at schools has been an important objective of countries around the world.

***To examine the relationships between academic achievement and demographic variables and socio-economic variables.***

The statistical analysis of the relationship between the student's age, student's sex, number of classrooms and number of computer rooms showed a significant effect on STEM subjects passed. The results of school type/ownerships, teachers' education and resource centres were some variables in the study.

A study by (Lamie, 2014) on the factors influencing the math achievement of high school student have identified and analyzed several factors that affect academic performance. His findings identify student's attendance, family structure, socioeconomic status, special education status, students who are English language learners (ELL), and gender. Hand et al. (2017) exploring the gender roles of teachers and students found that high school female students reported to have lower self-efficacy in mathematics and science compared male. According to (Sengul, Zhang & Leroux,2019), found that students in public school were having lower academic achievement compared to the private high schools' students. However, the multilevel analysis on the number of STEM subjects that was carried, reveal that there was no association between private and public. According to Abadoo (2018), a study on factors contributing to academic performance, found age to have a positive significant relationship with academic performance.

***To examine to what extent students' factors, teacher's factors and school factors affect the students' academic performance in STEM subjects.***

According to Tjihenuna (2016), due to the shortage of qualified teachers and large inflow of learners and shortage of classrooms, some tent classes has been erected to accommodate all the learners. Studies affirm that the classroom size can result in outstanding outcomes

Sengul et al. (2019) findings indicated that students, who had a positive perception about their relationship with their teachers, came from families including two biological parents, and had high SES and high math achievement

Bumgarner and Brooks-Gunn (2013) also stated that there were various factors indicating the influence of SES on students' academic achievement such as parental education, parenting, health, instructional strategies, and environmental conditions. Research indicates that family structure can smooth or limit the ways that family members can have influence on students' academic performance (Ralo, 2016; Wu et al., 2012). No study has been done so far to investigate the influence of students' perception of the quality of teacher.

# CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

## 5.1. Introduction

This chapter presents the conclusion and recommendations for the topic under study. The main objective of the study was to investigate the factors affecting academic performance in STEM subjects, in secondary schools in Namibia, using the Namibia Senior Secondary Certificate Ordinary Level examination results for the year 2019 obtained from the Directorate of National Examinations and Assessment (DNEA).

## 5.2. Limitation of the study

Due to financial and time constraints, student perceptions, teacher's qualification in specific subjects and parental socio-economic status, were not considered in this study. The study was limited to the available secondary data from Directorate of National Examinations and Assessment (DNEA) and Ministry of Education MOE and some variables were not considered due to the high level of confidentiality in the dataset. The student perceptions, teacher's qualification in specific subjects and parental socio-economic status, were not considered in this study, however future researchers should consider several interviews and meeting with the parents and open-ended questionnaire should be passed to the students. Additionally, the interview with the teachers will be necessary in the academic performance in order to yield important information about their satisfaction and this is necessary to teachers for them to overcome their unwillingness to the training procedural.

## 5.3. Delimitation of the study

Due to the nature of the study, the study was limited to grade 12 NSSCO students of 2019. Primary data are normally collected to address specific research at hand and use the correct procedures that will fit the research problem best. It is advisable for future research to collect primary data and avoid aggregated data, since the secondary data sources can yield to significant uncertainties which has not been given enough attention during data collection. In Addition, using secondary data can presents researchers with a number of distinctive problems

## 5.4. Conclusions

The findings from chapter 4 revealed that most of independent variables in the study were significate associated with academic performance. It is noted in the multilevel model that, there are variable within the schools as well as between schools. Overall the study also determined that the sex have a significant impact on the student's performance in STEM. According to (Mushtaq and Khan, 2012) opined that, libraries and resource Centre's are one of the places that students were found to have a significant relationship with student's performance.

## 5.5. Recommendations

Based on the findings of the study, the following recommendations were made:

a) The school and other concerned body must ensure that strictly qualified teachers are employed in order to enhance the quality of education from the lower level and Teacher-level factors should also be examined to understand their influence on instructional approaches to address students' needs.
b) The responsible parties must ensure that, the school infrastructures are taken care, because these infrastructures have a significance impact on students' academic performance.
c) An emphasis on classrooms size should be put on, especial the STEM fields where practical is taking place and teachers are required to engage with all students.
d) The government should give attention to education system and the Ministry of Education should give training and retraining of teachers when necessary and teacher's salary should be reasonable. Incentives

program for teachers with outstanding performance per subject should be encouraged.

