FACTORS INFLUENCING THE PERCEIVED DIFFICULTIES OF SENIOR HIGH SCHOOL STUDENTS IN ELECTIVE MATHEMATICS

By

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CERTIFICATION

I hereby declare that this submission is my own work towards the MSc. degree and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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ABSTRACT

Elective Mathematics, currently, is one of the important subject requirements for admission into attractive programmes such as medicine, engineering, business, statistics, mathematics, actuarial science, economics, business administration, and architecture, among others in tertiary institutions in Ghana. However, greater proportion of the country‟s senior high school students is "maths phobic." Therefore, this thesis attempted to identify and model the socio-demographic variables that influence students‟ perceived difficulties in the subject. The study was conducted among 100 randomly selected students from two senior high schools in the Krachie East District of the Volta Region using both primary and secondary data. The binary logistic regression model was employed in the SPSS statistical software. The study concluded that respondents‟ programmes of study, ethnicity, and mothers‟ highest educational levels were there significant predictors of their perceived difficulties in Elective Mathematics.

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DEDICATION

To my wife, Doris Boateng and my son, Daniel Abotowuro.

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CHAPTER ONE

INTRODUCTION

1.1 Background of study

"Perceived Difficulty" in Elective Mathematics is the situation whereby students naturally consider the subject to be difficult. These include difficulty in applying formulae, using measurements, writing out phases of calculations, writing numbers, and spatial perception. However, mathematics in general and Elective Mathematics in particular is known as one of the gate-keeping subjects for success in all fields of life. It is a common saying that mathematics is a mother of all subjects and a backbone for development. The ability of any nation to compete successfully in the global market today, to a large extent, depends on the mathematical literacy of its citizens. According to Anamuah-Mensah (2007), the utilisation of science, mathematics and technology has been interlinked with the improvement in productivity and wealth creation of a nation. This explains why it is important to have skilled human resources in science, mathematics and technology as a nation. The key to the economic development of Ghana, therefore, depends on the development of a strong science, mathematics and technology base.

Mathematics as a discipline has great input in the scientific and technological development of any nation. Knowledge in mathematics is applied in almost every school subject. It is, therefore, significant that a lot of emphasis is laid on the teaching and learning of the mathematics from the basic level to the senior high school level. The study of mathematics in Ghana starts at the primary level through to the senior high school level, and it is compulsory for all students because it is recognised as a tool in many other subjects (like chemistry, physics, geography, economics, and so on). In the

Senior High School level, we have Core and Elective Mathematics. While the Core Mathematics is studied by all students, the Elective Mathematics is studied by General Science, some Business Accounting, Geography, Agriculture and Technical students only.

Mathematics enjoys a lot of recognition and respect from policy makers, educational institutions and the world of work. The study of mathematics is important because it is associated with more of academic and career opportunities and at the same time acts as one of the critical filters for entry into higher educational programmes and even in the world of work (Anamuah-Mensah, 2007). Thus, without sufficient knowledge in mathematics, one may not climb the academic ladder. In addition, people who resort to learning a trade because of their inability to make the required grade for further studies end up using mathematics as an important tool for performing their duties in their work places.

One of the general aims of teaching mathematics is to communicate effectively using symbols and explanations through logical reasoning (Ministry of Education, Science and Sports [MOESS], 2007). The study of mathematics also develops the power of logical thinking, accuracy and spatial awareness. Despite the importance of mathematics in human development, many investigations have shown that students in secondary schools are not very much interested in mathematics (Eshun, 2000; Awanta, 2000). Yara (2009) showed that majority of students saw mathematics as a subject with many technical terms which are difficult to remember.

For example, statistics from the West African Examinations Council (WAEC) on performance of students in Elective Mathematics from 2007 to 2014 has generally been poor. Table 1.1 presents the details.

Table 1.1: WASSCE Results from 2007-2014

Year	Pass (A1-C6)		Fail (D7-F9)		Total
	No.	%	No.	%	
2007	13,685	36.5	23,817	63.5	37,502
2008	15,352	35.7	27,608	64.3	42,960
2009	17,862	35.7	32,189	64.3	50,051
2011	32,711	68.1	15,304	31.9	48,015
2012	44,185	75.2	14,546	24.8	58,731
2013	63,078	47.0	71,177	53.0	134,255
2014	15,484	20.5	60,135	79.5	75,619

Source: WAEC IT Department, 2014.

A glance at Table 1.1 indicates that the average pass rate over the 7-year period was 45.5%. This means that more than half (54%) of Elective Mathematics candidates fail every year. The implication is that the subject poses difficulties to students in the Senior

High School levels. The result of this is the poor performance of students in the subject nationwide with particular emphasis with those in the Krachi East District of the Volta Region necessitated this study. The fear of mathematics is caused by several factors; some being real and others are simply perceived. Unearthing these factors is the preoccupations of this thesis.

1.2 Study area profile

Dambai is the capital of the Krachi East District in the Volta Region of Ghana. The district can be located at the North Western comer of the Volta Region of Ghana and lies between latitudes 7° 40°N and 8° 15°N and longitudes 0° 6°E and 0°20. In terms of population, the Ghana Statistical Service through its 2010 Population and Housing Census revealed that out of a total of 116,804, 52% were males and the remaining being females. The district has 25 kindergartens (KG) with a total enrolment of 1,994, 52 primary schools with a population of 6,467 and 12 Junior High Schools (JHSs) with an enrolment of 1,685 pupils. There are seven trained teachers and 40 attendants in the KG, 160 trained and 15 pupil teachers in primary schools and 78 trained and two pupil teachers in the Junior High Schools. In the two Senior High Schools in the district, students are studying both Core and Elective Mathematics. The performance of the students in these subjects is worrying.

1.2 Problem statement

The importance of mathematics to an individual and society is acknowledged worldwide (Githua, 2013). Mathematics is among the important subjects on the curriculum of most countries. In Ghana, while Core Mathematics is compulsory for every student sitting the

West African examinations by WAEC, Elective Mathematics is optional and usually studied by General Science, Technical, Agriculture Science, Geography and Business Accounting students. The past rate in especially Elective Mathematics has been worrying. With a particular reference to Senior High school students in the Krachie East District, their performance in Elective Mathematics is a pain in the necks of their respective school authorities every year. Statistics available from two schools in the district say that out of a total number of 1,552 Elective Mathematics students who wrote WASSCE between years 2005 and 2012, only 575 passed. This represents 37%. Specifically, in the Oti Senior High Technical School, out of the 964 candidates, 399 representing 41.4% passed the subject, while 176 passed out a total of 585 representing 30.1% (GES, 2012).

The above scenario is disturbing and, therefore, calls for an in-depth exploration into the reasons for this poor performance among students in the subject in the district. Uniquely, this thesis will employ a multiple logistic regression modelling technique to study the determinants of perceived difficulties in the subject.

1.4 Objectives of the study

The main objective of the study is to model the determinants of perceived difficulties of students studying Elective Mathematics in Senior High Schools in the Krachie East District. The study has the following specific objectives:

1. to determine the significant determinants that influence students‟ perceived difficulties in the subject; and

2. to model the determinants of perceived difficulties students encounter in Elective Mathematics.

1.5 Methodology

Data will be gathered from 100 Elective Mathematics students who will be randomly selected from two Senior High Schools in the Krachie District using the questionnaire. This number is deemed representative because it represents 64.5% of a total of 156 Elective Mathematics students in the two schools. The data analysis will be done in the SPSS and Microsoft Excel. Since the response variable is categorical and binary, a multiple binary regression will be used to develop a model that will be able to determine the real determinants of the perceived difficulties of the students. Logistic regression is a widely used tool for the statistical analysis of observed proportion or rates. According to Koch and Edwards (1985), logistic regression consists of fitting a linear logistic model to an observed proportion or rate in order to measure the relationship between the outcome variable and one or more explanatory variables. For a binary response variable, y , denote its two categories by 1 and 0. Commonly, the generic terms success (in this, difficult which is an interest group) and failure (not difficult which is the reference group) are used for these two outcomes. Logistic regression is also capable of including interactions among independent variables (Tabachnick and Fidell, 2001).

1.6 Justification

Over the years, the performance of students in Elective Mathematics in the Krachie East District has been very unimpressive. Although it is believed that a success in the subject at the Senior High School level will enable students to be admitted into several programmes in the university and polytechnics. It is therefore imperative that the causes of this fate be investigated and addressed. The findings of the study will help in improving the teaching and learning of Elective Mathematics in the SHS level. The outcome of the study will lend support to the efforts being made by Government and Ghana Education Service to promote the study of mathematics, science and technology among students. Also, the result of the study will also add to the body of existing knowledge on students‟ perceived difficulties in mathematics.

1.7 Scope and Limitation

This thesis is restricted to the objectives and variables of the research and data from the students in the Oti Senior High Technical School and Asukawkaw Senior High School in the Krachie East District of the Volta Region. The research work will be characterised by some constraints. Some of these setbacks will include time and willingness of the students to respond to the questionnaires.

1.8 Thesis organisation

This thesis is organised into five chapters. Chapter one is made up of introduction, which comprises the background of the study, study areas, problem statement and objective of the study. It also presents the justification and limitations of the study. Chapter two highlights related literature on the topic with ideas of different authors whose findings have been defined in relation to the topic under study. Chapter three focuses on methodological review in the light of mathematical and statistical tools that are relevant to the analyses of the data gathered. Basically, the study seeks to use time series model for the analyses. Chapter four deals with the analysis of data and the results, while chapter five presents of conclusion and recommendations.

1.9 Chapter summary

The chapter gave an introduction to the thesis report highlighting on issues relating to background of the study, problem statement and objectives guiding the study, methodology and justification of the study. In addition to these, are limitations as well as thesis organisation. The chapter concludes with this summary.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter reviews related literature on the perceived factors influencing students‟ difficulties in mathematics. The researcher identifies previous studies and findings related to this research study. The literature is reviewed under the following subheadings:

1. Perceptions and Attitudes;
2. Demographic Factors Related to Mathematics Achievement;
3. Teacher Factors; and
4. Environmental Influence on Students‟ Academic Performance.

