**KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY**

# LOGIT MODEL FOR THE DETERMINANTS OF DRUG DRIVING: A CASE OF COMMERCIAL DRIVERS IN GHANA

By

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A THESIS SUBMITTED TO THE DEPARTMENT OF MATHEMATICS, KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF MSc INDUSTRIAL MATHEMATICS

October 16, 2014

# Declaration

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



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# Dedication

This thesis is dedicated to my parents Osman Amande and Fati Dambaba. My siblings Sadia Osman, Memuna Osman and Bukari Osman.

# Abstract

Generally, significant proportion of road accidents can be attributed to drug driving globally. The recent rise in the number of road traffic accidents by a report of the Ghana National Road Safety Commission in 2012, calls for a review of drug driving. This study was conducted to asses the use of drugs by commercial drivers in Ghana and to determine the social factors that contribute to drug driving.

A self administered questionnaire was used. A sample of 300 questionnaires were administered and duly edited thereafter to ensure consistency as well as clarity and reliability.

The purposive sampling approach was used to select commercial bus and cargo terminals of some regions based on the locations of the terminals and the population of vehicles.

The backward elimination regression model-building technique was used to select the significant variable(s) into a fitted logistic regression model. A 5 percent statistical significance level is required for a variable to stay in a model.

All respondents were male adults within the active productive age and 41 percent are illiterate. Approximately, 34 percent of the respondents admitted using drug when driving and 70 percent learn how to drive from unapproved driving institutions.

Level of education, Time used to drive, Mode of training and Distance traveled were the most significant variables associated with the use of drug by commercial drivers.

There are significant association between Levels of educational, Distance traveled, Time (hours) used to drive and Drug Use by commercial drivers in Ghana. Drug driving is a threat to the transportation industry and measures should be taking to address this problem.

# Acknowledgments

My profound gratitude goes to the Almighty ALLAH, the giver of life and wisdom for guidance, protection and direction, which has made this work a success.

I am deeply grateful to my supervisor Dr. A. Y. Omari Sasu for his patience, support and inspiration throughout this work.

My special acknowledgment goes to all the lecturers at the Department of Mathematics who made valuable contributions in shaping this work in content, organisation and structure at its various stages, I say the good lord bless you (MASHA ALLAH). Among these notable individuals include the Dean of the Institute of Distance Learning Prof. I. K.Dontwi, the Head of Department of Mathematics Prof. S. K. Amponsah, Dr. Gabriel Asare Okyere, Dr. K. Boadi, Dr. Peter Amoako Yirenkye and Mr. Francis Ohene Boateng.

My heart felt and sincere appreciation goes to Mr. Tawiah Richard of Ejisu Senior High School and Mr George D. K. Adjavon for their immense contributions and support.

My profound gratitude goes to all Institute of Distance Learning Industrial Mathematics students who helped me in divers ways.

I am grateful to all tutors of Aduman Senior High School for their care and support throughout this work.

# Contents

# List of Tables

# List of Figures

# Chapter 1

# Introduction

## 1.1 Background to the Study

A drug can be defined as any chemical which is taken in order to treat or prevent an illness or disease. But these substances are mostly abuse as a result of their pleasant effects or reactions in the human system.

Drug driving is the action or offense of driving a motor vehicle while under the influence of drugs, especially those that are illegal.

Substance use and abuse by commercial drivers when driving should be of concern to both users and the general public.

Studies revealed by Yasmine Pepa (2011) published in the Canadian Center on Substance Abuse indicated that, driving after drug use is a growing issue that is as prevalent as driving after alcohol use and that drug impairment may also be a contributing factor to collisions and fatal road crashes. Many drugs can affect the physical and cognitive processes necessary to operate a vehicle safely, posing a serious risk to the driver and other road users.

## 1.2 Problem Statement

According to a report by the Ghana National Road Safety Commission in 2012, substance use (Drug) among commercial drivers is one of the most serious challenges confronting the transportation industry in Ghana. The report indicated that, thirteen thousand, five hundred and twelve (13535) crashes have been recorded resulting over two thousand and sixty nine (2069) deaths.

In December, 2012, approximately 246 people died and about 1260 were injured in car accidents. According to the Commission, the major cause of road accidents in Ghana is due to over speeding. This accounts for 60 percent of car crashes in the country. This rising figures calls for review of the causes of these accidents.

In most cases, driving under the influence of drugs (chemical substances) are associated with these road accidents. In 2011, there were 2330 road accidents bringing it to an average of 7 accidents per day across the country. Statistics on road accidents in Ghana by the National Road Safety Commission (2010) indicated 19 fatalities per 1000 vehicles. This showed that 43 percent of the fatalities involved pedestrians and 53 percent involved occupants of vehicles.

In a research conducted by Ahlm et al. (2009) on the prevalence of alcohol in injured Swedish drivers, the result indicated that 38 percent of the fatally injured drivers tested positive to alcohol.

It is therefore important to understand the social determinants of the abuse of these substances in order to reduce the number of accidents on our major roads by commercial vehicle drivers. Generally, alcohol is considered a recreational beverage when consumed in moderation for enjoyment and relaxation during social gatherings. However, when consumed basically for its physical and mood altering effects, it is a sub-stance abuse. Drugs slows down physical responses and progressively impairs mental functions.

Commercial vehicle drivers who are involved in road accident can be hazardous for both the driver and other vehicle occupants. This problem is kept in check in most developed countries by strict substance abuse monitoring mechanisms. However, most African countries still show high number of commercial vehicle drivers abusing various substances.

A significant number of drivers use stimulants to keep them awake and relieve fatigue during their long journeys. Africa has the highest annual number of road traffic injury and accident related deaths. Despite the existence of laws against driving while intoxicated, the effectiveness of these laws in controlling the problem is questionable.

## 1.3 Objectives of the Study

### 1.3.1 General Objective

The general objective of the study is to determine the significant contributory factors influencing the use and abuse of substances, especially drugs, alcohol and tobacco by commercial vehicle drivers in Ghana as well as its social consequences and to provide solutions to remedy the situation.



### 1.3.2 Specific Objectives

- To determine the factors that influence the use and abuse of substance by commercial drivers in Ghana.
- To determine the types of substances that are usually abused by these commercial drivers.
- To develop a model for substance abuse by drivers.

## 1.4 Scope of the Study

Generally, the scope of this study is to define explanatory variables in terms of determinants of substance abuse by commercial vehicle driver. These shall include but not be limited to;

- Demographic factors such as: Age, Educational Status, Religion, Marriage Status.
- Working conditions: Distance traveled and number of hours used in continuous driving.
- Types of Vehicles: The vehicles considered in the study are; Trailers(long vehicle), Coaches, Mini Bus, Dumper truck and Taxi Cap.

- Training: How commercial drivers learn how to drive and its association with road traffic accidents.

- Occupational factors: The correlation between commercial driver involvement in road traffic accidents and operational pressure from employer policy on terms of employment.

## 1.5 Approach and Methodology



### 1.5.1 Data Collection

A self administered questionnaire was used to conduct field surveys on factors that influence the use and abuse of substance by a commercial drivers. Informed verbal consent was obtained from each respondent before commencement of interview.

### 1.5.2 Sampling

The purposive sampling approach was used to select commercial bus terminals and cargo terminals of the regions based on the location of the terminals and the population of vehicles. The selected regional capitals are namely Accra, Ho, Kumasi, Bolga and Tamale. A total of 300 questionnaires were administered and duly edited thereafter to ensure consistency as well as clarity and reliability.

### 1.5.3 Data Analysis

In order to identify the factors that influence the use and abuse of substances by commercial drivers, the quantitative methods were used. This is because they provide sufficient information about the relationship between the variables under investigation to enable prediction and control over future outcomes.
The dependent variable being studied is dichotomous hence the choice of logistic regression technique as the empirical method of estimation under the quantitative method. Variables such as age, time spent, religious status were analyzed

descriptively.

## 1.6 Justification of the Study

With a lot of evidences associated with increasing road traffic accidents among commercial drivers in the country which has a direct impact on development, drug use becomes an important issue in the transportation industry.

The identification of factors that influence the use and abuse of drugs will provide knowledge for policy makers, the Ghana National Road Safety Commission (GNRSC) and the Motto Traffic Transport Unit (MTTU) of the Ghana Police Service.

This study would outline detail information on the causes and factors influencing the abuse of Drugs (Chemical Substances) by commercial vehicle drivers in Ghana and also suggest to policy makers alternative methods available to remedy the situation.

The study will also contribute to knowledge by filling gaps in research literature on the social determinants of substance abuse by commercial drivers in Ghana. Moreover, it is important to address the social consequences of substance abuse by commercial drivers, a serious social problem with social and economic costs.

Finally, this study would provide guidance to develop effective intervention strategies to address the problem of substance abuse by most commercial drivers.

## 1.7 Organisation of the Study

Chapter one is the introduction of the Study. This comprises of the background of the study, problem statement, objectives of the study, methodology and justification of the study. Chapter two elaborates on review of literature. This reviews ideas of different authors whose findings have been defined in relation to the topic under study.

Chapter three highlights on methodology. This focuses on statistical tools that are relevant to the analyses of the data collected from commercial drivers. Descriptive Statistics and the binary logistic regression model were used in the study. Chapter four deals with data analysis and discussion of results.

Chapter five comprises conclusion and recommendations of the study. Finally, the entire project report ends with references and appendices as a support to the researcher's investigation.

# Chapter 2

# Literature Review

## 2.1 Introduction

In this section there is a review of work of several authors regarding drug driving by commercial drivers globally. Researches, publications and authors opinion are looked at. Below are focuses of the review: Alcohol, Cannabis (marijuana) and chemical substances such as inhalants and amphetamines.

## 2.2 Alcohol

A significant proportion of road traffic accidents can be attributed to alcohol and marijuana use while driving globally. A study was conducted by Mir et al., (2012) to assess usage of alcohol and marijuana in Pakistani commercial drivers. A sample of bus and truck drivers were interviewed at the largest commercial vehicle terminals.

Time location cluster sampling was used to assess the basic demographic profile, substance abuse habits of the drivers while on the road, and reasons for usage of illicit substances while driving were recorded. This is to identify the associations between driver characteristics and alcohol and marijuana use. Ten percent of truck drivers used alcohol and 34 percent used marijuana while driving on Pakistani roads.

Statistically, different patterns of usage are seen between population subgroups based on age, ethnicity, education, and marital status. Mir et al., (2012). This study is to compare whether or not those prevailing conditions are similar to commercial drivers in Ghana.

In November, 2012, thirteen thousand, five hundred and twelve (13535) crashes have been recorded resulting over two thousand and sixty nine (2069) deaths in Ghana. In December, 2012, approximately 246 people died and about 1260 were injured in car accidents.

According to the Commission, the major cause of road accidents in Ghana is due to over speeding. This accounts for 60 percent of car crashes in the country. This rising figures calls for review of the causes of these accidents.

In most cases, driving under the influence of drugs (chemical substances) are associated with these road accidents. This study is to determine the social factors associated with substance use by commercial drivers.

In 2011, there were 2330 road accidents bringing it to an average of 7 accidents per day across the country. Statistics on road accidents in Ghana by the National Road Safety Commission (2010) indicated 19 fatalities per 1000 vehicles. This showed that 43 percent of the fatalities involved pedestrians and 53 percent involved occupants of vehicles.

Alcohol is generally the commonest substance detected in accident-involved drivers. The use of alcohol is generally not accepted in every society and yet it is the commonly detected drug among some commercial drivers. In a research conducted by Ahlm et al. (2009) on the prevalence of alcohol in injured Swedish drivers, the result indicated that 38 percent of the fatally injured drivers tested positive to alcohol.

A research conducted by Verster (2009) on several commercial drivers and their Blood Alcohol Concentration (BAC) to determined the association between (BAC) and road traffic accidents for these drivers. It was found that a relationship between (BAC) and the risk of becoming involved in a road traffic accident existed. Testing driver performance at various stages of different Blood Alcohol Concentration (BAC) is key to understanding the effects of alcohol on driver performance and impairment.

