Addis Ababa University

Addis Ababa Institute of Technology

School of Graduate Studies

Assessment and Modelling of Driver Behaviour in Dilemma Zone of Signalized Intersection

Thesis for the partial fulfilment of the Master of Science in Road and Transport Engineering

By: SOLOMON TSEGAYE MENGESTIE

June, 2022

Addis Ababa Ethiopia

ADDIS-ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF GRADUATE STUDIES

SCHOOL OF CIVIL AND ENVIROMENTAL ENGINEERING

ASSESSMENT AND MODELLING OF DRIVER BEHAVIOUR IN DILEMMA ZONE OF SIGNALIZED INTERSECTION

BY: SOLOMON TSEGAYE MENGESTIE

A THESIS SUBMITTED TO SCHOOL OF GRADUATE STUDIES OF

ADDIS ABABA UNIVERSITY

IN PARTIAL FULFILMENT OF THE RQUAIRMENT OF MASTER OF SCIENCE

IN

ROAD AND TRANSPORT ENGINEERING

CIVIL ENGINEERING DEPARTMENT

ADVISOR: DR. BIKILA TEKLU

ADDIS ABABA UNIVERSITY INSTITUTE OF TECHNOLOGY

SCHOOL OF GRADUATE STUDIES

SCHOOL OF CIVIL AND ENVIROMENTAL ENGINEERING

Thesis Approval Sheet

This is to certify that the thesis presented by **Solomon Tsegaye Mengestie** entitled ***"Assessment and Modelling of Driver Behaviour in Dilemma Zone of Signalized Intersection"*** is submitted in partial fulfilment of the Degree of Master of Science in Civil and Environmental Engineering (Road and Transport Engineering) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

APPROVED BY BOARD OF EXAMINERS:-

Dr. Bikila Teklu		14/06/22
Advisor	Signature	Date
Dr. Getu Segni		15/06/2022
Internal Examiner	Signature	Date
Mr. Mesay Shemsu		14/06/2022
External Examiner	Signature	Date
Dr. Mebruk Mohammed	Mebruk Mohammed (Dr.-Ing.) Dean ... & Environmental Engineering	
Chairman (Department of Graduate Committee)	Signature	Date

Acknowledgment

Firstly, I would like to thank my God who allowed me to live healthily and succeeded this study. Next, I would like to express my sincere gratitude and deepest thank to Dr. Bikila Teklu for his valuable support, constant advice and considerable helps to the end of this thesis during this difficult season since COVID 19 pandemic. I would like to extend my deepest thank to my co-advisor Yohannes Legesse for his encouragement and valuable advices during this thesis. I also would like to express my appreciation to the staff of the AAiT School of Civil and Environmental Engineering for their polite response to what I want and ask.

Finally, I wish to acknowledge the financial support of the Ethiopian Roads Administration (ERA).

Abstract

Driving behaviour at signalized intersections is the main contributing factor to the operational and safety level of road users. Improper decision of drivers when signal changes from green to yellow might lead to right angle collision or rear end collision. This is mostly due to a driver becomes indecisive whether to pass or stop at the intersection on the yellow onset, which is called dilemma zone. The main motive of the study is to investigate the factors that influence the driver behaviour in dilemma zone at signalized intersection. The output of this study is used for transport planner, geometric designer and traffic management agency for evaluation of existing urban intersections and identifying factors which are used for decreasing accidents occurred at the intersection.

For this research matter, the data was collected at four signalized approaches by collecting field data using video capturing technique in order to investigate the driver behaviour. Frame by frame manual extraction by using VLC media player resulted in a total of 397 driver responses at the yellow onset. After manual extraction binary logistic regression model is developed by using SPSS 22.0 in order to represent the observed behaviour. The factors which are found to be important in drivers stop/go decisions are distance from stop line, vehicle's approach speed and vehicle type. From 397 driver responses 41 of them which are 10.33% of driver responses at the yellow onset were red light runners.