2.1 Perceptions and Attitudes

Attitude like most abstract terms in English language has more than one meaning. Attitude lacks a precise definition. However, references can be made to some few writers on the subject. Kyriacou (as cited in Nabie, 2002) defines attitude as one‟s feeling towards a particular object or class of objects. According to Zanna and Rempel (1988), attitude is a disposition to respond favourably or unfavourably toward some person, thing, event, place, idea or situation. Attitudes are the thoughts and feelings that motivate someone to act as though he likes or dislikes something or somebody. Eshun (2000) defines attitudes as a mental and neutral state of readiness organised through experiences exerting a directive or dynamic influence upon the individuals‟ response to all objects and situations with which it is related. It can be inferred from the above definitions that attitudes are learnt from diverse situations. For instance, one can internalise the attitudes of those among whom he lives and from other public sources and institutions such as the mass media and education.

2.1.1 Perception/Attitude towards Mathematics

Anthony (2000) reported a study of perceptions of factors influencing success in mathematics and emphasised the role of motivation. Similarly, Eshun (2000b) explains attitude toward mathematics as an inclination to an aspect of mathematics that an individual acquires through his/her beliefs and experiences but which could be changed. Nabie (2002) also, defines attitudes toward mathematics as the acquisition of behaviours or feelings that turn to influence the choice of actions towards mathematics. All the definitions suggest that attitudes are learnt and can be changed. The fact that attitudes are learnt and are capable of being changed is a major significance for studying them.

Nkani (1993) indicated in his study of college students‟ attitudes towards arithmetic and quantitative scores on American College Examination that non-intellective factors such as attitude and emotional make-up have an important bearing upon students‟ success with their subjects. Attitudes towards mathematics may affect students‟ willingness to learn mathematics. Kidd (2003) says that for many people the feeling of dislike, frustration, and failure could have effect on their attitudes.

2.1.2 Mathematics Anxiety

Anxiety is a state of arousal caused by a threat to the wellbeing of an individual. An anxious person feels endangered in some way, and he is tensed and ready to respond.

Being anxious is a common human experience but for some people feelings of this kind disorganises their mental functioning. Despite the fact that some anxiety can be motivating, excessive anxiety can cause downshifting in which the brain"s usual processing mechanisms start to alter by lessening perceptions, preventing short term memory and behaving in more primitive reactions (McKee, 2002).

Many definitions have been given for mathematics anxiety. According to Foire (1999), mathematics anxiety is the panic, helplessness, paralysis, and mental disorganisation that arises among some people when they are required to solve a mathematical problem. Mathematics anxiety is an emotional and cognitive fear of mathematics. Russell (2008) notes that mathematics anxiety or fear of mathematics is quite common and, according to Zaslavsky (1994), people of all races and economic backgrounds fear mathematics, but women and minorities are most hindered by it. She reported a research which pointed out that around the seventh grade girls start to qualm their capabilities to study mathematics. Levine (1995) indicates that more females, to a large extent, experience mathematics anxiety than males.

Preis and Biggs (2001) describe a cycle of mathematics avoidance: In phase one, the person experiences unhelpful reactions to mathematics situations. These may result from past negative experiences with mathematics, and lead to a second phase in which a person dodges mathematics situations. The avoidance of mathematics situations leads to phase three, poor mathematics preparation, which brings them to phase four, poor performance in mathematics. This generates more negative experiences with mathematics and brings us back to phase one.

Some research findings indicate that there is a relationship between mathematics anxiety and mathematics achievement. Awanta (2000) says that relationship between anxiety and learning of mathematics is complex. Anxiety as a form of arousal of alertness can be helpful in learning but too much anxiety, particularly when combined with perceived lack of ability can hinder learning. Zakaria and Nordin (2008) found that there is a relationship between mathematics anxiety and achievement. They found that the mean achievements of low, moderate and high anxious groups were significantly different. Their findings also revealed a low (r= -0.32), but significant negative correlation between mathematics anxiety and achievement. Callahan and Clennon (as cited in Eshun, 2000) showed that high anxiety is associated with lower achievement in mathematics.

2.1.3 Self-confidence

Self-confidence is one of the attitudinal variables found to influence students‟ achievement and participation in mathematics. Hannula et al. (2004), in their longitudinal study on self-confidence, indicated that the learning of mathematics is influenced by the student„s mathematics related beliefs, especially self-confidence. Bae et al. (2000) also argue that achievement gaps appear more closely related to attitudes than to course taking. Based on their analysis of National Assessment of Educational Progress (NAEP) data trends, Bae et al. (2000) found that females are less likely than males to think they were good at mathematics. A study conducted by Cann (2009) revealed that in all the schools in Wales girls were more likely than boys to report feelings of anxiety and a lack of confidence in mathematics.

Jones and Smart (1995) see lack of confidence to be the main reason for girls‟ low participation in mathematics. Ma and Kishor (1997) found that confidence, which is a major component of self-concept, correlates positively with achievement, with correlation coefficients larger than 0.40 at the secondary school level. Fennema and Franke 1992) also indicated that confidence in mathematics learning correlates highly with achievement than any affective variable and achievement. An analysis of the educational longitudinal study of 1988, revealed that eighth grade girls tended to have less interest in mathematics as a field of study (Morin, 2003).

2.2 Demographic Factors Related to Mathematics Achievement

Various demographic factors have been known to be related to mathematics achievement. Gender, family structure, and parent‟s educational level are factors that have been analysed as predictors of mathematics achievement.

2.2.1 Gender

Early adolescence can be a critical time for girls‟ development of academic interests and attitudes. Many girls think that being bright is in conflict with being popular. High academic success can easily be in direct conflict with the social aspects of adolescence concerning learning opportunities, student/teacher interactions, and mathematic performance (Lee, 1996).

Fennema and Franke (1992) have suggested that learning habits that involve working independently on high-level tasks may enable some children to do better in math and science. Evidence also exists that males and females have different learning styles and that females excel at a higher rate when learning mathematics through rules. They pointed out that young girls are socialised to be dependent, and they receive more protection and more assistance in doing tasks from their parents and teachers than boys receive. As a result of the reinforcement of dependence, when children enter school, females tend to be more dependent on others and males tend to be more self-reliant. Females as young as Grade 6 and 7 rate being popular and well-liked as more important than being perceived as competent or independent. Boys, on the other hand, are more likely to rank independence and competence as important. It is clear that both girls and boys have learned to equate maleness with opportunity and femininity with constraint

(Sadker and Sadker, 1994).

2.2.2 Family Structure

Research has shown that adolescents in single-parent families do not do as well academically as adolescents in two-parent families (Kurdek and Fine, 1993). Studying the parental factors that influence adolescents‟ academic achievement can provide insight to parents about how to enhance their behaviors toward their adolescents so that they may make the most of their academic experience. Understanding how behaviours and resources of single parents affect adolescents in households is important for families, school/home partnerships, and to serve as a basis for more appropriate family life education.

A study conducted by Fluty (1997) examined single-parent behavioural control, involvement, and interpersonal and educational resources in relation to adolescents‟ mathematic achievement test scores. More than 3,000 adolescents from single parent homes were used in the study. Educational resources (encyclopedias, atlas, or books located in the home), interpersonal resources, and parental school involvement positively influenced mathematics achievement scores. For example, the more involved parents were in their children‟s school lives, the higher the mathematics scores.

Marital status was inversely related to adolescents‟ mathematics achievement scores. Adolescents who lived in divorced or separated homes performed better in mathematics than adolescents from never married or widowed families. Socioeconomic status was positively related to mathematics scores. Adolescents who lived in homes where parents attended college and had a high socioeconomic status scored higher on mathematics achievement tests than adolescents who lived in homes where parents had not attended college. Results from the study indicated that adolescents whose single parents were involved in their school lives earned higher scores on mathematic achievement tests than parents who were less involved. Results also suggested that children in single-parent homes might be at an academic risk more so than children from two-parent families (Fluty, 1997).

Conservative politicians feel that changes in the traditional family structure have harmful effects for children in terms of their educational development. In 1990, almost one third of all children were born into single parent families. Many children spend time in a stepfamily or with parents who cohabitate rather than marry. All of these changes can have a profound impact upon a child‟s social and educational development.

The findings in this study did not agree with the research that stated children from single parent families do not do as well academically as children from two parent families. In fact family structure did not have an impact on student attitudes toward mathematics or student‟s mathematic achievement.

2.2.3 Parents' Educational Level

A study conducted by Coleman et al. (1966) demonstrated that student achievement was correlated highly with family background factors such as income, parents‟ educational attainment, and family structure. A child‟s attitude towards education may be shaped by the parents‟ attitude toward education or parents‟ level of education. Schwartz (1999) suggested that parents or guardians may be illiterate or have very little education, and, therefore, not see the importance of doing well in school and furthering education. They may not understand why it is important for their child to take advanced level courses as they progress through school.

Although students can receive support and positive reinforcement at school, they may not receive the same support and reinforcement at home due to the lack of awareness from parents. Campbell et al. (2000) analysed the highest level of education of either parent. Results on parent education level are available back to 1978 in the area of mathematics. In each subject area, math, reading, and science, and each age group, students who reported higher parental education levels tended to have higher average scores. Since reports of

9year-olds about parent education level may not have been reliable, the results were not included in the executive summary. Among 13- and 17-year-old students at the highest level of parental education, college graduation, scores in 1999 were similar to those in 1978. Among those students whose parents‟ highest education level was some education after high school, 13-year-olds showed overall gains across the assessment years. Among students whose parents‟ education did not go beyond high school graduation, score increases across the years were evident for 17-year-olds and for those students whose parents did not complete high school. The overall gains in math were evident at ages 13 and 17. More schools and school systems are finding that in order to educate a student and break down barriers to learning, it is necessary to reach out to families and do all possible to involve and educate these families (Funkhouser and Gonzales, 1997).