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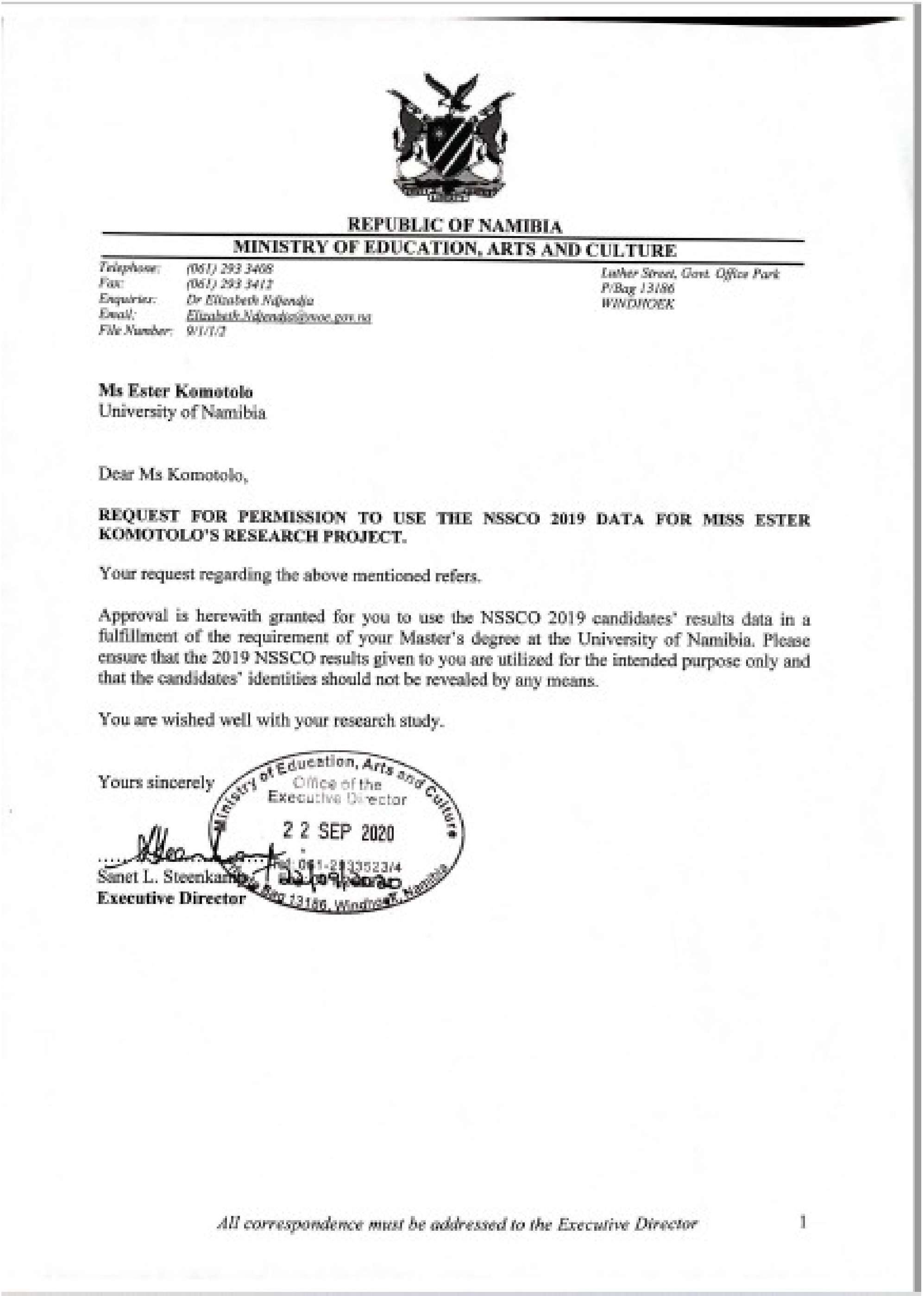
## APPENDICES