In 2009, the rate was highest among young adults aged 18 to 25 (12.8 percent). In addition, it reported that, in 2009, an estimated 12 percent of persons aged

20 or older (30.2 million persons) drove under the influence of alcohol at least once in the past year. This percentage has dropped since 2002, when it was 14.2 percent. Driving under the influence of an illicit drug or alcohol was associated with age.

In 2009, an estimated 6.3 percent of youth aged 16 or 17 drove under the influence. This percentage steadily increased with age to reach a peak of 24.8 percent among young adults aged 21 to 25. Beyond the age of 25, these rates showed a general decline with increasing age. This study intends to investigate whether or not driving under the influence of drug really depends on age. Also in 2009, among persons aged 12 or older, males were more likely than females (17 percent versus 9 percent, respectively) to drive under the influence of an illicit drug or alcohol in the past year.

Roadside studies conducted in the United States found that 17 percent of the drivers had a Blood Alcohol Concentration (BAC) above the legal limit. Williams (2006). By comparing this figure to the European roadside studies Gjerde et al. (2008), the percentage is a bit higher. Taking into account that the legal limit for driving in the United States of America can be higher than in Europe (0.08 percent versus 0.05 percent).

A simulated driving study conducted by Calhoun et al., (2004) reported that a low dose of alcohol may have a protective effect on driving ability. While in France, a study conducted by Mura et al., (2003) found that 26 percent of the drivers showed a blood alcohol concentration above the legal limit(0.05 percent).

In conclusion, there exist a substantial evidence that driving under the influence of alcohol should be avoided. Studies revealed by Yasmine Pepa, (2011) published in the Canadian Center on Substance Abuse indicated that: driving after drug use is a growing issue that is as prevalent as driving after alcohol use and that drug impairment may also be a contributing factor to collisions and fatal road crashes. Many drugs can affect the physical and cognitive processes necessary to operate a vehicle safely, posing a serious risk to the driver and other road users. In his study ,drivers were asked to provide voluntary breath and oral fluid samples to test for the presence of drugs and alcohol. The survey found that 7.2 percent tested positive for drugs and 9.9 percent had been drinking. Drugs and driving is a more complex issue than drinking and driving. There is a need for further studies to better understand the behaviour and to help guide appropriate policies and programs to deal with it effectively.

## 2.3 Cannabis and Tobacco

No studies have been performed on the prevalence of driving under the influence of nicotine and there is no data on nicotine involvement in traffic accidents. Smoking a cigarette can be regarded as a secondary task that may potentially distract from the primary driving task, or at least causes the driver to divide his attention between both activities when lighting up and extinguishing the cigarette Penning et al., (2010). Nicotine is known for its cognitive enhancing effects by reducing reaction time and increasing alertness. It can be hypothesized that smoking may actually improve driving performance. A few driving studies have focused on the effects of nicotine abstinence on driving performance Penning et al. (2010). A research conducted by Heintra et al., reported no difference in simulated driving performance between those who smoked a cigarette during the test and control subjects. Penning et al., (2010) however, indicated that when smokers had to refrain from smoking, they performed significantly worse. Surprisingly, a study conducted by Sherwood (1995) confirmed that driving performance of craving smokers significantly improved to normal (nonsmoker) levels after allowing them a cigarette.

Cannabis is to be the next most common drug of abuse found in drivers after alcohol Penning et al., (2010). A study from New Zealand reported that almost 21 percent of young drivers admitted that they had driven at least once after smoking cannabis Ferguson et al., (2008). Approximately 60 percent of the interviewed Australian nightclub attendees reported that they were driven home by someone under the influence of tetrahydrocannabinol (THC) or that they drove themselves after smoking cannabis Degenhardt et al. (2006)

Roadside studies by Penning et al., (2010) indicated that 15 percent of drivers drive under the influence of one or more drugs of abuse. After drug use, drivers are more often culpable for an accident than non-users. A study conducted by Penning et al., (2010) indicated that drivers most frequently tested positive for the use of alcohol or cannabis. These two drugs affect driving ability in a dose dependent matter and result in poor vehicle control, especially when used in combination.

The study concluded that most drugs of abuse negatively affect driving ability, especially when used in combination. It is of concern that a substantial number of drug users are not aware that their driving is impaired.

Overall, marijuana is the most prevalent illegal drug detected in impaired drivers, fatally injured drivers, and motor vehicle crash victims. Other drugs also implicated include benzodiazepines, cocaine, opiates, and amphetamines. Soderstrom et al., (2001). This study is to use a mathematical model to determine whether those conditions are the same in developing countries, especially Ghana.

A study conducted by the State of Maryland (2007), indicated that 11 percent of the licensed adolescent drivers reported driving under the influence of marijuana on three or more occasions, and 10 percent reported driving while using a drug other than marijuana (not including alcohol). Evidence from both real and simulated driving studies indicates that marijuana can negatively affect driver attentiveness, perception of time and speed, and ability to draw on information obtained from past experiences.

A study of fatally injured drivers in Australia showed that when marijuana was present in the blood of the driver, he or she was much more likely to be at fault for the accident. Drummer et al., (2004). The matter of concern is not the rising figures nor the statistics of drug or alcohol use by commercial vehicle drivers but factors associated with the use of these chemical substances. This study is therefore to determine the social factors associated with substance by drivers as well as the commonest substances that are abuse by these drivers in Ghana.

## 2.4 Drugs

Generally, inhalants are commonly abused drugs by some commercial drivers in Ghana. The findings of Rio and Alvarez (1995) indicated that 0.1 percent of Spanish drivers admitted to have driven at least once after non medical use of inhalants. Moreover, researchers in Australia indicated that 5 percent interviewed drug users admitted ever driven under the influence of an inhalant Darke et al., (2003). Investigations among US students indicated that 5.2 percent had abused inhalants before the ages of 18 years and approximately 62 percent of them had driven a car while under the influence of alcohol or drugs Bennett et al., (2000). Beckman et al., (2006) examined the effects of inhalants on psycho-motor functioning. The result indicated that inhalants significantly impaired auditory reaction time, coordination and estimation. Moreover, memory function was also affected. Researchers also concluded that the subjects were much more tired after using isoflurane and sevoflurane.

Dinwiddie (1994) reported that inhalants are abused, they can cause hallucinations and distortions in perception as well. In addition, impaired muscle coordination and body balance may lead to road traffic accidents. Kurtzman et al., (2001) supported these findings and added, slurred speech, euphoria and decreased reflexes as commonly reported side effects.

Majority of commercial drivers test positive for methamphetamine. The presence of methamphetamine in commercial drivers is so alarming and needs attention by authorities in the transportation industry. Commercial vehicle drivers are known to use chemical substances such as methamphetamines to stay awake during prolonged driving.

Crouch et al., (1993) reported that 7 percent of fatally injured truck drivers had used methamphetamines, when compared to 13 percent who had used cannabis or alcohol. However, some studies reported very high percentages of commercial drivers who use amphetamines. Methamphetamine use among commercial drivers is of great concern in respect of road traffic safety.

Miller et al., (1993) investigated the effects of methamphetamine in narcoleptic patients and healthy subjects. Methamphetamine improved performance of narcoleptic patients in the driving simulator in a dose dependent manner.

Silber et al., (2005) tested the effects of dexamphetamine, a drug with similar effects as methamphetamine. This drug significantly impaired simulated driving performance during daytime testing. But night-time testing showed no significant differences from placebo were found. Gustavsen et al., (2006) reviewed literature on amphetamine and methamphetamine and the findings are that low dosages of amphetamine significantly improve psychomotor performance of fatigued subjects. Logan (2002) came out with the conclusion that most studies that examined the behavioral effects of stimulant drugs report an increase in risk taking behaviuor and impaired decision making.

Logan (2002) concluded that both low and high dosages of methamphetamine may have an effect on driving performance.

Drivers on cocaine and amphetamine show no impairment on basic driving skills, but often overestimate their driving skills. In combination with impaired decision making, this increases risk taking during driving. Only few studies looked at the effects on driving of other drugs of abuse, such as ketamine, inhalants and anabolic steroids, but suggest a negative effect on driving performance. Penning et al., (2010)

According to the National Highway Traffic Safety of the United States of America (2007) National Roadside Survey indicated that more than 16 percent of weekend, nighttime drivers tested positive for illegal, prescription, or over-the-counter medications.

More than 11 percent tested positive for illicit drugs. Another study by the same institution found that in 2009, among fatally injured drivers, 18 percent tested positive for at least one drug. Illicit, prescription, or over-the-counter, an increase from 13 percent in 2005. Together, these indicators are a sign that continued substance abuse education, prevention, and law enforcement efforts are critical to public health and safety.

According to the National Survey on Drug Use and Health (2009) of the United States of America, an estimated 10.5 million people aged 20 or older reported driving under the influence of illicit drugs during the year prior to being surveyed. This corresponds to 4.2 percent of the population aged 20 or older, similar to the rate in 2008 (4 percent) and not significantly different from the rate in 2002 (4.7 percent).

A research conducted by (Lisa Sharwood) of the University of Sydney, Australia, and colleagues in the British Medical Journal in 2013, indicated that using caffeine can cut long-distance drivers risk of crashing. Long distance commercial drivers regularly experience frequent night-time driving, and drowsiness. But their alertness is critical to safety for the driver and other road users.

Long distance drivers of commercial vehicles who were involved in a crash between 2008 and 2011 were compared to similar drivers who had not had a crash in the previous year. Overall, 43 percent of the drivers admitted that they used substances containing caffeine such as tea, coffee, caffeine tablets, or energy drinks for the express purpose of staying awake.

In addition, three percent said they took illegal stimulants. Several risk factors including age, health, sleep patterns, distance driven, and breaks were taken into account, the drivers who used caffeine to stay alert had a 63 percent reduced risk of crashing. The research findings indicated that caffeine substances are associated with a reduced risk of crashing for long distance commercial motor vehicle drivers. This research investigates the link between use of substances and the risk of a crash.

In recent years, more attention has been given to drugs other than alcohol that have increasingly been recognized as hazards to road traffic safety. Some of this research has been done in other countries or in specific regions within the United States, and the prevalence rates for different drugs used vary accordingly.

A number of studies have examined illicit drug use in drivers involved in motor vehicle crashes, reckless driving, or fatal accidents. One study found that about 34 percent of motor vehicle crash victims admitted to a Maryland trauma center tested positive for drugs only, about 16 percent tested positive for alcohol only. Approximately 10 percent tested positive for alcohol and drugs, and within this group, 50 percent were younger than age 25 years. Walsh et al., (2004).

The study shows that more people tested positive for drugs compared with alcohol. This represents one geographic location, so findings cannot be generalized. In fact, the majority of studies among similar populations have found higher prevalence rates of alcohol use compared with drug use.

Studies conducted in several localities have found that approximately 4 to 14 percent of drivers who sustained injury or died in traffic accidents tested positive for delta-9-tetrahydrocannabinol, the active ingredient in marijuana. Ramaekers et al., (2004).

In a study of fatally injured drivers from three Australian states (Victoria, New South Wales, and Western Australia), drugs other than alcohol were present in most of the cases. Drummer et al., (2003). These included cannabis, stimulants, benzodiazepines, and other psychotropic drugs. Almost 10 percent of the cases involved both alcohol and other drugs.This study is to determine the significant factors associated with the use of these drug.

According to the Centers for Disease Control and Prevention (2008), vehicle accidents are the leading cause of death among young people aged 16 to 20. It is generally accepted that because teens are the least experienced drivers as a group, they have a higher risk of being involved in an accident compared with more experienced drivers. When this lack of experience is combined with the use of marijuana or other substances that impact cognitive and motor abilities, the results can be tragic.

Road crashes kill more people in Ghana than communicable diseases. The public often blame drivers for over speeding and doing wrong overtaking. Technically, human errors, vehicle breakdowns, non-road worthy vehicles, poor road conditions and environmental factors like poor weather conditions can be said to be the major causes of accidents everywhere in the world.

Unfortunately the blame game has not helped us in any way since no effort is made to address the problem itself at the end of the day. There are currently too many accidents on our roads. Hounarable Saka (2013).