It is important to view the student as a whole person who is shaped by the entire family in order for students to be successful. Research has shown that parents‟ educational level does impact student achievement. This study supports the research in that the parents‟ educational level significantly impacted each of the math achievement scores. The parents‟ educational level also impacted student attitudes toward mathematics.

2.3 Teacher factors

2.3.1 Impact of Teachers' Professional Training on Students' Achievement

There is a common thought that professional qualification of a teacher is a very essential merit of every effective teacher, though some studies indicate otherwise. Ball and Cohen (1999) were of the view that teachers should have an in-depth understanding of meanings and connections in subject matters and not just procedures and isolated information. Lockhead and Komenan (1980) in a review of teacher quality on the achievement of students noted that 60% of 60 studies that examined the effect of teacher education on student behaviour found positive relationship.

There are different views on the impact that a teacher‟s training has on students‟ achievement in mathematics. The findings of different researchers on the relationship between teacher training and student achievement in mathematics are contradicting.
Some researchers in mathematics education indicate that students‟ achievement is a function of teacher education programs. Researchers who are of this view assume that when teachers of mathematics are well-trained the students they teach will also achieve more in mathematics. Those with the opposing view see teachers‟ training to have very little influence on students‟ achievement in mathematics.

Some research findings have indicated that the training of mathematics teachers positively relate to student learning outcomes in the subject. Bressoux (1996), using a quasiexperimental design, found that teacher professional training in mathematics increases students‟ performance in mathematics. Darling-Hammond (1992) reviewed over one hundred studies on the subject and concluded that fully prepared (trained) teachers are more effective in the classroom and their students demonstrates the larger achievement gains than those teachers unprepared. Angrist and Lavy (2001), for instance, claimed that there is a strong relation between teacher training and student achievement in mathematics. Findings by other researchers have also indicated a stronger and more consistent positive result of professional educational training on teachers" effectiveness. Adeyeye and Arifolo (1999) in their study of impacts of teachers" professional qualification and academic qualification on students in Chemistry in Eketi State found that a statistically significance difference exist between the academic achievement of students taught by professional and non-professional teachers in Chemistry in secondary school level. Those taught by professional teachers showed a better overall academic achievement in Chemistry in Ekiti State. Dildy (1982), investigating the results of a randomised trial, found that teacher training increases student performance. A similar finding by Monk (1994) in studying student"s mathematics and science achievement found that the education coursework of a teacher had a strong positive influence on students learning and was sometimes more influential than extra subject matter preparation.

In Ghana, teachers are supposed to be trained in the various teacher training colleges and the universities of education (University of Cape Coast and University of Education, Winneba). In the two universities mentioned, the training is done in specific subjects of specializations of the teacher trainees. However, there are some teachers who have been recruited into the teaching field without the prerequisite training in education this untrained teachers may have a negative influence on Junior Secondary School students" achievement in mathematics. For children to receive quality education, we need qualified, competent and committed teachers. That is to say, to ensure quality education is to emphasise teacher quality. Darling-Hammond (2000) says that the effects of wellequipped teachers on students" achievement can overshadow student background factors such as language, poverty and minority status. She further argues that other kinds of investment such as reduced class size, overall spending on education and teacher salaries do not relate more strongly to students achievements than teacher quality.

A study that examined the mathematics achievement of elementary school students also found that students taught by new, uncertified teachers did significantly worse on achievement tests than did those taught by new certified teachers (Laczko-Kerr and Berliner, 2002). Some other findings by other researchers however, contradict the earlier findings discussed. Other literatures reveal that the training of mathematics teachers contributes very little to students" achievement in mathematics. Wiley and Yoon (1995) and Cohen and Hill (2000), for example, find teacher development programmes to have at least small impact on student performance.

2.3.2 Teachers' Subject of Specialisation/Qualification and Students' Achievement In addition to the professional training of teachers, literature has also revealed that the mathematics teachers" subject of specialty and teachers" qualifications have significant influence on students" achievement in mathematics. Findings on studies on subject areas of teachers in which advanced degrees were earned have been consistent in revealing a positive effect of teacher degree on students" achievement. Darling-Hammond and Sykes (2005) found that among the variables used in assessing teacher quality, the percentage of teachers with full certificate and a major in the field is a more powerful predictors of student achievement that teacher education levels.

Wayne and Youngs (2003) indicates that certification in a particular subject area, in this case, mathematics, may result in more effective teaching. Byrne (as cited in DarlingHammond, 2001), summarised the results of over thirty studies relating to teachers subject matter knowledge on students achievement. The results revealed a positive relationship. Begle (1979) found that the number of credits a teacher had in mathematics methods courses had a strong correlation with student performance than was the number of mathematics courses or other indicators of teacher preparation. A Pedagogical-content knowledge in mathematics has been found to be one major tool that gets the mathematics teacher to execute his duty as a subject teacher well and the students to achieve more in mathematics. Thus, to say for example, what teachers know both about subject-matter and students, determine how they select teaching methods and instructional materials and how well they present the materials in the class. Trends in International Mathematics and Science Studies (TIMSS, 1999) report indicates that teachers,, major areas of study during their post-secondary teacher preparations give some indication of their preparation to teach mathematics and also, higher achievement in mathematics is associated with teachers having a bachelor‟s degree and or master‟s degree in mathematics.

The National Commission on Teaching and America‟s Future (1996) says a major factor that can make a distinction in improving students‟ achievement is knowledgeable and skillful teachers. The finding suggests that teachers‟ subjects of specialisation and mastery are important elements in students‟ learning of the subjects. Work by other researchers also supports that teachers‟ qualification and subject-content specialisation influence students‟ learning outcomes. Goldhaber and Brewer (2006) using a nationallyrepresentative data provided in National-Education Longitudinal Study of 1988 to find the impact of teachers" holding masters degrees on high school students" mathematics achievement showed the essence of the subject in which the degree was awarded. The study revealed that students achievement gains in mathematics were positively associated with those assigned to teachers who earned their degrees in mathematics. Clotfelter et al. (2006) based on students test scores performance, argue that even the weakest student gain much improvements in teacher quality. Carpenter and Fennema (as cited in Fennema and Franke 1992), found that in the aspects of mathematics where the teacher was more knowledgeable, teaching and consequently learning was richer.

2.3.3 Teachers' Years of Teaching Experience and Students' Achievement

In addition to teacher professional qualification and subject-content specialisation, other factors may impact students" achievement in mathematics. One of such factors is years of teaching experience of the teacher. Research findings have indicated positive correlations between years of teaching experience and higher student achievement. Teacher"s inexperience is shown to have a strong negative effect on student performance. Conversely, experienced teachers produce higher student achievement. Teachers with more than five years in the classroom seem to be more effective than new teachers.

Rivkin et al. (2005) in analysing the UTD Texas Schools Project data showed that students of experienced teachers attained considerably higher levels of achievement than did students of teachers with one to three years of experience. Similarly, Fetler (2001) in analysis of mathematics achievement and dropout rates in a sample of California high schools found that schools whose dropout rates were within the highest 10 percent had 50 percent more new teachers than did schools in the lowest 10 percent. Ehrenberg and Brewer (1994) also found that teacher experience was positively related to white and

African American student gain scores, but negatively related to Hispanic gain scores. Goldhaber and Brewer (1996) also found that teacher experience is positively related to high school students" achievement. Greenwald et al. (1996) examined data from 60 studies and found a positive correlation between years of teacher experience and student test scores. Another study by Murnane and Phillips (1981) suggest that teachers with less teaching experience normally produce smaller learning gains in their students compared with teachers with more teaching years of teaching experience.

Rosenholtz (1986) also argues that teachers with less than three years of teaching experience are not effective as more experience teachers. Hawkins et al. (1998) specify that teaching experience can be viewed as a resource to which students have access. Teachers with more teaching experience have worked with a feeler multiplicity of students and have developed a greater stock of instructional strategies. Hawkins et al. (1998) found that in 1996 the amount of general teaching experience for teachers of fourth-grade mathematics indicated that students who were taught by teachers with less than five years of teaching experience had performance below the performance of students whose teachers had 6-10 years or 25 or more years of teaching experience. Ferguson (1991) found in his study of over 900 school districts in Texas that teacher experience was positively associated with student achievement gains at the district level.

On the contrary, more knowledgeable teachers in educational settings with no opportunity for staff development may become dormant in their performance. Teacher‟s age also count in his performance, older teachers may grow tired in their teaching. In his study of high school mathematics and science teachers, Monk (1994) found that teacher experience had no effect on student performance.

2.4 Environmental Influence on Students' Academic Performance

Researchers have been interested for a long time in the classroom environment‟s influence on students‟ motivation and learning. The general consensus has been that environments "characterised by mutual respect, high standards, and a caring attitude are more conducive to student persistence to other environment" (p. 103). Awanta (2000) said that influence in the classroom does not always flow from the teacher. He affirms that students do influence each other and can even influence the behaviour of their teachers. He indicates that according to research carried out by Newcomb (as cited in Awanta, 2000), many students confirm to peer group norms some of which are in contradiction to those held by educators and teachers. Students do influence the behaviour of their teacher. He says, "behaviour in classroom is bi-directional, that is, behaviour of the participants are influenced not only by what the teacher does, but also what students do" (p. 107). Copeland further states that where there is an enabling environment, where students have a positive perception for themselves and their peers and where they have satisfaction for their individual needs, "they persist in academic tasks and work cooperatively with the teachers to meet the demands of classroom life" (p. 113). The way teachers handle their classes are important factors that influence the way classes develop norms which they establish for social and academic work. This, he sees, as important function of teachers. Providing leadership is a critical executive function performed by teachers.