### Appendix 1: Ethical Clearance certificate

## Appendix 2: Permission letter



REPUBLIC OF NAMIBIA

MINISTRY OF EDUCATION, ARTS AND CULTURE

Telephone: (061) 293 3408
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File Number: 9/1/1/2

Luther Street, Govt. Office Park
P/Bag 13186
WINDHOEK

**Ms Ester Komotolo**
University of Namibia

Dear Ms Komotolo,

**REQUEST FOR PERMISSION TO USE THE NSSCO 2019 DATA FOR MISS ESTER KOMOTOLO'S RESEARCH PROJECT.**

Your request regarding the above mentioned refers.

Approval is herewith granted for you to use the NSSCO 2019 candidates' results data in a fulfillment of the requirement of your Master's degree at the University of Namibia. Please ensure that the 2019 NSSCO results given to you are utilized for the intended purpose only and that the candidates' identities should not be revealed by any means.

You are wished well with your research study.

Yours sincerely

Ministry of Education, Arts and Culture
Office of the Executive Director
22 SEP 2020
Tel: 061-2933523/4
Private Bag 13186, Windhoek, Namibia

Sanet L. Steenkamp
**Executive Director**

*All correspondence must be addressed to the Executive Director* 1

**Appendix 3:** R Code

```
#Multilevel Analysis

#Loading  the Data in R

library('readxl')

Academic <- read_xlsx("C:/Users/Esther/Documents/Thesis/Data
Cleaning.xlsx")


summary(Academic)

#Installing packages/Calling the packages

library(lme4)

library(merTools)

library(lmerTest)

library(MASS)

library(nlme)
```

***#categorizing age***

```
library(dplyr)

cademic$`CANDIDATE AGE` <- floor(runif(24407 , min = 15, max = 40))


findInterval(Academic$`CANDIDATE AGE`, c(17,18,19,20,21,40))

Academic <- Academic %>% mutate(agegroup =
case_when(Academic$`CANDIDATE AGE` >= 22  &
Academic$`CANDIDATE AGE` <= 40 ~ '22+ years',

                                Academic$`CANDIDATE AGE` >= 21  &
Academic$`CANDIDATE AGE` <= 21 ~ '21 years',

                                Academic$`CANDIDATE AGE` >= 20  &
Academic$`CANDIDATE AGE` <= 20 ~ '20 years',

                                Academic$`CANDIDATE AGE` >= 19  &
Academic$`CANDIDATE AGE` <= 19 ~ '19 years',

                                Academic$`CANDIDATE AGE` >= 18  &
Academic$`CANDIDATE AGE` <= 18 ~ '18 years',

                                Academic$`CANDIDATE AGE` >= 15  &
Academic$`CANDIDATE AGE` <= 17 ~ "17 and below years"))

# end function
```

*#Testing the Assumptions of Multilevel Models*

```
library("ggplot2")
library("HLMdiag")
library("DHARMa")
library("Matrix")

qqnorm(Academic$`Number of Stem Subject Passed`)
qqline(Academic$`Number of Stem Subject Passed`)

#creates a fitted vs residual plot
Plot.M4 <- plot(M4)
Plot.M4



#bar graph
barplot(table(Academic$agegroup),
        main="Age Count of STEM Students",
        xlab="Age group",
        ylab="count",
        border="black",
        col="blue",
        density=40
)
barplot(table(Academic$Ownership),
        main="School type",
        xlab="school type",
        ylab="count",
        border="black",
```

```
        col="blue",
        density=40
)

hist(Academic$`Number of Stem Subject Passed`,probability=T,
main="Histogram of STEM Subject Passed",xlab="STEM Passed")

lines(density(Academic$`Number of Stem Subject Passed`),col=2)
```

***#Intercept only model***

```
M1<-lmer(`Number of Stem Subject Passed`~1+(1|`CENTRE NAME`),REML
= FALSE,data=Academic)

summary(M1)
```

***# Run random intercept and slope model***

***# level1 predictors***

```
M2<-lmer(`Number of Stem Subject Passed`~1+`CANDIDATE
GENDER`+agegroup+Ownership+(1|`CENTRE NAME`),REML =
FALSE,data=Academic)

summary(M2)

anova(M1,M2)
```