In order to assess the driver's behaviour when they see yellow traffic lights, driver attitudinal survey was conducted. Based on the collected questionnaire data, 32.4% have been involved in an accident at an intersection and 27.3% end up red light runners by sometimes try to catch the yellow light. In addition based on the questionnaire data, factor analysis, was conducted. Factor analysis was done to form few factors from 14 original conditions that affect the decision to cross or stop when the drivers see yellow light based on correlation between each reason. Based on the result of analysis, 14 original conditions was grouped in to five few factors which are understandable and easy for interpretation. These are Emotion and understanding of the driver, Roadway and variable control condition, Comfort to drive, Presence of vehicle and police and Past experience of driver which were contributed to explained 59.56 % of variance.

Keywords: - Driver behaviour, Dilemma zone, Red light runners, Yellow signal, Stop/Go decisions

Table of Contents

List of Figures

List of Tables

Chapter One: Introduction

Research in the area of road safety has been developed as traffic flow and vehicle numbers have increased. This increase has been accompanied by a gradual increase in the accident frequencies that result in serious injuries and fatalities. Road traffic accidents reflect global health and safety issues. In addition to the suffering and psychological harm experienced by people injured and families of loved ones, traffic accidents cause an economic problem in most countries.

The yellow indication is used to alert drivers that the signal is preparing to change to a red indication. At the onset of yellow, drivers must make a decision to either continue through the intersection or to stop prior to entering the intersection. This decision has serious safety consequences as an abrupt stop may cause a rear-end accident while proceeding through the intersection may lead to a right-angle collision. At high speed intersections, defined as intersections where the approach speeds exceed 60 km/hr., this problem is of great concern.

Safety at signalized intersections depends on a number of factors among which are the layout of the site, the traffic volumes at the approaches, the phasing and the time settings of the traffic signal and of course the human behaviour of both drivers and pedestrians. Among them human behaviour is one of the most important factor which leads to accidents.

With this in mind, it is worth investigating in depth signal compliance and car-following behaviour microscopically for the case of vehicles approaching traffic signals. Studying these concepts may lead to an understanding of drivers’ responses to signal changes. This could change the possibility of accident occurrence particularly at signalised junctions (such as rear end collisions and red light running phenomena).

As the signal changes from green to yellow, vehicles travelling at high speeds to clear the intersection are often caught in a zone called a dilemma zone in which they have to decide, whether to cross or stop at the intersection. There are two types of dilemma zones which are known in many studies, type I and type II dilemma zone as shown in the figure below. An area where a driver can neither pass safely through the intersection nor comfortably stop prior to the stop line, when they see a yellow signal is termed as type I dilemma zone. And Type II dilemma zone is an area where the driver is indecisive to stop or cross at the onset of yellow signal. However, the first type of dilemma zone can be eliminated by providing sufficient yellow duration, but the indecisive zone persists as it is associated with the driver's decision making behaviour.

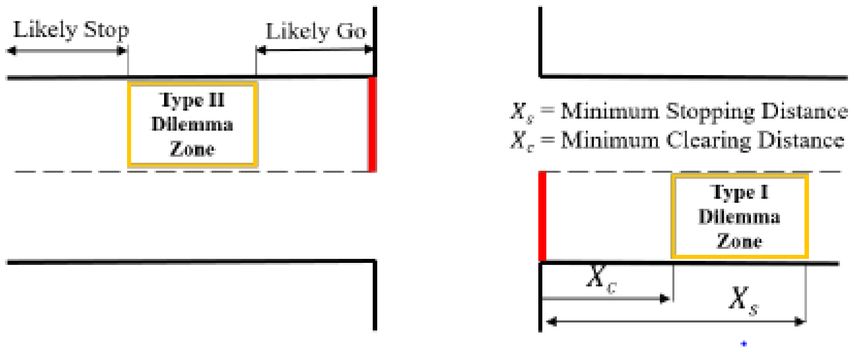


Figure 1: Type I and Type II Dilemma Zones

A dilemma zone occurs for the situation in which Xs > Xc and the areas overlap as illustrated in Figure 1.1. Several strategies have been developed to alleviate the dilemma zone problem although the more complex methods involve large area detection and will be perused here. Vehicles traveling faster than the average speed will enter the intersection sooner than required and pose no problem. Vehicle traveling slower than the average speed will experience the yellow signal before they reach the stop line, however, it is quite likely that they will have reached the end of the dilemma zone (distance Xc) and will be able to safely accelerate into the intersection.