Educators are very much concerned with the workings and influence of the peer group and associated characteristics of students" culture within the school. They end with an appeal to teachers to take into account the fact that peer relationships have a strong influence on what occurs in the school and the classroom. The performance of students is invariably affected by the attitude put up by teachers and their peers. They admitted that students are affected positively or negatively depending on whether they are favourable or unfavourable perceived by their teachers and peers. They conclude that high rate of success is achieved if classrooms are well-managed and students are given enough engaged time. This depends on the ability of the teacher to manage the classroom as an effective learning environment when transitions are orderly and brief.

A conducive academic environment, they say, motivates students to attain high level of achievement. On the other hand, if the environment is not challenging enough, any individual within the community will have a low level of achievement and motivation. They talked about socially harmful environmental influences that run counter to school and societal norms. In such a case, he advices heads of schools and educational officers to work with parents to consider all the environmental factors that affect children in the community and find appropriate solutions to them.

Agu and Hamad (2000) are also of the view that parental expectations among others have a great influence on the academic performance of boys and girls. They also state that quite a number of studies have proved that teachers expectation of students" academic performance have a strong influence of the actual performance of the students.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

Statistical modelling is about finding general laws from observed data, which amounts to extracting information from the data. According to de Vries (2001), “there is no best model, only better models.” However, White and Bennetts (1996) suggested that a good statistical model is the one that provides a good approximate mathematical representation of the data being modelled with particular emphasis being on structure or patterns in the data. This chapter presents theoretical analyses of binary logistic regression.

3.1 Data Sources and Analysis

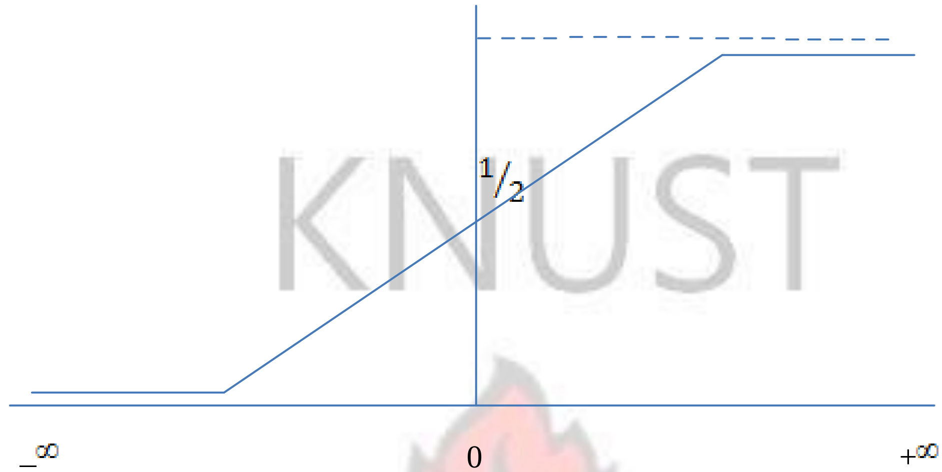
Primary data were gathered from 100 randomly selected Elective Mathematic students from two Senior High Schools in the Krachie East District of the Volta Region. The binary logistic modelling was by regression the variable “How do you perceive Elective Mathematics?” with options like “Difficult” and “Not difficult” on several dependent variables.

3.2 The Logistic Function

To explain the logistic regression, we show here the logistic function, which describes the mathematical form on which logistic model is based. Let the function be called $f\ (z)$, is given by

$$f(z) = \frac{1}{1+e^{-z}} \qquad (3.1)$$

When the value of this



function are plotted, z varies from –∞ to +∞ and its shape is given z

Figure 3.1: Shape of logistic function

From the graph, the range of $f(z)$ is between 0 and 1, irrespective of the value of z. The model is designed to describe a probability, which is always some number between 0 and 1. Another characteristic of the logistic model is derived from the shape of the logistic function, which is an elongated S shape. As shown in Figure 3.1, if we begin at $z = -\infty$ and move to the right, then as z increases, the value of $f(z)$ hovers close to zero for a while, then starts to increase dramatically toward 1, and finally levels off around 1 as z increases toward $z = +\infty$.

3.2.1 Logistic Model

The response variable in logistic model is usually dichotomous, that is the response variable can take the value 1 with probability of success p, or the value zero with the probability of failure 1 – p. This type of variable is called a Bernoulli (or binary) variable.

As mentioned previously, the independent or predictor variable in logistic regression can take any form. That is logistic regression makes no assumption about the distribution of the independent variables. They do not have to be normally distributed, linearly related, or of equal variance within each group. The relationship between the predictor and response variables is not a linear function in logistic regression, instead, the logistic regression function is used, which is the logit transformation of p:

To obtain the logistic model from the logistic function, we write z as the linear sum

$$z = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \qquad (3.2)$$

Where the x‟s are independent variables of interest and α and the β_i‟s are constant terms representing unknown parameters.

Substituting equation 3.1 into 3.2 we obtain,

$$f(z) = \frac{1}{1 + e^{-(\alpha + \sum \beta_i x_i)}}$$

For notational convenience, we will denote the probability statement as simply p(x) where x is a notation for the collection of variables x_1 through x_k.

Thus the logistic model may be written as

$$p(x) = \frac{1}{1 + e^{-(\alpha + \sum \beta_i x_i)}}$$

However, since the above logistic model is non-linear, the logit transformation would be used to make it linear, this is given by

$$Logit\ p(x) = In_e\left[\frac{p(x)}{1 - p(x)}\right] \qquad (3.3)$$

Where

$$p(x) = \frac{1}{1+e^{-(\alpha+\sum\beta_i x_i)}} \qquad (3.4)$$

This transformation allows us to compute a number, called logit p(x), for an individual with independent variable given by x.

By substituting equation 3.4 into 3.3, we obtain

$$In_e\left[\frac{p(x)}{1-p(x)}\right] = In_e\left[\frac{\left(\frac{1}{1+e^{-(\alpha+\sum\beta_i x_i)}}\right)}{\left(\frac{e^{-(\alpha+\sum\beta_i x_i)}}{1+e^{-(\alpha+\sum\beta_i x_i)}}\right)}\right]$$

$$= In_e\left[e^{(\alpha+\sum\beta_i x_i)}\right]$$

$$= \alpha + \sum \beta_i x_i$$

$$Logit\ p(x) = \alpha + \sum \beta_i x_i$$

$$\therefore Logit\ p(x) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \qquad (3.5)$$

Thus, the Logit of *p*(x) simplifies the linear sum. The quantity *p*(x) divided by 1–*p*(x), whose log value gives the Logit, describes the odd for a malaria patient being dead, with independent variables specified by *x*.

$$\frac{p(x)}{1-p(x)} = \text{odds for individual x} \qquad (3.6)$$

The goal of logistic regression is to correctly predict the category of outcome for individual cases using the most parsimonious model. To this end, a model is created that includes all predictor variables that are useful in predicting the response variable (Kleinbaum and Klein, 1994).

3.2.2 Logistic Regression with a Single Variable

The logistic or logit function is use to transform an „S"-shape curve into an approximately straight line and to change the range of the proportion from 0 – 1 to $-\infty$ to $+\infty$. The logit function is defined as the natural logarithm (In) of the odds of an event. That is,

$$logit = In\left(\frac{p}{1-p}\right)$$

Where *p* is the probability of an event.

$$logit\ (p) = \alpha + \beta x \qquad (3.7)$$

Although this model looks similar to a simple linear regression model, the underlying distribution is binomial and the parameters α and β cannot be estimated in exactly the same way as for simple linear regression. Instead the parameters are usually estimated using the method of maximum likelihood, which is discussed below.

3.3 Binary Logistic Regression

This regression model is obtained by regressing binary response variable on a set of explanatory variables. The main components of the binary logistic regression are discussed below:

1. Random component: The distribution of Y is *Binomial.*
2. Systematic component: *X'*s are explanatory variables (can be continuous, discrete, or both) and are linear in the parameters $\beta_0 + \beta x_i + \cdots + \beta_0 + \beta x_k$.
3. Link function: Logit

$$\eta = Logit(\pi) = \log\left(\frac{\pi}{1-\pi}\right) \qquad (3.8)$$

3.3.1 Logistic Regression with Single Independent Variable.

The general formula for the logistic regression model with single variable is;

$$\pi(x) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}} \tag{3.9}$$

The transformation of $\pi(x)$ that is central to the study of logistic regression is the logit *transformation.* The transformation is defined in terms of $\pi(x)$, as:

$$g(x) = \left[\frac{\pi(x)}{1-\pi(x)}\right] \tag{3.10}$$

$$g(x) = \ln\left(\frac{\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}}{1-\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}}\right)$$

$$g(x) = \ln\left(\frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}} \times \frac{1+e^{\beta_0+\beta_1 x}}{1}\right)$$

$$g(x) = \ln\left(e^{\beta_0+\beta_1 x}\right)$$

$$g(x) = \log_e e^{\beta_0+\beta_1 x}$$

$$g(x) = \beta_0 + \beta_1 x \tag{3.11}$$

The importance of this transformation is that g(x) has many of the desirable properties of a linear regression model. The logit, g(x), is linear in its parameters, may be continuous, and may range from $-\infty$ to $+\infty$; depending on the range of *x*.