Blaming drivers at accident scenes is never a solution to solving the problem. Finding what could make a driver to drive under the influence of drug is key to addressing the problem of accidents on our roads. Why do commercial drivers take those chemical substances? These calls for the review of literature on drugged driving and factors associated with it.

A Roadside studies by Penning et al., (2010) indicated that one to fifteen percent of drivers drive under the influence of one or more drugs of abuse. Findings of this study showed that drivers most frequently test positive for the use of alcohol or cannabis. These two drugs affect driving ability and result in poor vehicle control.

Drivers on cocaine and amphetamine show no impairment on basic driving skills, but often overestimate their skills. In combination with impaired decision making, this increases risk taking during driving.

Only few studies looked at the effects on driving of other drugs of abuse, such as amphetamine, inhalants and anabolic steroids, but suggest a negative effect on driving performance. Most drugs negatively affect driving ability, especially when used in combination with alcohol or another drug. It is of concern that a substantial number of drug users are not aware that their driving is impaired. Penning et al., (2010)

There is too much drinking going on in the Ghanaian culture. Alcohol is integrated into almost all the key activities and driving is no exception. When a child is born, he is christen with alcohol. When someone dies, he is bid farewell with plenty of alcohol. Alcohol is usually used in supplications to the gods. When good things happen which call for celebration, they call for booze. When sad and depressed events occur it calls for even more alcohol. Peers jeer at each other if one refused to drink. Typically, they say that as a man your mouth should smell of alcohol a little bit. Dowries for a wife involve considerable quantities of alcohol.When one is found guilty at the chief's court, his punishment includes several bottles of Schnapps. When Policemen seek to extort bribes from motorist, euphemistically ask for "a little drink". Drinking and driving is so common on our roads and many commercial vehicle drivers are often involved in road accidents to detriment of the ordinary Ghanaian. Tin Cutter (2011).
effectively.
A Comparison of Drug and Alcohol-involved Motor Vehicle Driver Fatalities, by looking at the characteristics of fatally injured drivers and the circumstances of fatal collisions involving those who test positive for drugs indicated that 33 percent of fatally injured drivers were positive for drugs. The findings indicated that the use of drugs by drivers is an issue distinct and needs a different approach to prevention, education and enforcement to reduce the number of fatal crashes involving drivers that use drugs. Seth Panyin Boamah (2013).
The findings provided a baseline from for closing the gap between continuous research related to alcohol impaired driving. The above mentioned findings calls for more detailed research on the factors that influence the use and abuse of these substances by commercial vehicle drivers, leading to those fatalities on most of our roads.
Progress has been made in Ghana in reducing the use of alcohol and drugs by commercial vehicle operators over the past few years. Drug use prevention and testing programs have been instituted by the Motto Traffic and Transport Unit

(MTTU) of the Ghana Police Service.

Random drug test continued to show an increase in the number of those testing positive. This calls for the review of current developments in the field and find out the factors influencing the use and abuse of these substances, the types of substance used and their sources in order to curb the menace.

# Chapter 3

# Methodology

## 3.1 Introduction

This chapter elaborates the conceptual framework of the methods employed by the study. It explains the various methods used to obtain the information from respondents. The study employed descriptive and quantitative methods for the data analysis.

Logistic regression analysis model, using R Software, was employed under the quantitative method to obtain the significant determinants of substance abuse by commercial vehicle drivers.

All factors that are believed to influence the use and abuse of substance by commercial drivers are considered. These are factors believed to contribute to the likelihood of substance abuse by drivers.

## 3.2 Logistic Regression Model

Logistic Regression Model as a non-linear regression model is a special case of Generalized linear model, where the assumptions of normality and constant variance residuals are not satisfied.

This model is a statistical technique for predicting probability of an event, given a set of independent variables. The objective of Logistic Regression Analysis is to find the best fitting model to show the relationship between a response variable and a set of explanatory variables.

Logistic Regression Model has an outcome which is categorical and usually binary (dichotomous). The key quantity in any regression is the mean value of the dependent variable called the conditional mean, given the value of the independent variable. It is assume in any linear regression that, this mean may be expressed as an equation linear in $X$ such as: $E(Y|x) = \beta_0 + \beta_1(X)$.

There is a possibility for $E(Y|x)$ to take on any value from -$\infty$ to + $\infty$

Let $\pi(X)$=$E(Y|x)$ represent the conditional mean of $Y$ given $X$. The Logistic regression model can be expressed as:

$$\pi(x) = \left[\frac{e^{\beta_0+\beta_1(X)}}{1+e^{\beta_0+\beta_1(X)}}\right]$$

The logit transformation defined in terms of $\pi(X)$ is as follows:

$$g(x) = ln[\frac{\pi(X)}{1-\pi(X)}]$$

The transformation is necessary because $g(x)$ has the 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 $X$.

For a dichotomous outcome we may express the value of the outcome variable $X$ as $y$= $\pi(X) + \varepsilon$ where $\varepsilon$ is the error.

The quantity $\varepsilon$ may assume one of two possible values. if $y = 1$, then $\varepsilon$ = 1- $\pi(X)$ with probability $\pi(X)$, and if $y = 0$, then $\varepsilon$ = -$\pi(X)$ with probability 1 - $\pi(X)$. Thus $\varepsilon$ has a distribution with mean zero and variance equal to $\pi(X)\,[1 - \pi(X)]$. That is the conditional distribution of the outcome variable follows a binomial distribution with probability given by the conditional mean, $\pi(X)$.

In linear regression the least squares method is used most often for estimation of unknown parameters say $\beta_0$ and $\beta_1$ that minimizes the sum of squared deviations of the observed values of $Y$ from the predicted values based upon the model. Under the usual assumptions for linear regression, the least squares method yields estimators while a number of desirable statistical properties. Unfortunately, when the least squares method is applied to a model with a dichotomous outcome, the estimators no longer have the same properties. The general method of estimation that leads to the least squares function under the linear regression model(when the error terms are normally distributed) is maximum likelihood. This is the method used to estimate the logistic regression parameters. To apply this method we need to construct first 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 maximise this function. Thus the resulting estimators are those that agree most closely with the observed data. If the response variable $Y$ is coded as 0 or 1, then the expression for $\pi(X)$ given in (1)provides the conditional probability that $Y$ is equal to 1 given $X$. That is $Pr(Y = 1|x)$ and this follows that the quantity $1-\pi(x)$ gives the conditional probability that $Y$ is equal to 0 given $X$. Thus for the 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 $1 - \pi(X_i)$.



For a binomial response

$$y_i = \begin{cases} 1 \text{ if event occur} \\ 0 \text{ if event does not occur} \end{cases} \tag{3.1}$$

In the simple case with only one predictor variable the logistic regression model will take on the following general form;

Let $\pi(x_i) = E(Y|x_i)$ It implies that $Y_i = \pi(x_i) + \epsilon$

it implies that $\epsilon_i = -\pi(x_i)$ with the probability of $1 - \pi(x_i)$ since $\epsilon_i$ can take any two possible values, the expected value is obtained through the following formula.

$E(\epsilon_i) = \epsilon_i P(\epsilon_i = \epsilon_2) + \epsilon_2 P(\epsilon_i = \epsilon_2)$

$= \pi(x_i) - \pi(x_i)^2 - \pi(x - i) + (\pi(x_i))^2$ Chatterjee et al. (2000).

The variance of the error terms can be determined in a similar manner

$Var(\epsilon_i) = E(\epsilon_i^2) - E(\epsilon_i)^2 - 0$

$= [1 - \pi(x_i)]^2\pi(x_i) + [-\pi(x - i)]^2[1 - \pi(x_i)]$

$= \pi(x_i) - [2\pi(x_i)]^2 + [\pi(x_i)]^2.$

$= \pi(x_i)[1 - \pi x_i]$

From $\pi(x_i) = \frac{e^{\beta_0 + \beta_1 x(i)}}{1+e^{(\beta_0+\beta_1 x_i)}}$

with $\pi x_i$ denoting the probability that $Y_i = 1$ Chatterjee et al. (2000) The odds of occurring can be defined as

ODDS $=\frac{Y=1}{Y=0} = \frac{\pi(x_i)}{1-\pi(x_i)}$

The odds are important to binary data set because they offer a ratio for the chances of an event occurring opposed to an event not occurring.Chatterjee et al. (2000)

For the logit transformation

$$\pi x_i[1 + e^(\beta_0 + \beta_1 x_i) = e^(\beta_0 + \beta_1 x_i)$$
$$= e^(\beta_0 + \beta_1 x_i)[1 - \pi(x_i)]$$
$$\frac{\pi(x_i)}{1-\pi(x_i)} = e^(\beta_0 + \beta_1 x_i)$$



Taking the natural log

$$\ln[\frac{\pi(x_i)}{1-\pi(x_i)}] = \beta_0 + \beta_1 x_i = g(x)$$
$$g(x) = logit\pi(x_i) = \beta_0 + \beta_1 x_i$$ Hosmer and Lemeshow (1989)

The importance of the transformation is that $g(x)$ has many of the desirable properties of a linear regression model. The logit $g(x)$ is linear in it's parameters, may be continuous and may range from $-\infty to + \infty$ depending on the range of $x$. $\beta_0$ gives the log odds for an outcome with zero values for all $xs$ i.e if we plug in 0 for all $xs$, in the formula, we find that, the logit of $\pi$ reduces simply to $\beta_0$

To fit the logistic model to a set of data, we need to estimate the values of $\beta_0$ and $\beta_1$, the unknown parameters through the method of maximum likelihood estimation where $L(\beta_0, \beta_1)$ is defined as the joint probability distribution for all data points.



Since the $Y_i's$ have a Bernoulli distribution, the joint probability density function in any one trial is

$$P(Y = y_i) = \prod_{i=1}^{n} \frac{n_i!}{y_i(n_i-y_i)}![\pi(x_i)]^{y_i}[1 - \pi(x_i)]^{n_i-y_i}$$
$$L(\beta_0, \beta_1) = \prod_{i=1}^{n} \pi(x_i)^y i[1 - \pi(x_i)]^{n_i-y_i}$$

Taking the logarithm

$$\ln L(\beta_0, \beta_1) = \ln \prod_{i=1}^{n} \pi(x_i)^y i[1 - \pi(x_i)]^{n_i-y_i}$$
$$= \sum_{i=1}^{n} \ln[\pi(x_i)]^{y_i} + [1 - \pi(x_i)]^{1-y_i}$$
$$= \sum_{i=1}^{n} y_i \ln[\pi(x_i)] + (1 - y_i) \ln[1 - \pi(x_i)]$$
$$= \sum_{i=1}^{n} y_i \ln(\frac{e^{\beta_0+\beta_1 x_i}}{1+e^{\beta_0+\beta_1 x_i}}) + (1 - y_i) \ln(1 - \frac{e^(\beta_0+\beta_1 x_i)}{1+e^(\beta_0+\beta_1 x_i)})$$

$= \sum_{i=1}^{n} y_i[(\beta_0 + \beta_1 x_i) - \ln(1 + e^{\beta_0+\beta_1 x_i})] - (1 - y_i)[\ln(1 + e^{\beta_0+\beta_1 x_i})] + [y_i \ln(1 + e^{\beta_0+\beta_1 x_i})]$

$= \sum_{i=1}^{n} y_i[(\beta_0 + \beta_1 x_i) - \ln(1 + e^{\beta_0+\beta_1 x_i})] - (1 - y_i)[\ln(1 + e^{\beta_0+\beta_1 x_i})] + [y_i \ln(1 + e^{\beta_0+\beta_1 x_i})]$

$= \sum_{i=1}^{n} y_i[(\beta_0 + \beta_1 x_i) - \ln(1 + e^{\beta_0+\beta_1 x_i})$ Hosmer and Lemeshow (1989)

In order to maximize the function we take the derivative with respect to each of the parameters. Then the resulting equations would be set to zero and solve simultaneously. This process can be simplified by performing the same analysis on the natural log of the likelihood function would result in the same value as maximizing the likelihood function itself.Neter et al. (1996)

$\partial \ln L(\beta_0, \beta_1)/\partial\beta_0 = \sum_{i=1}^{n}(y_i - \frac{e^{\beta_0+\beta_1 x_i}}{1+e^{\beta_0+\beta_1 x_i}})$

$=\sum_{i=1}^{n}(y_i - \pi(x_i))$

$\sum_{i=1}^{n}(y_i - \pi(x_i)) = 0$

Similarly

$\partial \ln L(\beta_0, \beta_1)/\partial\beta_1 = \sum_{i=1}^{n}(y_i x_i - x_i\frac{e^{\beta_0+\beta_1 x_i}}{1+e^{\beta_0+\beta_1 x_i}})$

$= \sum_{i=1}^{n}(y_i x_i - x_i\pi(x_i)) = 0.$

Because the likelihood equations are not linear, solving these equations simultaneously requires an iterative procedure that is normally left to a software package.Neter et al. (1996) .