Many researchers are trying to contribute in evaluating contributing factors to dilemma zone, introducing traffic signal algorithm to mitigate the issues related to dilemma zone, and modelling driver's behaviour in dilemma zone. However, more research needs to be done. Approaching speed and distance to intersection at the time of yellow indication are the most influential factors to dilemma zone.

Understanding this dilemma driver behaviour has a significant effect on reducing the dilemma zone and maximizing safety at signalized intersections. This study focuses in identifying the factors influencing the dilemma zone driving behaviour, such as effect of vehicle and distance from the intersection at the onset of yellow. The questionnaire will be analysed using SPSS 22.0 software.

1.1 Statement of the Problem

At signalized intersections with high approach speeds drivers are more likely to face a dilemma zone at the onset of the yellow light, where a decision to stop may result in a rear-end collision while continuing through the intersection may produce a right-angle accident

Studying drivers' behaviour at urban intersections with direct observations provides quite useful information and subsequent knowledge that can lead to proper measure taking. From all possible factors which are contributing to the traffic signal related crashes, one of the major causes is complexity of driver's decision-making process at the intersection dilemma zone (Gates and Noyce, 2010).

The identification of stop-go decision zones and the modelling of such a dynamic decision making process have important implications, such as the proper design of signal change and clearance intervals, the improvement of stop-go decision models embedded in the microscopic traffic simulation software and the development of effective dilemma protection strategies.

Therefore, this research will try to assess the factors influencing the dilemma zone driving behaviour, such as effect of vehicle speed, vehicle type and distance from the intersection at the onset of yellow.

1.2 Hypothesis and Research Question

1.2.1 Hypothesis

By assessing factors influencing the dilemma zone driving behavior, we can arrive at the model which can enable us to determine the drivers' behavior during yellow time.

The research hypotheses aimed at addressing this principal theory encompass driver behavior when they see the yellow indication at signalized intersections which have higher speeds in order to clearly see the driver's dilemma behavior, the impact of vehicle type on dilemma zone protection, and driver understanding of yellow traffic light indications. The specific research hypotheses have been developed. The next sections provide additional information on the development of the proposed research hypotheses.

- The Type II dilemma zone boundaries can be identified from the driver behavior at the time of stop/go action when the driver is exposed to the yellow traffic light indication, vehicle speed, vehicle type and position at high-speed signalized.

In this case, the main concern is related to the drivers' decision to proceed through the intersection or to stop the vehicle before crossing the stop line. This behavior is highly related to the speed and position of the each vehicle. The most basic contribution to this hypothesis will be the development of an improved which will be updated database of observed driver behavior when they face the yellow traffic light while approaching the yellow traffic light.

The main theory of the proposed research will be examined by evaluating the identified research hypotheses associated with driver understanding and behavior upon exposure to the yellow traffic light. It is likely that additional research questions may be developed through the search of completing the existing hypotheses which discussed above.

1.2.2 Research Question

The present study's main research question is there for;

- ✓ How drivers behave at the yellow time of signalized intersection?
- ✓ Is the drivers' chose to stop or proceed when they face a yellow signal?
- ✓ What are the factors influencing the dilemma zone driver behavior and how these factors affect the driver's behavior at the dilemma zone?

1.3 Objective of the Thesis

1.3.1 General Objective

The general objective of the study is to assess and develop comprehensive knowledge of the driver behavior in the dilemma zone of signalized intersections.

1.3.2 Specific Objective

The specific objectives of the study include the following:

- ✓ To describe the driving behavior at dilemma zone of signalized intersection;
- ✓ To assess the effects of vehicle type, speed of the vehicle and distance from the intersection on the drivers decision to stop safely or to proceed through the intersection before the end of the yellow interval and develop a model which represents the drivers behaviour at dilemma zone of signalized;
- ✓ To identify and assess the possible condition that affects the driver's decision making when they see yellow traffic light.