3.3.2 Fitting the Single Logistic Regression Model

The method of estimation used in fitting the logistic regression model is the maximum likelihood. In order to apply this method we must first construct a function, called the *likelihood function.* This function expresses the probability of the observed data as a function of the unknown parameters. The *maximum likelihood estimators* of these parameters are chosen to be those values that maximize this function. Thus, the resulting estimators are those which agree most closely with the observed data. We now describe how to find these values from the logistic regression model. If Y is coded as 0 or 1 then the expression $\pi(x)$ provides (for an arbitrary value of $\boldsymbol{\beta} = (\beta_0, \beta_1)$, the vector of

parameters) the conditional probability that Y is equal to 1 given x. This will be denoted as P(Y = 1 | x). It follows that the quantity $1 - \pi(x)$ gives the conditional probability that Y is equal to zero given x, P(Y = 0 | x). Thus, for those pairs (x_i, y_i) where y_i = 1, the contribution to the likelihood function is $\pi(x_i)$ and for those pairs where y_i =0, the contribution to the likelihood function is $1 - \pi(x_i)$, where the quantity $\pi(x_i)$ denotes the value of $\pi(x)$ computed at x_i. A way to express the contribution to the likelihood function for the pair (x_i, y_i) is through the expression:

$$\pi(x_{i,})^{y_i}\,[1 - \pi(x_i)]^{1-y_i} \tag{3.12}$$

Since the observations are assumed to be independent, the likelihood function is obtained as the product of the terms given in equation (3.8) as

$$l(\boldsymbol{\beta}) = \prod_{i=1}^{n} \pi(x_{i,})^{y_i}\,[1 - \pi(x_{i,})]^{1-y_i} \tag{3.13}$$

The principle of maximum likelihood states that we use as our estimate of $\boldsymbol{\beta}$ the value which maximises the expression in equation (3.12) However, we will work with the log of equation (3.13). This expression, the *log likelihood* is given as:

$$\mathrm{L}(\boldsymbol{\beta}) = \ln[l(\boldsymbol{\beta})] = \sum_{i=1}^{n}\{y_i \ln[\pi(x_{i,})] + (1 - y_i)\ln[1 - \pi(x_{i,})]\} \tag{3.14}$$

To find the value of $\boldsymbol{\beta}$ that maximises $\mathrm{L}(\boldsymbol{\beta})$, we differentiate $\mathrm{L}(\boldsymbol{\beta})$ with respect to β_0, β_1 partially and set the resulting expressions equal to zero.

These equations, known as the *likelihood equations*, are;

$$\sum[y_i - \pi(x_i)] = 0 \tag{3.15}$$

and

$$\sum x_i[y_i - \pi(x_i)] = 0 \tag{3.16}$$

3.3.3 Testing for Significance of the Single Independent Variable

In logistic regression, comparison of observed to predicted values is based on the log likelihood function defined in equation (3.14). The comparison of observed to predicted values using the likelihood function are based on the following expression:

$$D = -2\ln\left(\frac{(\text{likelihood of the fitted model})}{(\text{likelihood of the saturated model})}\right) \tag{3.17}$$

The quantity inside the large brackets in the expression above is called the likelihood ratio. Such a test is called the likelihood ratio test. A saturated model is one that contains many parameters as there are data points. Using equation (3.14) and (3.17) becomes

$$D = -2\sum_{i=1}^{n}\left[y_i \ln\left(\frac{\pi_i}{y_i}\right) + (1-y_i)\ln\left(\frac{1-\pi_i}{1-y_i}\right)\right] \tag{3.19}$$

From equation (3.14), $\pi_i = \pi(x_i)$. The statistic, D, in the equation is called the *deviance.* This plays the same role as the residual sum of square plays in linear regression. It is identically equal to the sum of square error (SSE). In an instance where the values of our outcome variable are 0 and 1 just as in this study, the likelihood of our saturated model is 1. Specifically it follows from the definition of a saturated model that $\pi_i = y_i$ and the likelihood is

$$l(\text{saturated model}) = \prod_{i=1}^{n} y_i^{y_i}(1-y_i)^{1-y_i} = 1$$

Thus, it follows from equation (3.13) that the deviance is

D = -2In (likelihood of fitted model) (3.20)

Assessing the significant of an independent variables require that we compare the value of D with and without the independent variables in the equation. The change in D due to the inclusion of the independent variable in the model is obtained as;

$$G = D(model\ without\ the\ variables) - D(model\ with\ the\ variables) \quad (3.21)$$

This statistic plays the same role in logistic regression as the numerator of the partial Ftest does in linear regression. Because the likelihood of the saturated model is common to both values of *D* being differenced to compute G, it can be expressed as

$$G = -2\ln\left[\frac{(\text{likelihood without the variable})}{(\text{likelihood with the variable})}\right] \quad (3.22)$$

For cases of a multiple independent variable, it is easy to show when the variables are not in the model, the maximum likelihood estimate of β_0 is $\ln\left(\frac{n_1}{n_0}\right)$ where $n_1 = \sum y_i$, and $n_0 = \sum(y_i - 1)$ and the predicted value is constant, n_1 /n. In this case, the value of *G* is;

$$G = -2\ln\left[\frac{\left(\frac{n_1}{n_0}\right)^{n_1}\left(\frac{n_0}{n}\right)^{n_0}}{\prod_{i=1}^{n}(\hat{\pi}_i)^{y_i}(1-\hat{\pi}_i)^{(1-y_i)}}\right] \quad (3.23)$$

Or

$$G = 2\{\textstyle\sum_{i=1}^{n}[y_i\ln(\hat{\pi}_i) + (1+y_i)\ln(1-\hat{\pi}_i)] - [n_1\ln(n_1) + n_0\ln(n_0) - n\ln(n)]\}$$

(3.24)

Under the hypothesis that β_1 is equal to zero, the statistic *G* follows a Chi-square distribution with 1 degree of freedom. Two other similar, statistically equivalent tests known is the Wald test and the Score test. The assumption needed for these test are the same as those of the likelihood ratio test in equation (3.23).

The Wald test is obtained by comparing the maximum likelihood estimate of the slope parameter, $\hat{\beta}_1$, to an estimate of its standard error. The resulting ratio, under the hypothesis that $\beta_1 = 0$, will follow a standard normal distribution.

$$W = \frac{\hat{\beta}_1}{SE(\hat{\beta}_1)} \tag{3.25}$$

Another test use in testing for the significance of a variable is the Score test. This test is based on the distribution theory of the derivatives of the log likelihood. The test statistic for the Score test (ST) is

$$ST = \frac{\sum_{i=1}^{n} x_i(y_i - \bar{y}_i)}{\sqrt{(y_i - \bar{y}_i)\sum_{i=1}^{n}(x_i - \bar{x}_i)}} \tag{3.26}$$

3.4 Confidence Interval Estimation of Single Logistic Regression Variable

The confidence interval estimators for slope and intercept are based on their respective Wald tests. The endpoints of a $100(1-\propto)\%$ confidence interval for the slope coefficient are

$$\beta_1 \pm z_{1-\propto/2}\mathrm{SE}(\hat{\beta}_1) \tag{3.27}$$

and for the intercept they are

$$\beta_0 \pm z_{1-\propto/2}\mathrm{SE}(\hat{\beta}_0) \tag{3.28}$$

In equation (3.28), $z_{1-\alpha/2}$ is the upper $100(1-\propto/2)\%$ point from the standard normal distribution and SE(.) denotes a model-based estimator of the standard error of the respective parameter estimator. The estimated values are provided in the output following the fit of a model and, in addition, many statistical software packages provide the endpoints of the interval estimates. The standard error is calculated using the logit of the linear part of the logistic regression model and, as such, is most like the fitted line in a linear regression model. The estimator of the logit is;

$$\hat{g}(x) = \hat{\beta}_0 + \hat{\beta}_1 x \tag{3.29}$$

The estimator of the variance of the estimator of the logit requires obtaining the variance of a sum. In this case, it is

$$V\hat{a}r[\hat{g}(x)] = Var(\hat{\beta}_0) + x^2 Var(\hat{\beta}_1) + 2xCov(\hat{\beta}_0, \hat{\beta}_1) \tag{3.30}$$

In general the variance of a sum is equal to the sum of the variance of each term and twice the covariance of each possible pair of terms formed from the components of sum. The endpoints of a $100(1-\propto)\%$ Wald-based confidence interval for the logit are

$\hat{g}(x) \pm z_{1-\propto/2}\mathrm{SE}[\hat{g}(x)]$ (3.31) where $\mathbf{SE}[\hat{g}(x)]$ is the positive square root of the variance estimator in (3.29).

3.5 The Multiple Logistic Regression Model

The general form of the multiple logistic regression model is;

$$\pi(x) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_p x_p}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_p x_p}} \tag{3.32}$$

From equation (3.32), p = the number of independent variables and P(Y=1/**x**) = π **(x) =** the conditional probability that the outcome is present. The logit of the multiple logistic regression model is given by;

$$g(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p \tag{3.33}$$

in which case the regression model is:

$$\pi(x) = \frac{e^{g(x)}}{1+e^{g(x)}} \tag{3.34}$$

3.5.1 Fitting the Multiple Logistic Regression Model

The method of estimation used in fitting a multiple logistic regression model is the maximum likelihood estimation method. The likelihood function is nearly identical to that given in equation (3.12) with only a change being that π **(x)** is now defined as in equation (3.33). There will be *p*+1 likelihood equations that are obtained by differentiating the log likelihood function with respect to the *p*+1 coefficients. The likelihood equation that results is expressed as;

$$\sum_{i=1}^{n}[y_i - \pi(x_i)] = 0 \quad \text{(3.35) and}$$

$$\sum_{i=1}^{n} x_{ij}[y_i - \pi(x_i)] = 0 \text{ for } j=1,2,\ldots, p. \quad (3.36)$$