Using only one predator variable

$Y_i = \pi x_i + \varepsilon_i = \frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1(x_i)}} + \varepsilon$

Logit function

$h(x_i) = \ln\frac{\pi(x_i)}{1-\pi(x_i)} = \beta_0 + \beta_1(x_i).$ Neter et al. (1996)

Since the logit function is written as a linear form with $\beta_1$ representing the slope. $\beta_1$ represents the change in $h(x_i)$for a unit change in $x$

it implies that

$b_1 = h(x + 1) - h(x_i)$

$=\ln[\frac{\pi(x_i+1)}{1-\pi(x_i+1)}] - \ln[\frac{\pi(x_i)}{1-\pi(x_i)}]$

$= \ln(odds2) - \ln(odds1)$
$b_1 = \ln \frac{odds2}{odds1}$
$e^{b_1} = \frac{odds2}{odds1}$
$e^{b_1} = oddsratio$ . Neter et al. (1996)

After finding the parameter estimate the value $e^(b_1)$ will represent the percentage increase in the probability that $Y = 1$ for each unit increase in $x$

After estimating the coefficients, we assess the significance of the variables in the model. This involves the formulation and testing of statistical hypothesis to determine whether the independent variables in the model are significantly related to the outcome variable. If the predicted values with the variable in the model are better or more accurate in some sense than when the variable is not in the model, then we feel that the variable in question is significant. In logistic regression, the comparison of observed to the predicted values is based on the log-likelihood function

$$\ln L(\beta_0, \beta_1) = \sum_{i=1}^{n} y_i[\ln(\pi(x_i)) + (1 - y_i)\ln(1 - \pi(x_i))].$$

The comparison of observed to the predicted values using the likelihood function is based on the following expression

$$\text{D}{=}-2\ln[\frac{\textbf{likelihood of the fitted model/current model/without variable}}{\textbf{likelihood of the saturated model/with variable}}].$$

Hosmer and Lemeshow (1989).

D is called the deviance. it provides a means of comparing the likelihood of the model that has been fit. The quantity in the bracket is called the likelihood ratio. Using the minus twice its log is necessary to obtain a quantity whose distribution is known and can therefore be used for hypothesis testing purposes such as a test called likelihood ratio test.

$$\text{D} = -2[\ln\textbf{( current model)}-(\ln\textbf{( saturated model)}]$$

Recall: General model of the form

$$y_i = \pi(x_i) + \varepsilon_i$$

$\hat{\pi}(x_i)$ - The current model serves as the estimator for $\pi(x_i)$. Recall:

$$\ln L(\beta_0, \beta_1) = \sum_{i=1}^{n} y_i[\ln(\pi(x_i)) + (1 - y_i)\ln(1 - \pi(x_i))].$$

Substituting into the deviance formula.

$$D=-2[\sum_{i=1}^{n} y_i \ln \hat{\pi}(x_i)+(1-y_i)\ln(1-\hat{\pi}(x_i))-\sum_{i=1}^{n} y_i \ln(y_i)+(1-y_i)\ln(1-y_i)]$$

$$D=[\sum_{i=1}^{n}(y_i \ln \hat{\pi}(x_i)-y_i \ln(y_i)+(i-y_i)\ln(i-\hat{\pi}(x_i))-(1-y_i)\ln(1-y_i)]$$

$$D= -2\sum_{i=1}^{n} y_i \ln[\frac{\hat{\pi}(x_i)}{y_i}]+(1-y_i)\ln[\frac{1-\hat{\pi}(x_i)}{1-y_i}].$$

Hosmer and Lemeshow (1989)

The deviance takes the likelihood of the current model where an element of error is present and subtract the likelihood of the saturated model where there is no error term present and then sums over the difference.

To assess the significance of an independent variable, we compare the value of D with and without the independent variable in the equation, the change in D due to the inclusion of the independent variable in the model G is given by:

G= Deviance of the model without the variable -Deviance of the model with the variable

The statistic G plays the same role in Logistic Regression that the partial F-test does in the linear regression. Because the likelihood of the saturated model is always common to both values of D being difference, it can be expressed as Hosmer and Lemeshow (1989)

In this study, the potential explanatory variables were examined to determine whether or not they are significant enough to be used in our models. The complete model contained all the explanatory variables and interactions believed to influence the level of substance abuse. From that initial stage, we performed regression analysis to select our significant variables.

## 3.3 Ordinal Regression Model

The application of the ordinal regression model is dependent, in large part, on the measurement scale of the variables and the underlined assumptions. If the measurement scale of our response variables is ordered (for example, every day, more than once a week, once a week, once a month and rarely or never), the ordinal regression model is a preferred modeling tool which does not assume normality or constant variance, but requires the assumption of parallel lines across all levels of the outcome. The ordinal regression model may take the following form if the logit link is applied:

$$In\frac{[P(Y<y_i|X)]}{[P(Y>y_j|X)]} = \beta_j + \beta_1 x_{j1} + \beta_2 x_{j2} + \ldots + \beta_p x_{jp}.$$

j = 1, 2,..., k and, where j is the index of categories of response variables. For multiple explanatory variables in the model, we would use:

$$\beta_1 x_{j1} + \beta_2 x_{j2} + \ldots + \beta_p x_{jp}.$$

## 3.4 Model Assumptions

For an ordinal regression model to hold, we need to ensure that the assumption of parallel lines of all levels of the categorical data is satisfied since the model does not assume normality and constant variance. Logistic regression does not assume a linear relationship between the dependent and independent variables, the dependent variables do not need to be normally distributed, there is no homogeneity of variance assumption, in other words, the variances do not have to be the same within categories, normally distributed error terms are not assumed and the independent variables do not have to be interval or unbounded.

## 3.5 Fitting the Data

Since we fit a logistic regression model, we assume that the relationship between the independent variables and the logits are equal for all logits. The regression coefficients are:
$\beta_0, \beta_1, \beta_2, \ldots \beta_p$, of the equation :
$\ln[\frac{\pi(x_i)}{1-\pi(x_i)}] = \beta_0 + \beta_1 x_i = g(x).$
The results would therefore be a set of parallel lines for each category of the outcome variables. This assumption can be checked by allowing the coefficients to vary, estimating them and determining if they are all equal. So our maximum likelihood parameter estimates, residuals and odds ratios were obtained from the final fitted logistic regression model.

## 3.6 Analysing the Data

Here, the logistic regression model was used to select the significant variables that are believed to contribute to substance abuse in drivers. Below are the steps showing the procedure used to perform our study. We first use questionnaire to identify potential variables that are believed to have a significant influence on substance abuse by commercial vehicle drivers. After identifying those variables,we use the logistic regression model to select those variables which are indicated to be significant. Finally, we examine our final outcome to determine if the model is well fit and if the variables selected are important predictors for our models.

- Use questionnaire to gather the potential variables for our model.
- Use basic descriptive statistics to analyse the demographic characteristics of commercial drivers.
- Apply logistic regression analysis to identify the significant variables associated with substance abuse. Finally, the backward elimination regression model-building technique was used to select the significant variable(s) into a fitted logistic regression model.
- Examine our final outcome from the R output to determine if the model is well fit and if the variables selected are important predictors for our models.

### 3.6.1 Assessment of the Fitted Model

When the coefficients are estimated, further steps are used in assessing the appropriateness, adequacy and usefulness of the model.
The significance of each of the explanatory (independent) variables is assessed by carrying out statistical tests of the significance of the coefficients. The overall goodness of fit of the model is then tested.
Finally, the model is validated by checking the goodness of fit and discrimination on a different set of data from that which was used to develop the model.

# Chapter 4

# Results and Analysis

## 4.1 Descriptive Statistics

### 4.1.1 Age Distribution

Majority of the commercial drivers are between the ages of 31-50 years. All of the respondents were male adults within the active productive age. The distribution also indicates that there are a few people within the ages of 21-30 years and the older from 61 years and above. There are clear indication of a large proportion of a driver population within a responsible age.

Table 4.1: Age Distribution

| Age(years) | Number of Driver(s) | Percentage |
|---|---|---|
| 21-30 | 41 | 14.0 |
| 31-40 | 92 | 30.7 |
| 41-50 | 87 | 29.0 |
| 51-60 | 55 | 18.0 |
| 61+ | 24 | 8.0 |

### 4.1.2 Religious Status

Majority of the respondents are Christians and Muslims. Interestingly, both religions frowns on stimulants and any thing that would make the brain interpret things abnormally. Approximately, 90 percent of the commercial drivers come from both religions and yet they are found to abuse drug in one way or the other.

Table 4.2: Religious Status

| Religious Status | Number of Driver(s) | Percentage |
|---|---|---|
| Christianity | 135 | 45.0 |
| Islam | 134 | 44.7 |
| Traditional | 31 | 10.3 |
| Others | 0 | 0.0 |

### 4.1.3 Educational Status

About 59 percent of the respondents meet the requirement of the Driver and Vehicle Licensing Authority (DVLA) of Basic Education Certificate Examination (BECE). The illiteracy level of the respondents is higher. About 41 percent of the commercial drivers interviewed have never being to school. This is of much concern because interpretation of road signs requires a certain level of basic education. This account for the significance or the likelihood of substance use by drivers. Majority of the commercial drivers do not even know the dangers associated with drug driving.

Table 4.3: Level of Education

| Level of Education | Number of Driver(s) | Percentage |
|---|---|---|
| Never being to school | 123 | 41.0 |
| Primary/J.H.S | 158 | 52.7 |
| Secondary | 19 | 6.3 |
| Tertiary | 0 | 0.0 |

### 4.1.4 Marital Status

Majority of the commercial drivers (respondents)are responsibly married and constituted approximately 66 percent of the total respondents. They are breadwinners who provide for the up keep of their families and should care much of road safety. Clearly, this explains why marital status is not a determinant or associated with substance abuse by commercial drivers. There are no association between marital status and the use of drug by commercial drivers.

Table 4.4: Marital Status

| Marital Status | Number of Driver(s) | Percentage |
|---|---|---|
| Single | 49 | 16.3 |
| Married | 197 | 65.7 |
| Devoice | 50 | 16.7 |
| Cohabiting | 4 | 1.3 |

### 4.1.5 Drug Use

Approximately, 34 percent of the commercial drivers(respondents)accept that they use some chemical substances to either enhance their performance or to keep them awake for hours of continuous driving. Most of the drivers do not even know that there is an association between drug use and road traffic accidents. Commercial drivers are of the view that the use of those chemical substances enables them to drive faster, gives them concentration and to be able to go for more trips which is a financial benefit. Car owners can be attributed to the use of drug by commercial drivers. Pressure from car owners makes majority of the drivers to indulge in drug use. If they are not able to go for more trips, means lack of competency and this would result in the collection of the car from them.

Table 4.5: Drug Driving

| Drivers who admitted using drug | Number of Driver(s) | Percentage |
|---|---|---|
| YES (1) | 102 | 34.0 |
| NO (0) | 198 | 66.0 |

### 4.1.6 Vehicle Type

The type of vehicle a commercial driver uses determines the time spent and the distance expected to cover. Respondents who travel for long hour are mostly those who use trailers and coaches (Long Buses). Generally,the type of vehicle a driver uses do not have direct relationship with the likelihood of drug use.But time spent on a journey influence the likelihood of substance use. This is why those who use trailers and coaches use chemical substances as they usually travel long distances.