1.4 Scope of the Study

The study will be subjected to four signalized intersections. Those of which has relatively higher posted speed limit in the city of Addis Ababa.

During the study only one approach will be used for the study. The target movement will only be for through movement.

1.5 Significance of the Study

Since the introduction of signalisation to the intersections it increases the safety and reduced the number of collisions at signalised intersections by 15%-30%, it seems less likely to be effective in reducing other types of accidents such as rear shunts (Kennedy and Sexton, 2009). Drivers have to make STOP/GO decisions after the onset of amber. Based on their speeds and positions from the stop line, some drivers hesitate when deciding whether to proceed through the junction or start decelerating for the red phase. This phenomenon has been recognised as the influence of the dilemma zone which can be defined as a critical area on the carriageway where drivers can neither clear the junction nor stop safely before the stop line (Gazis et al., 1960). It may cause red light violations and possibly severe accidents at the intersection area if drivers decide to cross, or start tailgating with other vehicles when stopping or decelerating suddenly during the amber interval.

This study is an attempt to investigate the complex behaviour governing such traffic situations at signalised junctions. It may be of interest to traffic, economic, health, social and safety agencies and may improve knowledge of the risk factors associated with road traffic accidents which may help in identifying appropriate solutions to reduce conflicts on the approach towards traffic light junctions.

1.6 Organization of the Thesis

This thesis is organized in to five chapters. In the first chapter introduction, significance of the study and objective to be achieved are discussed. In chapter two, a review of literature appropriate to this thesis is stated. In chapter three methodologies used for this thesis, data collection and analysis techniques were discussed. In chapter four results from the data's from questionnaire and video recording will be analysed and discussed. Finally, in chapter five conclusion, recommendation and future works were presented.

Chapter Two: Review of Literature

An intersection is where two or more roads converge, diverge, meet or cross, within which are included the carriageway and roadside design features which facilitate orderly traffic movement in that area. However, they are critical element of a road section in which they have a high risk of accident occurrence without taking into consideration the provision of traffic light signals and road traffic regulations or priority rules.

A primary goal of intersection design is to limit or reduce the severity of potential road user conflicts, minimizing impedances, eliminating the need for lane changes and merge manoeuvres, and minimizing the required distance to traverse an intersection all help improve the operational efficiency of an intersection. To achieve optimal safety and operational levels at an intersection the needs of all possible road users must be considered in the designing of intersection.

2.1 The problem with traffic light signals

Intersections are the most researched places to study and identify the risky factors affecting traffic movement. This is because of the interaction between different road users, particularly near or at the centre of an intersection, which may pose hazards to all road users and reduce the safety level. Kennedy and Sexton (2009) revealed that 19% of all accidents in London occurred at signalised intersections.

A traffic light signal is designed to minimise the delays and to control interaction between road users in the intersection area. Despite the implementation of traffic signals to improve traffic efficiency and safety; particularly at junctions by separating conflicting traffic movements in time and space, junctions with traffic signal lights continue to be one of the main accident points (Hanna, et. al., 1976; Hakkert and Mahalel, 1978; Short, et. al., 1982; Retting, et. al., 1995). Red light running crashes are the most frequent type of accident (Retting, et. al., 1995); which occurs when drivers cross the stop line after the red light has appeared (Baguley, 1988). Among these accidents, right angle collisions have received considerable attention because of the severity and casualties involved (Mahalel and Prashker, 1987; Datta, et. al., 2000). On average, 10 casualties per day had been reported as the consequence of red light violations in the U.K. in 2010 (Dft, 2010). This figure has increased by 3.4% since 2009 (Dft, 2009). Red light violation had also been reported to have killed 676 people and injured an estimated 113000 people in the U.S. in 2009 (IIFHS, 2011).