As in the univariate model, the solution of the likelihood equation requires special statistical software packages. In calculating the standard error, we will have to find the estimates of the variance and covariance of our coefficients. The method of estimating variances and covariance of the estimated coefficients follows from the theory of maximum likelihood estimation which states that the estimators are obtained from the matrix of second partial derivatives of the log likelihood function. The general form of these partial derivatives is;

$$\frac{\partial^2 L(\beta)}{\partial \beta_j^2} = -\sum_{i=1}^{n} x_{ij}^2 \pi_i (1-\pi_i) \tag{3.37}$$

and

$$\frac{\partial^2 L(\beta)}{\partial \beta_j \partial \beta_l} = -\sum_{i=1}^{n} x_{ij} x_{il} \pi_i (1-\pi_i) \tag{3.38}$$

for j,l = 0,1,2,..,p where πi denotes $\pi(\mathbf{x}_i)$ and p denotes the number of covariates in the model. If (p+1) ×(p+1) matrix containing the negative of the terms given in equations (3.37) and (3.38) be denoted as **I(*β*).** This matrix is called the *observed information matrix.* The variances and covariances of the estimated coefficients are obtained from the inverse of this matrix which is denoted as

$$Var\,[\mathrm{I}(\beta)] = \mathrm{I}^{-1}(\beta) \tag{3.39}$$

The estimated standard errors of the estimated coefficients can also be used. This is denoted as;

$$\mathrm{SE}(\hat{\beta}_j) = \left[V\hat{a}r(\hat{\beta}_j)\right]^{1/2} \tag{3.40}$$

for j = 0,1,2,…,p. A formulation of the information matrix which is useful for the model fitting and assessment of the fit is $\mathbf{I}(\boldsymbol{\beta}) = \mathbf{X}'\mathbf{V}\mathbf{X}$ where **X** is an n by p + 1 matrix containing the data for each subject, and V is and n by n diagonal matrix with general element $\hat{\pi}_i(1-\hat{\pi}_i)$. That is, the matrix **X** is

$$\mathrm{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1p} \\ 1 & x_{11} & x_{12} & \cdots & x_{1p} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & x_{11} & x_{12} & \cdots & x_{1p} \end{bmatrix}$$

The matrix **V** is

$$\mathrm{V} = \begin{bmatrix} \hat{\pi}_1(1-\hat{\pi}_1) & 0 & \cdots & 0 \\ 0 & \hat{\pi}_2(1-\hat{\pi}_2) & \cdots & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & \cdots & 0 & \hat{\pi}_n(1-\hat{\pi}_n) \end{bmatrix} \tag{3.41}$$

3.5.2 Testing for the Significance of the Multiple Logistic Regression Parameters As in the univariate, the first step in this process is usually to assess the significance of the variables in the model. The likelihood ratio test for overall significance of the p coefficients for independent variables in the model is performed in exactly the same manner as in the univariate case. The test is based on the statistic **G** given in equation (3.22). The only difference is that the fitted values, π, under the model are based on the vector containing p + 1 parameters, $\boldsymbol{\beta}$. Under the null hypothesis that p "slope" coefficients for the covariates in the model are equal to zero, the distribution of **G** will be chi-square with p degrees-offreedom. The Wald test is obtained by comparing the maximum likelihood estimate of the slope parameter, β_j to an estimate of its standard error. The resulting ratio, under the hypothesis that H 0: $\beta_j = 0$, for j = 0,1,2,...,p will follow a standard normal distribution.

$$W = \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \tag{3.42}$$

3.5.3 Confidence Interval Estimation in Multiple Logistic Regression

The confidence interval estimators for the logit are a bit more complicated for the multiple variable model than the results in equation (3.30). The basic idea is the same only there are now more terms involved in the summation. It follows from equation (3.27) that the general expression for the estimator of the logit for a model containing p covariates

$$\hat{g}(x) = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_p x_p \tag{3.43}$$

An alternative way to express the estimator of the logit in the equation (3.29) is through the use of the vector notation as g(**x**) = **x′** $\boldsymbol{\beta}$, where the vector $\boldsymbol{\beta}' = (\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_p)$ denotes the estimator of the p+1 coefficients and the vector $\mathbf{x}' = (x_0, x_1, x_2, \ldots, x_p)$ represent the constant and a set of values of the p-covariates in the model, where x_0=1.

The expression for the estimator of the variance of the estimator of the logit in equation (3.38) is

$$V\hat{a}r[\hat{g}(x)] = \sum_{j=0}^{p} x_j^{\,2}\mathrm{Var}(\hat{\beta}_j) + \sum_{j=0}^{p}\sum_{k=j+1}^{p} 2x_j x_k Cov(\hat{\beta}_j, \hat{\beta}_k) \qquad (3.44)$$

This can be expressed much more concisely by using the matrix expression for the estimator of the variance of the estimator of the coefficients. From the expression for the observed information matrix, we have that,

$$V\hat{a}r(\hat{\beta}) = (X'VX)^{-1} \qquad (3.45)$$

It follows from equation (3.31) that an equivalent expression for the estimator in equation (3.39) is

$$V\hat{a}r[\hat{g}(x)] = X'V\hat{a}r(\hat{\boldsymbol{\beta}})$$

$$= X'(X'VX)^{-1} \qquad (3.46)$$

3.6 Odds Ratios

The odds of the outcome being present among individuals with Y = 1 is defined as (1)/[1- π(1)]. Similarly, the odds of the outcome being present among individuals with Y = 0 is defined as (0)/[1- π(0)]. The *odds ratio*, denoted by OR, is defined as the ratio of the odds for Y= 1 to the odds for Y = 0, and is given by the equation:

$$OR = \frac{\pi(1)/[1-\pi(1)]}{\pi(0)/[1-\pi(0)]} \qquad (3.47)$$

Table 3.1: Values of the logistic regression model when the independent variable is dichotomous

Outcome variable (Y)	Independent Variable (X) x = 1 x = 0

y = 1 y = 0 Total	$\pi(1) = \frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1}}$ $1-\pi(1) = \frac{1}{1+e^{\beta_0+\beta_1}}$	$\pi(0) = \frac{e^{\beta_0}}{1+e^{\beta_0}}$ $1-\pi(0) = \frac{1}{1+e^{\beta_0}}$
	1.0	1.0

$$OR = \frac{\left(\frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1}}\right)\Big/\left(\frac{1}{1+e^{\beta_0+\beta_1}}\right)}{\left(\frac{e^{\beta_0}}{1+e^{\beta_0}}\right)\Big/\left(\frac{1}{1+e^{\beta_0}}\right)}$$

$$= \frac{e^{\beta_0+\beta_1}}{e^{\beta_0}}$$

$$= e^{(\beta_0+\beta_1)-\beta_0}$$

$$OR = e^{\beta_1}$$

Hence, for logistic regression with a dichotomous independent variable coded 1 and 0, the relationship between the odds ratio and the regression coefficient is

$$OR = e^{\beta_1} \qquad (3.48)$$

The interpretation given for the odds ratio is based on the fact that in many instances it approximates a quantity called the relative risk. This parameter is equal to the ratio (1)/π

0. It follows from equation (3.48) that the odds ratio approximates the relative risk if [1- (0)] / [1- (1)] ≈1. This holds when π(x) is small for both x =1and x = 0.

3.6.1 Confidence Limits for Odds Ratio

This is obtained by finding the confidence limits for the log odds ratio. Then, exponentiate these limit to obtain limits for the odds ratio. In general, the limits for a 100(1-α) % confidence interval for the coefficient are of the from

$$\hat{\beta}_1 \pm Z_{1-\alpha/2} \times SE(\hat{\beta}_1) \tag{3.49}$$

The corresponding limits for the odds ratio obtained by exponentiating these limits are;

$$\exp\left[\hat{\beta}_1 \pm Z_{1-\alpha/2} \times SE(\hat{\beta}_1)\right] \tag{3.50}$$

3.7 Chapter summary

This chapter has described the methodological approach adopted in this study. Emphasis was laid on the data type and sources as well as the binary logistic approach employed. This approach has several features which make it particularly useful and popular.

CHAPTER FOUR

DATA ANALYSIS AND RESULTS

4.0 Introduction

This chapter presents the data collected, techniques employed in the data analysis and the results that emerged from the analysis. It is divided into two sections, namely: preliminary analysis and further analysis. The preliminary analysis presents the demographic information of the respondents, whilst the further analysis concentrates on the development of the binary regression model for determining the perceived difficulties of the students. All the 100 Elective Mathematics students made of 50 each from Oti Senior High/Technical and Asukwakwa Senior High Schools who were randomly selected for the study completed and returned their copies of the questionnaire for analysis. This resulted in the study achieving a 100% retrieval rate.

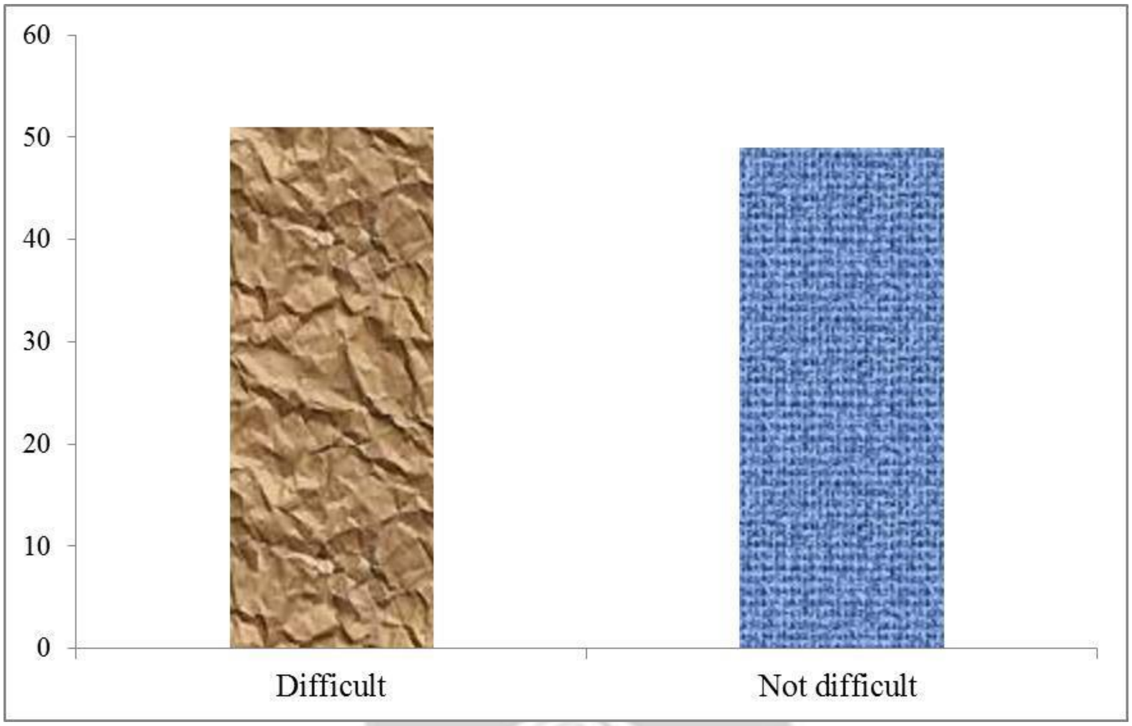


Figure 4.1: Percentage bar chart showing the perceived difficulties in Elective Mathematics among students

From Figure 4.1, we observed that out of the 100 students 51 perceived difficulty in Elective Mathematics, while 49 students claimed they had no difficulties in the subject. This indicates that more students perceived the subject to be difficult than not difficult. As defined earlier, "Perceived Difficulty" in Elective Mathematics is the situation whereby students naturally consider the subject to be difficult. These include difficulty in understanding of mathematics language, applying formulae, using measurements, writing out phases of calculations, writing numbers, and spatial perception.