Table 4.6: Type of Vehicle

| Type of vehicle | Number of Driver(s) | Percentage |
|---|---|---|
| Trailer truck | 67 | 22.3 |
| Coaches/Bus | 58 | 19.3 |
| Cargo truck | 75 | 25.0 |
| Dumper truck | 36 | 12.0 |
| Mini Bus | 28 | 9.3 |
| Taxi | 36 | 12.0 |

### 4.1.7 Mode of Training

Generally, the manner in which commercial drivers learn how to drive is a source of concern for safety. The table bellow indicates that nearly 70 percent do not learn from the approved driving institutions. They either learn how to drive from their friends, family members, self taught or learning on job. Driving school do not only teach one how to drive but also on the dangers associated with stimulants and propellants. Safety and safe driving is the priority of every driving institution.

Table 4.7: Mode of Driver Training

| Training | Number of Driver(s) | Percentage |
|---|---|---|
| Driving School | 87 | 29.0 |
| Family/Friends | 59 | 19.7 |
| Learning on Job | 55 | 18.3 |
| Self Tutoring | 49 | 16.0 |
| Other | 50 | 16.7 |

### 4.1.8 Time(Hrs)used to drive

The table bellow clearly indicates that more than 60 percent of the respondents used to drive for long hours ranging from 9 hours and above in a single trip. There is a relationship between substance use and hours of continuous driving. Stress and fatigue on the part of the respondents influences the use of some chemical substances. As the illiteracy rate of the respondents is high, they are unaware of the dangers associated with use of these drugs.

Table 4.8: Time used to drive

| Time(Hrs) | Number of Driver(s) | Percentage |
|---|---|---|
| 6 | 28 | 9.3 |
| 7 | 24 | 8.0 |
| 8 | 64 | 21.3 |
| 9 | 59 | 19.7 |
| 10+ | 125 | 41.7 |

### 4.1.9 Commonest Drugs Used by Drivers

Below are the commonest drugs usually administered by commercial drivers. In all, 102 respondents admitted to using some drugs as stimulants when driving. This represent 34 percent of the total respondents.

Table 4.9: Types of Drug Use by Drivers

| Name of Drug | Common or Local Name(s) | How administered |
|---|---|---|
| Cannabis | Marijuana,Wee,Ganja | Smoke |
| Opiates(Opium) | Codeine, Morphine, Pethidine | Drink |
| Volatile Inhalants | Spray, Glue, Gases | Inhale |
| Tranquilizers(Sedatives) | Volume (5,10), Blue-Blue | Swallow |
| Cocaine or Heroine | White powder, Brown sugar, Crack | Sniff |
| Alcohol | Akpeteshi,Beer | Drink |
| Amphetamines(Stimulants) | Nescafe, Ataya | Drink |
| Cola Nuts | Goro, Bissi | Chew |
| Cigarette | King Size,555,Embassy | Smoke |

### 4.1.10 Reasons for Drug Use

The table bellow are the reasons given by the respondents for the use and abuse of chemical substances. This indicates that illiteracy on the part of most of the respondents is a source of concern for road traffic safety. The commonest among the reasons are: Feel sleepy without drug,relieves fatigue, to drive for long hours and pressure from car owners. Few of the commercial drivers (respondents) are of the view that there are no regular checks for drug driving as well as strict drug policy for drivers.

Table 4.10: Reasons for Drug Use

| Reason | Number of Driver(s) | Percentage |
|---|---|---|
| To get peace and calm | 14 | 4.67 |
| Feel sleepy without drug | 34 | 11.33 |
| Addiction(Dependence) | 6 | 2.00 |
| Relieves fatigue | 26 | 8.67 |
| Difficult to drive without drug | 33 | 11.00 |
| Get pleasure while driving | 22 | 7.33 |
| Do not know | 5 | 1.67 |
| Feels relaxed and drives easier | 27 | 9.00 |
| To be able to drive faster | 25 | 8.33 |
| To stay awake while driving | 47 | 15.67 |
| Pressure from car owners | 27 | 9.00 |
| No strict drug policy for drivers | 9 | 3.00 |
| No regular checks for drug driving | 12 | 4.00 |
| Weight control behaviour | 13 | 4.33 |



## 4.2 Logistic Regression Analysis

### 4.2.1 Analysis of Maximum Likelihood Estimates

The output shows the coefficients, their standard errors, the z-statistic (Wald z-statistic), and the associated p-values. The logistic regression coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variable. For every one unit change in distance traveled(800km), the log odds of drug use (versus not drug use) increases by 5.6288 and for every unit change in 700km, the log odds of drug use verses not use increases by 6.2005.

For a one unit increase in time (9hrs), the log odds of being a drug user increases by 3.3789 and every unit change (7hrs), the log odds of being a drug user increases by 0.9470. Commercial drivers who learn on job, self taught and learn from friends are statistically significant but driving school is not significant. Marital status is not statistically significant and therefore is not a determinant of drug use. Commercial drivers who travel long distances above 700 kilometers have significant p-values. This means that distance is a significant determinant of drug use by drivers.

Table 4.11: Maximum Likelihood Estimate(Model 1)

| Coefficients | Estimate | Std. Error | z value | $Pr(>\|z\|)$ |
|---|---|---|---|---|
| (Intercept) | -9.5176 | 2.8415 | -3.350 | 0.000810 *** |
| age[21-30] | 0.0000 | | | |
| age[31-40] | -2.5937 | 1.1842 | -2.190 | 0.028502 * |
| age[41-50] | -2.4622 | 1.2467 | -1.975 | 0.048277 * |
| age[51-60] | -2.0518 | 1.3342 | -1.538 | 0.124095 |
| age[61+] | -0.8094 | 1.2458 | -0.650 | 0.515888 |
| distance[100] | 0.0000 | | | |
| distance[200] | 2.0036 | 1.8626 | 1.076 | 0.282053 |
| distance[300] | -0.4490 | 2.3589 | -0.190 | 0.849028 |
| distance[400] | 0.4749 | 2.2327 | 0.213 | 0.831568 |
| distance[500] | 0.9555 | 2.1976 | 0.435 | 0.663724 |
| distance[600] | 2.8958 | 2.3134 | 1.252 | 0.210670 |
| distance[700] | 6.2005 | 2.2884 | 2.710 | 0.006738 ** |
| distance[800] | 5.6288 | 2.2048 | 2.553 | 0.010682 * |
| distance[900+] | 7.6054 | 2.3340 | 3.259 | 0.001120 ** |
| education[Never] | 0.0000 | | | |
| education[primary/JHS] | -1.4316 | 0.5744 | -2.492 | 0.012692 * |
| education[secondary] | -4.6529 | 1.4413 | -3.228 | 0.001246 ** |
| mstatus[single] | 0.0000 | | | |
| mstatus[married] | 1.4788 | 1.0258 | 1.442 | 0.149406 |
| mstatus[devoice] | 1.6542 | 1.1288 | 1.465 | 0.142801 |
| mstatus[cohabiting] | -15.0934 | 1559.8634 | -0.010 | 0.992280 |
| religion[christianity] | 0.0000 | | | |
| religion[islam] | 0.4423 | 0.6033 | 0.733 | 0.463455 |
| religion[traditional] | 2.4259 | 0.9491 | 2.556 | 0.010591 * |
| time[6] | 0.0000 | | | |
| time[7] | 0.9470 | 1.6971 | 0.558 | 0.576826 |
| time[8] | 2.1849 | 1.1605 | 1.883 | 0.050100 |
| time[9] | 3.3789 | 1.2721 | 2.656 | 0.007903 ** |
| time[10+] | 4.0090 | 1.1156 | 3.594 | 0.000326 *** |
| training[driving school] | 0.0000 | | | |
| training[friends] | 4.7524 | 0.8723 | 5.448 | 5.09e-08 *** |
| training[learning on job] | 5.4805 | 1.0253 | 5.346 | 9.01e-08 *** |
| training[self tutoring] | 1.6451 | 0.8461 | 1.944 | 0.051861 . |
| training[other] | 0.7260 | 0.8414 | 0.863 | 0.388197 |
| vehicle[trailer] | 0.0000 | | | |
| vehicle[mini bus] | 1.0255 | 1.1606 | 0.884 | 0.376900 |
| vehicle[dumper truck] | 1.6553 | 1.5397 | 1.075 | 0.282337 |
| vehicle[cargo truck] | -1.3082 | 0.7798 | -1.678 | 0.093430 . |
| vehicle[coaches] | 0.6760 | 1.9613 | 0.345 | 0.730355 |
| vehicle[taxi] | 1.2415 | 1.5229 | 0.815 | 0.414950 |

### 4.2.2 Odds Ratios(OR)

We are 95 percent confident that for a one unit increase in time, the odds of drug use by a commercial driver who drives for more than 10 hours versus not using drug increases by a factor of 5.509293e+01. The odds of drug use for a commercial driver using a dumper truck is between 2.894950e-01 and 1.353064e+02.

We are 95 percent confident that for a one unit increase in distance, the odds of drug use by a commercial driver who drives for than 900 kilometers versus not using drug increases by a factor of 2.008983e+03.

Table 4.12: ODDS RATIOS

| Variable | OR | 2.5 percent | 97.5 percent |
|---|---|---|---|
| (Intercept) | 7.354505e-05 | 1.428725e-07 | 1.121890e-02 |
| age[31-40] | 7.474196e-02 | 6.577162e-03 | 7.091162e-01 |
| age[41-50] | 8.524946e-02 | 6.531945e-03 | 9.100546e-01 |
| age[51-60] | 1.285092e-01 | 8.534147e-03 | 1.683472e+00 |
| age[61+] | 4.451276e-01 | 3.460478e-02 | 4.824807e+00 |
| distance[200] | 7.415634e+00 | 2.332663e-01 | 4.701014e+02 |
| distance[300] | 6.382445e-01 | 4.814157e-03 | 7.583486e+01 |
| distance[400] | 1.607809e+00 | 2.433147e-02 | 2.136692e+02 |
| distance[500] | 2.599846e+00 | 3.893110e-02 | 2.136692e+02 |
| distance[600] | 1.809758e+01 | 2.624222e-01 | 2.632232e+03 |
| distance[700] | 4.930109e+02 | 9.634324e+00 | 8.423085e+04 |
| distance[800] | 2.783408e+02 | 6.355358e+00 | 4.002675e+04 |
| distance[900+] | 2.008983e+03 | 3.548114e+01 | 3.683694e+05 |
| education[primary] | 2.389364e-01 | 7.227582e-02 | 7.044533e-01 |
| education[secondary] | 9.533762e-03 | 3.869645e-04 | 1.147145e-01 |
| mstatus[married] | 4.387837e+00 | 6.140997e-01 | 3.521826e+01 |
| mstatus[devoice] | 5.228772e+00 | 5.852233e-01 | 5.030545e+01 |
| mstatus[cohabiting ] | 2.786201e-07 | 5.652233e-01 | 9.621607e+29 |
| religion[islam] | 1.556342e+00 | 4.807932e-01 | 5.267230e+00 |
| religion[traditional] | 1.131217e+01 | 1.897967e+00 | 8.108981e+01 |
| time[7] | 2.578066e+00 | 8.673554e-02 | 7.682196e+01 |
| time[8] | 8.889540e+00 | 1.039258e+00 | 1.058949e+02 |
| time[9] | 2.933885e+01 | 2.825415e+00 | 4.539337e+02 |
| time[10+] | 5.509293e+01 | 7.644572e+00 | 6.543038e+02 |
| training[friends] | 1.158582e+02 | 2.418215e+01 | 7.684636e+02 |
| training[on job] | 2.399782e+02 | 3.893176e+01 | 2.264460e+03 |
| training[self taught] | 5.181556e+00 | 1.023111e+00 | 2.937798e+01 |
| training[other] | 2.066831e+00 | 3.862077e-01 | 1.101892e+01 |
| vehicle[mini bus] | 2.788545e+00 | 3.074893e-01 | 3.069662e+01 |
| vehicle[dumper truck] | 5.234497e+00 | 2.894950e-01 | 1.353064e+02 |
| vehicle[cargo truck] | 2.703109e-01 | 5.435443e-02 | 1.201289e+00 |
| vehicle[coaches] | 1.965929e+00 | 3.906809e-02 | 9.421414e+01 |
| vehicle[taxi] | 3.460717e+00 | 2.210596e-01 | 9.827966e+01 |