***# level 2 predictors***

```
M3<-lmer(`Number of Stem Subject Passed`~1+`COMPUTER ROOM: PER
REGION`
           +`LIBRARIES, MEDIA OR RECOURCE CENTRES: PER
REGION`
            +`SPECIALIST TEACHING ROOMS`+`CLASSROOMS PER
REGION`
            +`TEACHERS WITHOUT FORMAL TEACHER TRAINING
PER REGION` +`TEACHERS WITH FORMAL TEACHER TRAINING PER
REGION`
           +(1|`CENTRE NAME`),REML = FALSE,data=Academic)

summary(M3)

anova(M3,M2)
```

**#Adding all level 1 and level 2 predictors**

```
M4<-lmer(`Number of Stem Subject Passed`~1+`CANDIDATE GENDER`+`COMPUTER ROOM: PER REGION`
        +`LIBRARIES, MEDIA OR RECOURCE CENTRES: PER REGION`
          +`SPECIALIST TEACHING ROOMS`+`CLASSROOMS PER REGION`
          +`TEACHERS WITHOUT FORMAL TEACHER TRAINING PER REGION` +`TEACHERS WITH FORMAL TEACHER TRAINING PER REGION`
           +Academic$agegroup+Academic$Ownership+(1|`CENTRE NAME`),REML = FALSE,data=Academic)
summary(M4)
anova(M3,M4)
anova(M1,M2,M3,M4)
```

***#ICC***

```
icc1<-M1@theta[1]^2/(M1@theta[1]^2 + (3.14159^2/3))
icc1
icc2<-M2@theta[1]^2/(M2@theta[1]^2 + (3.14159^2/3))
icc2
icc3<-M3@theta[1]^2/(M3@theta[1]^2 + (3.14159^2/3))
icc3
icc4<-M4@theta[1]^2/(M4@theta[1]^2 + (3.14159^2/3))
icc4
```

***#testing the relationship between each explanatory variable and Dependent Variables***

```
M.1<-lmer(`Number of Stem Subject Passed`~1+`CANDIDATE GENDER`+(1|`CENTRE NAME`),REML = FALSE,data=Academic)
M.2<-lmer(`Number of Stem Subject Passed`~1+agegroup+(1|`CENTRE NAME`),REML = FALSE,data=Academic)
```

```
M.3<-lmer(`Number of Stem Subject Passed`~1+Ownership+(1|`CENTRE NAME`),REML = FALSE,data=Academic)

M.4<-lmer(`Number of Stem Subject Passed`~1+`TEACHERS WITH FORMAL TEACHER TRAINING PER REGION`
          +(1|`CENTRE NAME`),REML = FALSE,data=Academic)

M.5<lmer(`Number of Stem Subject Passed`~1+`COMPUTER ROOM: PER REGION`
          +(1|`CENTRE NAME`),REML = FALSE,data=Academic)

M.6<-lmer(`Number of Stem Subject Passed`~1
          +`LIBRARIES, MEDIA OR RECOURCE CENTRES: PER REGION`
          +(1|`CENTRE NAME`),REML = FALSE,data=Academic)

M.7<-lmer(`Number of Stem Subject Passed`~1+`SPECIALIST TEACHING ROOMS`
          +(1|`CENTRE NAME`),REML = FALSE,data=Academic)

M.8<-lmer(`Number of Stem Subject Passed`~1+`CLASSROOMS PER REGION`
                  +(1|`CENTRE NAME`),REML = FALSE,data=Academic)

M.9<-lmer(`Number of Stem Subject Passed`~1  +`TEACHERS WITHOUT FORMAL TEACHER TRAINING PER REGION` +
          +(1|`CENTRE NAME`),REML = FALSE,data=Academic)

M.10<-lmer(`Number of Stem Subject Passed`~1 +`TEACHERS WITHOUT FORMAL TEACHER TRAINING PER REGION` +`TEACHERS WITH FORMAL TEACHER TRAINING PER REGION`
             +(1|`CENTRE NAME`),REML = FALSE,data=Academic)
```