4.1 Preliminary Analysis: Test of Association using the Chi-Square or Fisher's Exact Tests

This section deals with the establishment of associations between the various sociodemographic variables and students‟ perceived difficulties in Elective Mathematics.

The study employed the Chi-square test, odds ratio and Fisher‟s exact test (if necessary) to determine the association between 11 demographic characteristics of the students and their perceived difficulties in the subject.

Table 4.1: School and perceived difficulty in Elective Mathematics

School	Perceived difficulty in the ubject		Total
	Difficulty	Not difficult	
Oti	22 (25.5)	28 (24.5)	50
Asukwakwa	29 (25.5)	21 (24.5)	50
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

The contingency table reveals that among the 51 students who perceived Elective Mathematics to be difficult, 29 representing about 58% were from Asukwakwa SHS, whiles the remaining 22 representing 42% were Oti Senior High/Technical School. A test of independence produced a Chi-square value of 1.961 with a *p*-value of .161. Therefore, we fail to reject the null hypothesis that a student‟s school and his perceived difficulty in Elective Mathematics were independent. This means that a student‟s perceived difficulty in the subject was irrespective of his/her school. Furthermore, the odds ratio computed as, OR=22*21/29*28=0.57, means the odds of perceiving Elective mathematics as difficult rather than not difficult were 43% lower for students from Oti Senor High Technical School than for Asukwakwa SHS students.

Table 4.2: Gender and perceived difficulty in Elective Mathematics

Gender	Perceived difficulty in the subject Difficulty	 Not difficult	Total
Males	31 (27.5)	23 (26.5)	54
Females	20 (23.5)	26 (22.5)	46
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

In terms of the association between gender and perceived difficulties in Elective Mathematics, a Chi-square value of 1.929 and an associated *p*-value of .165 were obtained; indicating that there was no significant association between them. The implication of this result is that difficulty in the subject among the students was no gender-based. The odds ratio, OR=31*26/20*23=1.75, means that the odds of perceiving Elective mathematics as difficult rather than not difficult were 75% higher among the males compared to their female counterparts. Thus, male students perceived Elective Mathematics as more difficult than the females.

Table 4.3: Age and perceived difficulty in Elective Mathematics

Age	Perceived difficulty in the subject Difficulty	 Not difficult	Total
Less than 15 years	3 (1.5)	0 (0.0)	3
15-18 years	17 (13.8)	10 (13.2)	27
19-22 years	27 (31.1)	34 (29.9)	61
23 years and above	4 (4.6)	5 (4.4)	9
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

The data in Table 4.3 reveals that out of the 51 students who perceived Elective Mathematics to be difficult, 27 (52.9%) were aged 19-22 years and 17 (33.3%) were between 15-18 years. However, a test of independence between age of the students and perceived difficult in the subject showed that there was no significant association between them since the Chi-square and *p*-values of 5.691 and .128, respectively were obtained.

Table 4.4: Programme of study-perceived difficulty contingency table

	Perceived difficulty in the subject		
Programme of study	Difficulty	Not difficult	Total
Business	28 (36.2)	43 (34.8)	71
General Arts	4 (2.6)	1 (2.4)	5
Technical	3 (1.5)	0 (1.5)	3
Agricultural Science	16 (10.7)	5 (10.3)	21
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

Out of the 51 students who perceived Elective Mathematics as difficult, most (54.9%) of them studied Business, 16 (31.4%) studied Agricultural Science and the remaining were General Arts and Technical students as shown in Table 4.4. A further analysis using the Chi-square test produced a value of 13.696 with 3 degrees of freedom and a *p*-value of .000. This means that programme of study and perceived difficulty in Elective Mathematics were associated. The implication is that students studying certain course do perceived Elective Mathematics more difficult than the others. It, therefore, means that programme of study could be a significant predictor of difficulty in the study.

Table 4.5: Ethnicity-perceived difficulty contingency table

Ethnicity	Perceived difficulty in the subject: Difficulty	Not difficult	Total
Nchunbang	10 (11.2)	12 (10.8)	22
Konkomba	12 (9.2)	6 (8.8)	18
Frafra	3 (2.9)	12 (7.7)	15
Dangme	9 (6.6)	4 (6.6)	13
Asante	2 (4.6)	7 (4.4)	9
Ewe	9 (6.1)	3 (5.9)	12
Krachi	6 (5.6)	5 (5.4)	11
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

Using the Fisher"s exact test, a *p*-value of .001 was obtained. This called for the rejection of the null hypothesis of independence. Ethnic background of the students significant determined their perception about Elective Mathematics. The study would, therefore, include ethnicity in the binary logistic regression as a potential determinant of difficulty in the subject.

Table 4.6: Residential status and perceived difficulty in Elective Mathematics

Status	Perceived difficulty in the subject: Difficulty	Not difficult	Total
Boarder	5 (5.1)	5 (4.9)	10
Day	46 (45.9)	44 (44.1)	90

Total	51 49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

From Table 4.6, it can be seen that overwhelming majority of the students (90%) were day students. Among those who perceived Elective Mathematics to be difficult, 46 (90.2%) were day students, whiles the remaining 5 (8.8%) were borders. To determine if there was any association between the two variables, a Chi-square test of independence was performed and a value of 0.004 with an associated *p*-value of .947 was obtained. This means that the two variables were not statistically dependent. Since residential status and perceived difficulty were not associated, the modelling will not include residential status as a predictor. Similarly, the study obtained a calculated odds ratio of 0.96; implying that the odds of perceiving Elective Mathematics as difficult versus not difficult was 4% less likely among the boarders than the day students.

Table 4.7: Fathers' educational level-perceived difficulty contingency table

	Perceived difficulty in the subject		
Educational level	Difficulty	Not difficult	Total
No formal education	27 (23.5)	19 (22.5)	46
Basic	12 (17.3)	22 (16.7)	34
Secondary	5 (3.1)	1 (2.9)	6
Poly/Coll. of Educ/Nurs Trg.	4 (4.6)	5 (4.4)	9
University	3 (2.6)	2 (2.4)	5

Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

It can be seen from Table 4.7 that as many as 46 representing 46% of the respondents had fathers with no formal education and 34 representing 34% with basic education. Also, 6 of them had fathers who attained secondary education, 9 and 5 had their fathers with having polytechnic or teacher training and university education, respectively. As to whether or not father‟s educational level and student perceived difficulties in Elective Mathematics were associated, the Fisher‟s exact test a *p*-value of .000; indicating that these two variables were associated. The implication is that father‟ educational level is a strong predictor of student‟s difficulties in the subject. Therefore, this variable should be included in the model for predicting student‟s perceived difficulties in Elective

Mathematics.

Table 4.8: Mothers' educational level-perceived difficulty contingency table

	Perceived difficulty in the subject		
Educational level	Difficulty	Not difficult	Total
No formal education	28 (33.2)	37 (31.8)	65
Basic	10 (9.7)	9 (9.3)	19
Secondary	13 (8.2)	3 (7.8)	16
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

Similar to the results in Table 4.7, Table 4.8 also reveals that 65 representing 65% of the respondents had mothers with no formal education. Nineteen and 16 of them respectively had mothers who had obtained basic and secondary levels of education. A test of independence was conducted and a Chi-square value of 7.512 and a *p*-value of .023 were obtained. The results indicate that there was a significant association between mother‟s educational attainment and a student‟s perceived difficulties in Elective Mathematics. Therefore, it can be predicted that mothers‟ educational level may significantly influence students‟ perceived difficulties in the subject, hence should be included in the model.

Table 4.9: Fathers' occupations and perceived difficulty in Elective Mathematics

Occupation	Perceived difficulty in the subject		Total
	Difficulty	Not difficult	
Farmers	34 (28.6)	22 (27.4)	56
Drivers	4 (3.1)	2 (2.9)	6
Businessmen/Traders	4 (9.7)	15 (9.3)	19
Fishermen	9 (6.1)	3 (5.9)	12
Civil/public servants	0 (3.6)	7 (3.4)	7
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

Among the students, a large proportion of them (68%) had their fathers who were farmers and fishermen, 19 representing 19% of the fathers were businessmen or traders. The remaining were either drivers or civil/public servants. A test for independence produced a Chi-square value of 19.574 with 4 degrees of freedom and a *p*-value of .001. This means that the occupation of fathers could be a factor in explaining students‟ difficulties in Elective Mathematics.

Table 4.10: Mothers' occupations and perceived difficulty in subject

Occupation	Perceived difficulty in t ıe subject		Total
	Difficulty	Not difficult	
Farmers	32 (28.0)	23 (27.0)	55
Traders	10 (16.8)	23 (16.2)	33
Fishmongers	9 (6.1)	3 (5.9)	12
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

From Table 4.10, 55 representing 55% of the students had farming mothers whiles 33 representing 33% were traders. Also, 12 representing 12% of the students‟ mothers were fishmongers. A null hypothesis of no dependence between mothers‟ occupations and perceived difficulties in Elective Mathematics was rejected since a Chi-square and *p*values of 9.558 and .008 were realised. This means that mothers‟ occupations significantly influenced how their wards perceived the subject.