## 4.3 Analysis of Deviance

### 4.3.1 Analysis of Deviance (Model 1:AIC=187.91)

The backward elimination regression model-building technique was used to select the significant variable(s) into a fitted logistic regression model. This technique begins with a full model (i.e. model with all the variables under study) and deletes variable one by one until the model begins to degrade. Each deletion of variables from the model is explained in a sequence of Models. A 5 percent statistical significance level is required for a variable to stay in a model. Table bellow shows the results obtained from the full model (Model 1). From this model, Level of education with (p-value=3.114e-05 ***), time used to drive with (p-value=0.0005852 ***) mode of training with (p-value=2.2e-16 ***) and distance traveled with (p-value=2.2e-16 ***) were the most significant variables associated with the use of drug by commercial drivers. The remaining variables such as age, religion and type of vehicle used were not significant. Therefore, this resulted to an Akaikes information criterion (AIC) statistic of 187.91

Table 4.13: Analysis of Deviance(Model 1:AIC=187.91)

| Variable | Df | Deviance | Resid. Df | Resid. Dev | $P(>\|Chi\|)$ |
|---|---|---|---|---|---|
| NULL | | | | 299 | 384.62 |
| age | 4 | 0.457 | 295 | 384.16 | 0.9775398 |
| distance | 8 | 114.079 | 287 | 270.09 | 2.2e-16 *** |
| education | 2 | 20.754 | 285 | 249.33 | 3.114e-05 *** |
| mstatus | 3 | 8.326 | 282 | 241.01 | 0.0397362 * |
| religion | 2 | 3.673 | 280 | 237.33 | 0.1593930 |
| time | 4 | 19.651 | 276 | 217.68 | 0.0005852 *** |
| training | 4 | 88.100 | 272 | 129.58 | 2.2e-16 *** |
| vehicle | 5 | 7.668 | 267 | 121.91 | 0.1754806 |

### 4.3.2 Analysis of Deviance (Model 2:AIC=186.54)

In Model 2, variable Age was dropped because it was the least significant with the highest p-value. This resulted in improving the Akaikes information criterion (AIC) by reducing it slightly from 187.91 to 186.54. Similarly to the results in Model 1, Level of education with(p-value=4.525e-05 ***), time used to drive with (p-value=0.0003287 ***) mode of training with (p-value=2.2e-16 ***) and distance traveled with (p-value=2.2e-16 ***) were the only variables that were significantly associated with the current use of drug in Model 2.

Table 4.14: Analysis of Deviance(Model 2)

| Variable | Df | Deviance | Resid. Df | Resid. Dev | $P(>\|Chi\|)$ |
|---|---|---|---|---|---|
| NULL | | | | 299 | 384.62 |
| distance | 8 | 113.542 | 291 | 271.08 | 2.2e-16 *** |
| education | 2 | 20.006 | 289 | 251.07 | 4.525e-05 *** |
| mstatus | 3 | 8.084 | 286 | 242.99 | 0.0443135 * |
| religion | 2 | 3.035 | 284 | 239.95 | 0.2193018 |
| time | 4 | 20.918 | 280 | 219.04 | 0.0003287 *** |
| training | 4 | 82.593 | 276 | 136.44 | 2.2e-16 *** |
| vehicle | 5 | 7.902 | 271 | 128.54 | 0.1616969 |

### 4.3.3 Analysis of Deviance (Model 3:AIC=187.1)

In model third(3rd) model, the AIC statistic became worst. It increased from 186.54 to 187.1) when the variable 'Religion' was dropped.

Table 4.15: Analysis of Deviance (Model 3:AIC=187.1)

| Variable | Df | Deviance | Resid. Df | Resid. Dev | $P(>\|Chi\|)$ |
|---|---|---|---|---|---|
| NULL | | | | 299 | 384.62 |
| distance | 8 | 113.542 | 291 | 271.08 | 2.2e-16 *** |
| education | 2 | 20.006 | 289 | 251.07 | 4.525e-05 *** |
| mstatus | 3 | 8.084 | 286 | 242.99 | 0.0443135 * |
| time | 4 | 21.594 | 282 | 221.40 | 0.0002414 *** |
| training | 4 | 80.134 | 278 | 141.26 | 2.2e-16 *** |
| vehicle | 5 | 8.158 | 273 | 133.10 | 0.1477385 |

### 4.3.4 Analysis of Deviance (Model 4:AIC=185.26)

Finally, in the fourth model, the AIC statistic became better when it was reduced from 187.1 to 185.26.

The variables: Level of education with (p-value=4.525e-05 ***), time used to drive with (p-value=0.0003287 ***) mode of training with (p-value=2.2e-16 ***) and distance traveled with (p-value=2.2e-16 ***) were the only variables that were significantly associated with the current use of drug in Model 4.

However, comparing the models 1, 2, 3 and 4 based on their AIC statistic, the fourth model was selected for yielding the least AIC at 185.26.

Table 4.16: Analysis of Deviance(Model 4:AIC=185.26)

| Variable | Df | Deviance | Resid. Df | Resid. Dev | $P(>\|Chi\|)$ |
|---|---|---|---|---|---|
| NULL | | | | 299 | 384.62 |
| distance | 8 | 113.542 | 291 | 271.08 | 2.2e-16 *** |
| education | 2 | 20.006 | 289 | 251.07 | 4.525e-05 *** |
| mstatus | 3 | 8.084 | 286 | 242.99 | 0.0443135 * |
| time | 4 | 21.594 | 282 | 221.40 | 0.0002414 *** |
| training | 4 | 80.134 | 278 | 141.26 | 2.2e-16 *** |

### 4.3.5 Test of Overall fitness of the fitted model

The measure of how well our model fit is the significance of our overall model. We test for whether our model with predictors fits significantly better than our model with just an intercept (null model). The test statistic is the difference between the residual deviance for the model with predictors and the null model. The chi-square of 121.91 with 267 degrees of freedom and an associated p-value of 7.093043e-16 which is less than 0.005 tells us that our model as a whole fits significantly better than an empty model.

Table 4.17: Overall fitness of the model

| Test | Value | DF | P-value |
|---|---|---|---|
| Chi-Square | 121.91 | 267 | 7.093043e-16 |

# Chapter 5

# Conclusions and Recommendations

## 5.1 Discussion

The objectives of this study were to determine the factors associated with drug driving among commercial drivers in Ghana and also to describe the socio-economic and demographic characteristics of the respondents.
Social determinants of substance abuse by commercial vehicle drivers in Ghana were identified. Some factors were significantly associated with substances (drug) abuse by commercial vehicle drivers. The following predictor variables are likely to influence the abuse of drug by commercial drivers: The distance covered, time (hours) used to travel, mode of training and the commercial driver educational level.
Low educational levels of commercial drivers was positively associated with substance use. About 281 respondents(representing 94 percent)of the drivers interviewed do not have a secondary education. Majority of them do not know the effects and dangers associated with drug driving. This is why the World Health Organisation (WHO) resolution adopted by the 58th World Health Assembly in 2005 called for a concerted effort at the global, regional, and country level to address the social determinants of harmful use of alcohol and reduce alcohol-related harm.
Majority of the commercial drivers learn how to drive from an unapproved driving schools. Approximately, 71 percent do not learn from the approved driving institutions. They either learn how to drive from their friends, family members, self taught or learning on job. Driving school do not only teach one how to drive but also educate beginners on the dangers associated with stimulants and pro-

pellants. Safety and safe driving is the priority of every driving institution.
From the model, Level of education with (p-value=3.114e-05 ***), time used to drive with (p-value=0.0005852 ***) mode of training with (p-value=2.2e-16 ***) and distance traveled with (p-value=2.2e-16 ***) were the most significant variables associated with the use of drug by commercial drivers. The remaining variables such as age, religion and type of vehicle used were not significant.

## 5.2 Major Findings



Stress on the part of commercial drivers who travel long distances is likely to influence the use of drug which is contrary to the findings of Bello et al., (2011). Moreover, pressure from car owners to ensure that their drivers go for more trips for financial gains influence some commercial drivers to resort to the use of drugs to keep them awake.
Significant number of road traffic accident in the country can be attributed to driver errors. These are errors on the part of the commercial driver.

## 5.3 Conclusions

The results obtained from the logistic regression model revealed that drug driving among commercial drivers in Ghana was strongly associated with educational levels, type of vehicle used, distance traveled and time(hours)used to drive.
A number of the commercial drivers admitted to using some chemical substances (drugs) before driving. Thirty four (34) percent of the commercial drivers admitted to using chemical substances to either enhance their performance or to keep them awake for long hours of continuous driving.
About sixty (60) percent of the commercial drivers usually drive for more than nine (9) in a trip. There are significant relationship between substance use and hours of continuous driving.
The most widely used substances (drugs) among commercial drivers in Ghana are

alcohol, cannabis (marijuana), volatile inhalants (spray, glues), amphetamines (stimulants such as nescafe, ataya) and cigarette.

## 5.4 Recommendations

The Ghana National Road Safety Commission should make a comprehensive assessment of the risk factors associated with the commercial driver working conditions, which contribute to road traffic. Driver error is attributed to the use of chemical substances(drugs) which impairs the driver's vision and reactions to road signs.

Although perception and knowledge about the dangers of drug driving were clear and universal, awareness should be created against the use and abuse of drugs and its consequences. More education should be given out to drivers to make them more informed about the side effects of the various drugs and the need to drive without the use of these substances.

The Ghana National Road Safety Commission in collaboration with the Ghana Private Road Transport Union(GPRTU) should organise regular seminar for commercial drivers on the dangers and effects associated with drug driving. Majority of the drivers do not know the health implications of drug driving.

The Motto Traffic Transport Unit (MTTU) of the Ghana Police Service should strengthened their regular checks on the major roads for substance abuse and over speeding as well. This would help reduce the intake and abuse of drug by commercial drivers in the country.

There is the need for rest stops along the major roads for rest, meals, and naps. The authorities of the various transport unions should enforce the patronage of these rest stop. This would compel commercial drivers to have enough rest after the long hours of continuous driving.

The Driver and Vehicle Licensing Authority should regulate system of issuing driving license to drivers. Majority of the commercial drivers learn how to drive through unapproved institutions and yet manage to acquire license through the so called "Goro boys". This is serious concern and should be address by the appropriate authorities in other to reduce the problems of drug driving in the country.