Table 4.11: Basic school attended-perceived difficulty contingency table

Basic school	Perceived difficulty in the ubject		Total
	Difficulty	Not difficult	
Government	38 (40.8)	42 (39.2)	80
Private	13 (10.2)	7 (9.8)	20

Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

The results in Table 4.11 indicate that 80 representing 80% of the students attended government basic schools. The remaining 20 representing 20% had their basic education in private schools. A Chi-square test value of 1.981 with a corresponding *p*-value of 0.161 was obtained. Therefore, we do not reject the null hypothesis of basic schools attended by the students was statistically independent of their perceived difficulties in the subject. An odds ratio, OR=38*7/13*42=0.49, was ascertained. This means that the odds of perceiving Elective mathematics as difficult rather than not difficult were 51% lower among products of government basic schools compared to their counterparts from private schools.

The study also collated the terminal Elective Mathematics examination scores of the respondents. These scores were then categorised and a cross-tabulation was constructed to see the association or otherwise between their performance in examinations and how they perceived the subject. Table 4.12 presents the details.

Table 4.12: Scores-perceived difficulty contingency table

	Perceived difficulty in the subject		
Score	Difficulty	Not difficult	Total
31-40	3 (3.6)	4 (3.4)	7
41-50	13 (13.3)	13 (12.8)	26
51-60	12 (12.8)	13 (12.2)	25

61-70	16 (13.8)	11 (13.2)	27
71-80	7 (6.6)	6 (6.4)	13
81-90	0 (1.0)	2 (1.0)	2
Total	51	49	100

Estimated expected frequencies for hypothesis of independence are in parentheses

It can be seen that the modal score of the students in Elective Mathematics during the last term was 61-70%. Thus, 27 representing 27% of the students obtained scores within that interval. Similarly, 26% and 25% of them scored between 41-50% and 51-60%, respectively. Thirteen representing 13% and 2 (2%) of the students respectively had 7180% and 81-90% in their examinations. A test of independence revealed that there was a significant association between their scores and their perceived difficulties in the subject.

This is because the Fisher"s exact test produced a *p*-value of .001. This means that we should reject the null hypothesis of independence, and include the respondents" examination scores in Elective Mathematics in the model for predicting perceived difficulties in the subject.

4.2 Modelling

This section presents the development of models for predicting perceived difficulties in the subject by students from two schools in the Krachie East District of the Volta Region. The test of association conducted earlier revealed that only 5 out of the 12 independent variables were significantly associated with students" perceived difficulties in the subject. These variables include programme of study, ethnicity, and mothers" educational levels.

Therefore, the models would include only those predictors.

The model for predicting students‟ perceived difficulties in Elective Mathematics should regress the dependent variable, perceived difficulties in Elective Mathematics, on the following independent variables: programme of study, ethnicity, and mothers‟ educational levels. Therefore, using the binary logistic regression (with options like "perceived difficult" and "perceived not difficult"), we obtain a model for predicting the probability of a student perceiving Elective Mathematics as a difficult subject.

Table 4.13: Classification table

Observed	Predicted		
	Difficulty in Elective Mathematics		Percentage correct
	Difficult	Not difficult	
Difficult	45	6	88.2
Not difficult	13	36	73.5
Overall percentage			81.0

Estimated expected frequencies for hypothesis of independence are in parentheses

The classification table above indicates that the model below had 81% ability to do reliable prediction of students‟ perceived difficulties in the subject. Specifically, the potential model had the 88.2% predictive value for predicting perceived difficulty for students and a 73.5% predictive ability for predicting perceived not difficult. These are the indicatives of an adequate model.

Table 4.14: Binary logistic regression model

	Sig.

Covariate	B	S.E.	Df	
Programme of study	**13.696**	**3.788**	**3**	.003
	13.100	2.948E4	1	
General Science	1.771 2.791	2.169	1	.000
Business	-	3.455E4	1	.183
		-	-	
General Arts				.085
	30.829			
Technical	0.347	**6.761**	10	-
	2.156	4.663E4	1	
Agricultural Science (ref)				
	11.565	5.663E4	1	
Ethnicity	3.143 6.644	7.882E4	1	.001
	7.877	8.027E4	1	.556
Nchunbangs				
		4.329E4	1	
Konkomba		6.663E4		.142
	0.171		1	
Frafra	7.273 2.019			.001
		3.332E4		
Dangme	5.085		4	.076
		4.477E4		
			1	
Asante	2.670	4.019E4	1	.010
		2.837E4		.005
Ewe			1	
Krachi (*reference)*	**7.512**			
Highest Educational Level of Fathers				.122
No formal education				.155
Basic	4.665 0.025	4.019E4	1	.024
Secondary				.102
			2	
		2.019E4		
	0.0065	4.663E4	1	
Polytechnic/College of Education/				
		3.019E4	1	
	18.545			
Nursing Training College				.680
University (reference)		4.019E4	1	
		7.507E4	1	
Highest Educational Level of Mothers				.023
No formal education				.031

Basic	.874
Secondary (reference)	
Examination scores	.799
Constant	1.000

We can see from Table 4.14 that when all the significant predictors identified using the Chisquare or Fisher"s exact test were simultaneously included in the binary logistic model, some of them turned out to insignificantly whiles the others remained statistically significant at 5% significance level. Those that remained significant include the respondents" programmes of study, ethnicity, and mothers" highest educational level.

Using the predictor"s last reference option, a significant difference was identified comparing perceived difficulties among General Science and Agricultural Science respondents. In them of ethnicity, there were real differences between how *Frafras, Asantes* and *Ewes* perceived the subject compared to their *Krachi* counterparts.

The highest educational attainment of mothers was significant with *p*-values of .023 and .008, respectively. Specifically, respondents" whose mothers had no formal education had real difficulties in the subject compared to with those whose mothers had secondary education. However, no significant difference was seen with respect to those whose mothers had basic education. Fathers" highest educational attainment and the respondents" examination scores were not significant in the model.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This chapter presents the conclusions drawn from the study and some recommendations made to encourage students to have positive perception about the study of Elective Mathematics.

5.1 Conclusions

The objective of this research was to identify significant demographic predictors of students‟ perceived difficulties in Elective Mathematics, and finally, to develop a binary logistic model for predicting the probability of a student perceiving Elective Mathematics as difficult. Both primary and secondary data were obtained for the study. The primary data were gathered using questionnaires administered to 100 randomly selected from the Oti Senior High/Technical and Asukwakwa Senior High schools. However, the secondary data included last term‟s scores of the 100 students in the subject. Chi-square and Fisher‟s exact tests and the binary logistic regression model were employed to determine the associations between the independent variables and the dependent variable. The following conclusions were drawn from the analyses:

1. The significant predictors of a student‟s perceived difficulty in Elective Mathematics were the programme of study, ethnicity, and mother‟s highest educational levels.
2. Variables such as a student‟s gender, age, residential status, father‟s educational levels, the basic school they attended as well as their examination scores were not significant predictors of a student‟s perceived difficulties in the subject.

5.2 Recommendations

On the basis of the findings of the research, the following recommendations were made:

1. School authorities should devise more innovative methods of teaching the subject across all programmes. This will ensure that, for example, Business and General Arts, would have positive perception about the subject like their General Science and Technical students who also study related subject like Physics.
2. Mothers in particular should strive to educate themselves to the highest level since it serves as a source of encouragement to their wards do well in subjects like Elective Mathematics at the senior high school level.
3. Any strategies to encourage students to have positive perception about the study of Elective Mathematics should not pay much credence to the student‟s gender, age, residential status, father‟s educational level, and the basic school attended. This is because they do significantly influence their perceptions about the subject.

4. There could be workshops and seminars for the students on how to cultivate positive mindset about Elective Mathematics.
5. Efforts should be made to change the mind-set of students that students of certain ethnic background are good at mathematics than the others.
6. School authorities and GES should regularly organise workshop for Elective Mathematics on simple, but effective ways of teaching of the subject at that level.

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APPENDIX

KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

(KNUST)

DEPARTMENT OF MATHEMATICS

QUESTIONNAIRE FOR STUDENTS

This study aims at assessing the factors influencing the perceived difficulties of Senior High School students in learning Elective Mathematics in Senior High Schools in the Krachie East District in the Volta Region of Ghana.” Please, complete the questionnaire as accurately and candidly as possible. All responses will be held in strict confidence. Thanks very much in anticipation of your co-operation.

Please tick [√] or write when applicable.

1. School: Oti Senior High/ Technical School [ ] Asukwakwa SHS [ ]

2. Gender: Male [ ] Female [ ]

3. Age (in years): Less than 15 [ ] 15 – 18 [ ]

19– 22 years [ ] 23 and above [ ]

4. Programme of study: General Science [ ] Business [ ] General Arts [ ]

Technical [ ] Agricultural Science [ ]

5. Ethnicity: ………………………………………………….…………………………………..

6. Residential status: Boarder [ ] Day [ ]

7. Highest educational level of father: No Formal Education [ ] Basic [ ] Secondary [ ] Polytechnic/College of Education/Nursing Training College [ ]

University [ ]

8. Highest educational level of mother: No Formal Education [ ] Basic [ ] Secondary [ ] Polytechnic/College of Education/Nursing Training College [ ]

University [ ]

9. Father‟s occupation: ……………………………….……………………………………

10. Mother‟s occupation: ……………………………………………………………………..

11. Basic school attended: Government [ ] Private [ ]

12. How do you perceive Elective Mathematics? Difficult [ ] Not difficult [ ]

13. Examination score in last term?..

14. In your views, how can the performance of the students be improved upon in Elective Mathematics in the District?

i. ……………………………………………..…………………….……………………

……………………………………………..……………………………………………

ii. ……………………………………………..……………..…………………………

……………………………………………..……………………………………………

iii. ……………………………………………..……………..…………………………

……………………………………………..……………..…………………………… **Thanks For Your Time!!!**