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# Appendix

## Appendix A

$> SPSSDATA < -read.spss("C: /Users/Shaibu/Desktop/SPSSDATA.sav", +use.value.$

$TRUE, max.value.labels = Inf, to.data.frame = TRUE)$

$> GLM.1 < -glm(substanceuse\ age+distance+education+mstatus+religion+$

$time + training + vehicle, family = binomial(logit), data = SPSSDATA)$



$> summary(GLM.1)$

Call:

glm(formula = substanceuse   age + distance + education + mstatus + religion

+ time + training + vehicle, family = binomial(logit), data = SPSSDATA)

Deviance Residuals:

Min  1Q  Median  3Q  Max

-2.10619  -0.22733  -0.03722  0.10746  2.86684

Table 5.1: Maximum Likelihood Estimates for Drug Use(Model 1)

| Variable | Estimate | Std. Error | z value | Pr(> $\|z\|$) |
|---|---|---|---|---|
| (Intercept) | -9.5176 | 2.8415 | -3.350 | 0.000810 *** |
| age[31-40] | -2.5937 | 1.1842 | -2.190 | 0.028502 * |
| age[41-50] | -2.4622 | 1.2467 | -1.975 | 0.048277 * |
| age[51-60] | -2.0518 | 1.3342 | -1.538 | 0.124095 |
| age[61+] | -0.8094 | 1.2458 | -0.650 | 0.515888 |
| distance[200] | 2.0036 | 1.8626 | 1.076 | 0.282053 |
| distance[300] | -0.4490 | 2.3589 | -0.190 | 0.849028 |
| distance[400] | 0.4749 | 2.2327 | 0.213 | 0.831568 |
| distance[500] | 0.9555 | 2.1976 | 0.435 | 0.663724 |
| distance[600] | 2.8958 | 2.3134 | 1.252 | 0.210670 |
| distance[700] | 6.2005 | 2.2884 | 2.710 | 0.006738 ** |
| distance[800] | 5.6288 | 2.2048 | 2.553 | 0.010682 * |
| distance[900+] | 7.6054 | 2.3340 | 3.259 | 0.001120 ** |
| education[primary/JHS] | -1.4316 | 0.5744 | -2.492 | 0.012692 * |
| education[secondary] | -4.6529 | 1.4413 | -3.228 | 0.001246 ** |
| mstatus[married] | 1.4788 | 1.0258 | 1.442 | 0.149406 |
| mstatus[devoice] | 1.6542 | 1.1288 | 1.465 | 0.142801 |
| mstatus[cohabiting] | -15.0934 | 1559.8634 | -0.010 | 0.992280 |
| religion[islam] | 0.4423 | 0.6033 | 0.733 | 0.463455 |
| religion[traditional] | 2.4259 | 0.9491 | 2.556 | 0.010591 * |
| time[7] | 0.9470 | 1.6971 | 0.558 | 0.576826 |
| time[8] | 2.1849 | 1.1605 | 1.883 | 0.050100 |
| time[9] | 3.3789 | 1.2721 | 2.656 | 0.007903 ** |
| time[10+] | 4.0090 | 1.1156 | 3.594 | 0.000326 *** |
| training[friends] | 4.7524 | 0.8723 | 5.448 | 5.09e-08 *** |
| training[learning on job] | 5.4805 | 1.0253 | 5.346 | 9.01e-08 *** |
| training[self tutoring] | 1.6451 | 0.8461 | 1.944 | 0.051861 . |
| training[other] | 0.7260 | 0.8414 | 0.863 | 0.388197 |
| vehicle[mini bus] | 1.0255 | 1.1606 | 0.884 | 0.376900 |
| vehicle[dumper truck] | 1.6553 | 1.5397 | 1.075 | 0.282337 |
| vehicle[cargo truck] | -1.3082 | 0.7798 | -1.678 | 0.093430 . |
| vehicle[coaches] | 0.6760 | 1.9613 | 0.345 | 0.730355 |
| vehicle[taxi] | 1.2415 | 1.5229 | 0.815 | 0.414950 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Null deviance: 384.62 on 299 degrees of freedom

Residual deviance: 121.91 on 267 degrees of freedom

AIC: 187.91

Number of Fisher Scoring iterations: 16

$> pchisq(121.91, 267) = 7.093043e - 16$

# Appendix B

$> exp(coef(GLM.2))$

Table 5.2: Coefficients

| | |
|---|---|
| Intercept | 7.354505e-05 |
| age[31-40] | 7.474196e-02 |
| age[41-50] | 8.524946e-02 |
| age[51-60] | 1.285092e-01 |
| age[61+] | 4.451276e-01 |
| distance[200] | 7.415634e+00 |
| distance[300] | 6.382445e-01 |
| distance[400] | 1.607809e+00 |
| distance[500] | 2.599846e+00 |
| distance[600] | 1.809758e+01 |
| distance[700] | 4.930109e+02 |
| distance[800] | 2.783408e+02 |
| distance[900+] | 2.008983e+03 |
| education[primary] | 2.389364e-01 |
| education[secondary] | 9.533762e-03 |
| mstatus[married] | 4.387837e+00 |
| mstatus[devoice] | 5.228772e+00 |
| mstatus[cohabiting] | 2.786201e-07 |
| religion[islam] | 1.556342e+00 |
| religion[traditional] | 1.131217e+01 |
| time[7] | 2.578066e+00 |
| time[8] | 8.889540e+00 |
| time[9] | 2.933885e+01 |
| time[10+] | 5.509293e+01 |
| training[ friends] | 1.158582e+02 |
| training[learning on job] | 2.399782e+02 |
| training[self tutoring] | 5.181556e+00 |
| training[other] | 2.066831e+00 |
| vehicle[mini bus] | 2.788545e+00 |
| vehicle[dumper truck] | 5.234497e+00 |
| vehicle[cargo truck] | 2.703109e-01 |
| vehicle[coaches] | 1.965929e+00 |
| vehicle[taxi] | 3.460717e+00 |

# Appendix C

Table 5.3: ODDS RATIO

| Variable | OR | 2.5 percent | 97.5 percent |
|---|---|---|---|
| (Intercept) | 7.354505e-05 | 1.428725e-07 | 1.121890e-02 |
| age[31-40] | 7.474196e-02 | 6.577162e-03 | 7.091162e-01 |
| age[41-50] | 8.524946e-02 | 6.531945e-03 | 9.100546e-01 |
| age[51-60] | 1.285092e-01 | 8.534147e-03 | 1.683472e+00 |
| age[61+] | 4.451276e-01 | 3.460478e-02 | 4.824807e+00 |
| distance[200] | 7.415634e+00 | 2.332663e-01 | 4.701014e+02 |
| distance[300] | 6.382445e-01 | 4.814157e-03 | 7.583486e+01 |
| distance[400] | 1.607809e+00 | 2.433147e-02 | 2.136692e+02 |
| distance[500] | 2.599846e+00 | 3.893110e-02 | 2.136692e+02 |
| distance[600] | 1.809758e+01 | 2.624222e-01 | 2.632232e+03 |
| distance[700] | 4.930109e+02 | 9.634324e+00 | 8.423085e+04 |
| distance[800] | 2.783408e+02 | 6.355358e+00 | 4.002675e+04 |
| distance[900+] | 2.008983e+03 | 3.548114e+01 | 3.683694e+05 |
| education[primary] | 2.389364e-01 | 7.227582e-02 | 7.044533e-01 |
| education[secondary] | 9.533762e-03 | 3.869645e-04 | 1.147145e-01 |
| mstatus[married] | 4.387837e+00 | 6.140997e-01 | 3.521826e+01 |
| mstatus[devoice] | 5.228772e+00 | 5.852233e-01 | 5.030545e+01 |
| mstatus[cohabiting] | 2.786201e-07 | 5.652233e-01 | 9.621607e+29 |
| religion[islam] | 1.556342e+00 | 4.807932e-01 | 5.267230e+00 |
| religion[traditional] | 1.131217e+01 | 1.897967e+00 | 8.108981e+01 |
| time[7] | 2.578066e+00 | 8.673554e-02 | 7.682196e+01 |
| time[8] | 8.889540e+00 | 1.039258e+00 | 1.058949e+02 |
| time[9] | 2.933885e+01 | 2.825415e+00 | 4.539337e+02 |
| time[10+] | 5.509293e+01 | 7.644572e+00 | 6.543038e+02 |
| training[friends] | 1.158582e+02 | 2.418215e+01 | 7.684636e+02 |
| training[on job] | 2.399782e+02 | 3.893176e+01 | 2.264460e+03 |
| training[self taught] | 5.181556e+00 | 1.023111e+00 | 2.937798e+01 |
| training[other] | 2.066831e+00 | 3.862077e-01 | 1.101892e+01 |
| vehicle[mini bus] | 2.788545e+00 | 3.074893e-01 | 3.069662e+01 |
| vehicle[dumper truck] | 5.234497e+00 | 2.894950e-01 | 1.353064e+02 |
| vehicle[cargo truck] | 2.703109e-01 | 5.435443e-02 | 1.201289e+00 |
| vehicle[T.coaches] | 1.965929e+00 | 3.906809e-02 | 9.421414e+01 |
| vehicle[T.taxi] | 3.460717e+00 | 2.210596e-01 | 9.827966e+01 |

# Appendix D

$> anova(GLM.1, test =' Chisq')$

Analysis of Deviance Table

Model: binomial, link: logit

Response: substanceuse

Terms added sequentially (first to last)



Table 5.4: Analysis of Deviance(Model 1)

| Variable | Df | Deviance | Resid. Df | Resid. Dev | $P(>\|Chi\|)$ |
|---|---|---|---|---|---|
| NULL | | | | 299 | 384.62 |
| age | 4 | 0.457 | 295 | 384.16 | 0.9775398 |
| distance | 8 | 114.079 | 287 | 270.09 | 2.2e-16 *** |
| education | 2 | 20.754 | 285 | 249.33 | 3.114e-05 *** |
| mstatus | 3 | 8.326 | 282 | 241.01 | 0.0397362 * |
| religion | 2 | 3.673 | 280 | 237.33 | 0.1593930 |
| time | 4 | 19.651 | 276 | 217.68 | 0.0005852 *** |
| training | 4 | 88.100 | 272 | 129.58 | 2.2e-16 *** |
| vehicle | 5 | 7.668 | 267 | 121.91 | 0.1754806 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Appendix E

$> GLM.2 < -glm(substanceuse\ distance + education + mstatus + religion + time + training + vehicle, family = binomial(logit), data = SPSSDATA)$

$> summary(GLM.2)$

Call:

glm(formula = substanceuse distance + education + mstatus + religion + time + training + vehicle, family = binomial(logit), data = SPSSDATA)

Deviance Residuals:

Min 1Q Median 3Q Max

-1.99974 -0.26949 -0.04451 0.14645 2.65885

Table 5.5: Maximum Likelihood Estimates for Drug Use(Model 2)

| Variale | Estimate | Std. Error | z value | $Pr(>\|z\|)$ |
|---|---|---|---|---|
| (Intercept) | -8.96774 | 2.61411 | -3.431 | 0.000602 *** |
| distance[200] | 0.68902 | 1.65014 | 0.418 | 0.676277 |
| distance[300] | -1.65742 | 2.11134 | -0.785 | 0.432451 |
| distance[400] | -0.78187 | 2.09797 | -0.373 | 0.709387 |
| distance[500] | -0.02632 | 1.99922 | -0.013 | 0.989497 |
| distance[600] | 1.99450 | 2.16177 | 0.923 | 0.356202 |
| distance[700] | 5.40173 | 2.08256 | 2.594 | 0.009492 ** |
| distance[800] | 4.60900 | 1.97807 | 2.330 | 0.019803 * |
| distance[900+] | 6.58080 | 2.09620 | 3.139 | 0.001693 ** |
| education[primary/JHS] | -1.25653 | 0.54170 | -2.320 | 0.020363 * |
| education[secondary] | -3.95778 | 1.30416 | -3.035 | 0.002408 ** |
| mstatus[married] | 0.02522 | 0.68637 | 0.037 | 0.970693 |
| mstatus[devoice] | 0.42124 | 0.84356 | 0.499 | 0.617527 |
| mstatus[cohabiting] | -16.26402 | 1560.48895 | -0.010 | 0.991684 |
| religion[islam] | 0.16486 | 0.55919 | 0.295 | 0.768127 |
| religion[traditional] | 1.73210 | 0.85800 | 2.019 | 0.043511 * |
| time[7] | 0.45795 | 1.63974 | 0.279 | 0.780028 |
| time[8] | 1.60822 | 1.07204 | 1.500 | 0.133574 |
| time[9] | 3.60290 | 1.24452 | 2.895 | 0.003791 ** |
| time[10+] | 3.68010 | 1.06065 | 3.470 | 0.000521 *** |
| training[friends] | 4.32541 | 0.79626 | 5.432 | 5.57e-08 *** |
| training[ on job] | 4.55293 | 0.84115 | 5.413 | 6.21e-08 *** |
| training[self tutoring] | 1.52307 | 0.79074 | 1.926 | 0.054089 . |
| training[other] | 0.44300 | 0.81219 | 0.545 | 0.585451 |
| vehicle[mini bus] | 1.57746 | 1.05324 | 1.498 | 0.134205 |
| vehicle[dumper truck] | 1.74451 | 1.46844 | 1.188 | 0.234832 |
| vehicle[cargo truck] | -0.85955 | 0.69520 | -1.236 | 0.216310 |
| vehicle[coaches] | 1.66035 | 1.72882 | 0.960 | 0.336859 |
| vehicle[taxi] | 1.95167 | 1.48451 | 1.315 | 0.188615 |



Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 384.62 on 299 degrees of freedom

Residual deviance: 128.54 on 271 degrees of freedom

AIC: 186.54

Number of Fisher Scoring iterations: 16

# Appendix F

$> anova(GLM.2, test =' Chisq')$

Analysis of Deviance Table

Model: binomial, link: logit

Response: substanceuse

Terms added sequentially (first to last)



Table 5.6: Analysis of Deviance(Model 2)

| Variable | Df | Deviance | Resid. Df | Resid. Dev | $P(>\|Chi\|)$ |
|---|---|---|---|---|---|
| NULL | | | | 299 | 384.62 |
| distance | 8 | 113.542 | 291 | 271.08 | 2.2e-16 *** |
| education | 2 | 20.006 | 289 | 251.07 | 4.525e-05 *** |
| mstatus | 3 | 8.084 | 286 | 242.99 | 0.0443135 * |
| religion | 2 | 3.035 | 284 | 239.95 | 0.2193018 |
| time | 4 | 20.918 | 280 | 219.04 | 0.0003287 *** |
| training | 4 | 82.593 | 276 | 136.44 | 2.2e-16 *** |
| vehicle | 5 | 7.902 | 271 | 128.54 | 0.1616969 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Appendix G

$> GLM.3 < -glm(substanceuse\ distance + education + mstatus + +time + training+vehicle, family = binomial(logit), data = SPSSDATA) > summary(GLM.3)$

Call:

glm(formula = substanceuse distance + education + mstatus + time + training + vehicle, family = binomial(logit), data = SPSSDATA)

Deviance Residuals:

| Min | 1Q | Median | 3Q | Max |
|---|---|---|---|---|
| -2.27005 | -0.24485 | -0.04767 | 0.15806 | 2.58416 |

Table 5.7: Maximum Likelihood Estimates for Drug Use(Model 3)

| Variale | Estimate | Std. Error | z value | $Pr(>\|z\|)$ |
|---|---|---|---|---|
| Intercept | -8.03034 | 2.51655 | -3.191 | 0.001418 ** |
| distance[200] | 0.32085 | 1.71594 | 0.187 | 0.851676 |
| distance[300] | -2.56104 | 2.15947 | -1.186 | |
| 0.235640 distance[400] | -0.40442 | 2.15257 | -0.188 | 0.850974 |
| distance[500] | -0.72894 | 2.01898 | -0.361 | 0.718068 |
| distance[600] | 1.28944 | 2.13163 | 0.605 | 0.545240 |
| distance[700] | 4.71805 | 2.02575 | 2.329 | 0.019857 * |
| distance[800] | 4.10021 | 1.95472 | 2.098 | 0.035941 * |
| distance[900+] | 5.86787 | 2.03730 | 2.880 | 0.003974 ** |
| education[primary/JHS] | -1.23349 | 0.53280 | -2.315 | 0.020607 * |
| education[secondary] | -3.91826 | 1.25399 | -3.125 | 0.001780 ** |
| mstatus[married] | -0.03727 | 0.66839 | -0.056 | 0.955536 |
| mstatus[devoice] | 0.61961 | 0.82698 | 0.749 | 0.453708 |
| mstatus[cohabiting] | -16.35340 | 1509.24646 | -0.011 | 0.991355 |
| time[7] | 0.35450 | 1.55029 | 0.229 | 0.819130 |
| time[8] | 1.71167 | 1.00445 | 1.704 | 0.088365 . |
| time[9] | 3.73016 | 1.19740 | 3.115 | 0.001838 ** |
| time[10+] | 3.54707 | 0.98052 | 3.618 | 0.000297 *** |
| training[friends] | 4.26256 | 0.78063 | 5.460 | 4.75e-08 *** |
| training[ on job] | 4.32546 | 0.80512 | 5.372 | 7.77e-08 *** |
| training[self tutoring] | 1.51902 | 0.78144 | 1.944 | 0.051909 . |
| training[other] | 0.47141 | 0.80271 | 0.587 | 0.557023 |
| vehicle[mini bus] | 1.51786 | 1.03647 | 1.464 | 0.143068 |
| vehicle[dumper truck] | 1.44297 | 1.42040 | 1.016 | 0.309683 |
| vehicle[cargo truck] | -0.85444 | 0.68522 | -1.247 | 0.212413 |
| vehicle[coaches] | 1.55552 | 1.66248 | 0.936 | 0.349447 |
| vehicle[taxi] | 2.18861 | 1.48478 | 1.474 | 0.140473 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 384.62 on 299 degrees of freedom

Residual deviance: 133.10 on 273 degrees of freedom

AIC: 187.1

Number of Fisher Scoring iterations: 16

# Appendix H

$> anova(GLM.3, test =' Chisq')$

Analysis of Deviance Table

Model: binomial, link: logit

Response: substanceuse

Terms added sequentially (first to last)



Table 5.8: Analysis of Deviance(Model 3:AIC=187.1)

| Variable | Df | Deviance | Resid. Df | Resid. Dev | $P(>\|Chi\|)$ |
|---|---|---|---|---|---|
| NULL | | | | 299 | 384.62 |
| distance | 8 | 113.542 | 291 | 271.08 | 2.2e-16 *** |
| education | 2 | 20.006 | 289 | 251.07 | 4.525e-05 *** |
| mstatus | 3 | 8.084 | 286 | 242.99 | 0.0443135 * |
| time | 4 | 21.594 | 282 | 221.40 | 0.0002414 *** |
| training | 4 | 80.134 | 278 | 141.26 | 2.2e-16 *** |
| vehicle | 5 | 8.158 | 273 | 133.10 | 0.1477385 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Appendix I

$> GLM.4 < -glm(substanceuse\ distance + education + mstatus + +time + training, family = binomial(logit), data = SPSSDATA) > summary(GLM.4)$

Call:

glm(formula = substanceuse distance + education + mstatus + time + training, family = binomial(logit), data = SPSSDATA)

Deviance Residuals: Min 1Q Median 3Q Max

-2.23638 -0.34303 -0.06108 0.14790 2.28132

Table 5.9: Maximum Likelihood Estimates for Drug Use(Model 4)

| Variale | Estimate | Std. Error | z value | Pr(¿—z—) |
|---|---|---|---|---|
| Variable | Estimate | Std. Error | z value | $Pr(> \|z\|)$ |
| (Intercept) | -6.9184 | 1.9089 | -3.624 | 0.000290 *** |
| distance[200] | 1.0913 | 1.5104 | 0.722 | 0.469998 |
| distance[300] | -1.4545 | 1.7927 | -0.811 | 0.417166 |
| distance[400] | 0.3206 | 1.7455 | 0.184 | 0.854261 |
| distance[500] | 0.2685 | 1.6524 | 0.163 | 0.870906 |
| distance[600] | 1.9717 | 1.5896 | 1.240 | 0.214851 |
| distance[700] | 3.4463 | 1.5164 | 2.273 | 0.023050 * |
| distance[800] | 3.0261 | 1.4201 | 2.131 | 0.033105 * |
| distance[900+] | 5.3457 | 1.5574 | 3.433 | 0.000598 *** |
| education[primary/JHS] | -1.1576 | 0.4960 | -2.334 | 0.019598 * |
| education[secondary] | -3.2700 | 1.1446 | -2.857 | 0.004280 ** |
| mstatus[married] | -0.0794 | 0.6328 | -0.125 | 0.900146 |
| mstatus[devoice] | 0.7018 | 0.7784 | 0.902 | 0.367237 |
| mstatus[cohabiting] | -16.8053 | 1496.6456 | -0.011 | 0.991041 |
| time[7] | 0.6353 | 1.3754 | 0.462 | 0.644133 |
| time[8] | 1.2985 | 0.8961 | 1.449 | |
| 0.147285 time[9] | 3.1217 | 1.0599 | 2.945 | 0.003227 ** |
| time[10+] | 3.1214 | 0.8388 | 3.721 | 0.000198 *** |
| training[friends] | 4.3004 | 0.7602 | 5.657 | 1.54e-08 *** |
| training[ on job] | 4.3071 | 0.7631 | 5.644 | 1.66e-08 *** |
| training[self tutoring] | 1.4465 | 0.7634 | 1.895 | 0.058112 . |
| training[other] | 0.6312 | 0.7691 | 0.821 | 0.411809 |

Signif. codes: 0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 384.62 on 299 degrees of freedom

Residual deviance: 141.26 on 278 degrees of freedom

AIC: 185.26

Number of Fisher Scoring iterations: 16

# Appendix J

$> anova(GLM.4, test =' Chisq')$

Analysis of Deviance Table

Model: binomial, link: logit

Response: substanceuse

Terms added sequentially (first to last)

Table 5.10: Analysis of Deviance(Model 4)

| Variable | Df | Deviance | Resid. Df | Resid. Dev | $P(>\|Chi\|)$ |
|---|---|---|---|---|---|
| NULL | | | | 299 | 384.62 |
| distance | 8 | 113.542 | 291 | 271.08 | 2.2e-16 *** |
| education | 2 | 20.006 | 289 | 251.07 | 4.525e-05 *** |
| mstatus | 3 | 8.084 | 286 | 242.99 | 0.0443135 * |
| time | 4 | 21.594 | 282 | 221.40 | 0.0002414 *** |
| training | 4 | 80.134 | 278 | 141.26 | 2.2e-16 *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1



# Appendix K

## Research Questionnaire

KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY DEPARTMENT OF MATHEMATICS (I D L)

RESEARCH QUESTIONNAIRE

Dear Respondent,

This is a research on the extent of substance abuse among commercial vehicle drivers in Ghana. We will therefore like you to take a little time to answer these questions. We will like to assure you that the answers you give will be strictly confidential and will not be held against you.

Questionnaire number:

Date :

# Section A: General Information

Please, tick or write where appropriate:

1. Age : 21-30 [ ] 31-40 [ ] 41-50 [ ] 51-60 [ ] 61 + [ ]

2. Gender: male [ ] female [ ]

3. Marital status: Single[ ] Married[ ] Devoice[ ] cohabiting[ ]

4. Religion: Christianity[ ] Islam[ ] Traditional[ ] Other(s)[ ]

5. What is your level of education? Primary [ ] Secondary [ ] Tertiary [ ]

## Section B: Main Information



6. Which of the following cars do you drive? Trailer [ ] Coahes[ ] Mini Bus [ ] Dumper truck [ ] Taxi [ ]

7. How did you learn driving? Driving School [ ] Family and Friends[ ] Learning on job [ ] Self taught [ ] Other means [ ]

8. Distance covered in Kilometers 900+ [ ] 800 [ ] 700 [ ] 600 [ ] 500 [ ] 400 [ ] 300 [ ] 200 [ ] 100 [ ]

9. How many hours do you drive in a day? 6 hours [ ] 7 hours [ ] 8hours [ ] 9 hours [ ] 10 hours [ ]

10. Do you use or have ever used any of the following drugs before driving? YES [ ] NO [ ]

| Name of Drug | Common or Local Name(s) |
|---|---|
| Cannabis | Marijuana,Wee,Ganja |
| Opiates(Opium) | Codeine, Morphine, Pethidine |
| Volatile Inhalants | Spray, Glue, Gases |
| Tranquilizers(Sedatives) | Volume (5,10), Blue-Blue |
| Cocaine or Heroine | White powder, Brown sugar, Crack |
| Alcohol | Akpeteshi,Beer |
| Amphetamines(Stimulants) | Nescafe, Ataya |
| Cola Nuts | Goro, Bissi |
| Cigarette | King Size,555,Embassy |
| | |

11. List the types of substance that are often used by commercial drivers.

| Name of drug | Any local name(s) | How administered or taken |
|---|---|---|
| | | |
| | | |
| | | |
| | | |
| | | |
| | | |

12. Why do you think drivers use drugs? Social/peer pressure [ ] for fun [ ] Long journey [ ] Tiredness [ ] Other(s)

13. Why do some drivers use drugs before driving? State reason(s)?

14. What programs would you like to see in place to help prevent substance abuse among Commercial drivers?