Deceleration characteristics of drivers, at the onset of a yellow- indication transition on high-speed approaches to a signalized intersection, affect appropriate yellow-phase timing because the length of the yellow indication should be sufficient for drivers to either stop safely or to proceed through the intersection before the end of the yellow interval. Driver deceleration rates play a critical role in most traffic simulation software and vehicle fuel consumption and emission models. Also intersection and deceleration lane design are governed by vehicle rates of acceleration and deceleration.

There are researches which suggest that red running is affected by the duration of the change interval (Zador, et. al., 1984; Retting and Greene, 1997; Datta, et. al., 2000; Bonneson and Zimmerman, 2004), driver's behaviour (Baguley, 1988; Chang, et. al., 1984; Chang, et. al., 1985; Retting, et. al., 1995; Retting, et. al., 1999) and junction factors (Mohamedshah, et. al., 2000). The interactions of these causes and factors were also used to describe intentional (Baguley, 1988; Retting, et. al., 1998) and unintentional red light running (Retting and Williams, 1996; Bonneson, et. al., 2002; Bonneson and Zimmerman, 2004). Intentional red running is associated with aggressive driving behaviour (Olson and Rothery, 1961; Williams, 1977; Van der Horst and Wilmink, 1986; Retting, et. al., 1999) and the latter is associated with driver's decision in a problem zone which has been defined in literature as the 'dilemma zone' (Gazis, et. al, 1960; Zegeer and Deen, 1978; Sheffi and Mahmassani, 1981).

In 2004 Bonneson and Zimmerman conducted a field study at multiple high speed signalized intersections to investigate the relationship between yellow signal timing and red light running. The authors concluded that increasing the standard yellow time by 1.0s led to a 50 percent reduction in red light running. The authors recommended that total yellow times not exceed 5.5 seconds even after the increase. The authors noted that drivers may recognize and adapt to the increased yellow times and conducted an analysis of this behaviour. This analysis found that drivers did adapt to the extended yellow times, however the adaptation did not counter the benefits gained by increasing the yellow times.

Finally, it can be concluded that rear-end collisions and signal violations traffic conflicts remain critical issues not only due to vehicles' defects and faulty traffic signals but also because of human behaviour.

2.2 Driver Behaviour at the Onset of Yellow

2.2.1 Dilemma Zone

According to the Traffic Signal Timing Manual (2008), the intent of the yellow light change is to provide a safe transition to the red light from the green light. When a yellow indication is triggered, the driver decides whether to stop safely or to proceed through the intersection before the end of the yellow interval. Incorrect driver decisions may result in either a rear-end collision, if the driver fails to come to a safe stop, or a straight crossing-path crash, if the driver does not have enough time to safely cross the intersection before the conflicting flow is released.

These decision process creates a fuzzy meaning to the drivers that they will find themselves in what is called the dilemma zone. Gazis et al. (1960) first introduced the concept of dilemma zone by analytical consideration and real-life observation when they examined the problem of the yellow light in traffic flow. According to Gazis et al., the dilemma zone is defined as *“a situation in which a driver may neither be able to stop safely after the onset of yellow indication nor be able to clear an intersection before the end of the yellow duration”.* Accordingly, the yellow interval dilemma on signalized intersection is considered as an example of the incompatibility of legislative procedures and physically attainable human behaviour.

Two types of dilemma zone have been studied by researchers considering vehicle types and driver decision (Hurwitz, Wang et al. 2012, Elmitiny, Yan et al. 2010, Papaioannou 2007, Hurwitz 2009, Koonce, Rodegerdts et al. 2008 Hurwitz, Knodler et al. 2011,). From the two types of dilemma zones, Type I, dilemma zone is where the driver can neither clear the intersection safely before the red light is on nor stop without slamming on the brakes. In Type II dilemma zone, which is known as option zone, is where the driver is able to pass through successfully based on drivers own decision. These two types of dilemma zone are illustrated in Figure below. Type I dilemma zone is eliminated by setting an appropriate yellow time when the designer design for the traffic light timing. In fact, the real challenge is in dealing with type II dilemma zone which in this case related to driver behaviour.

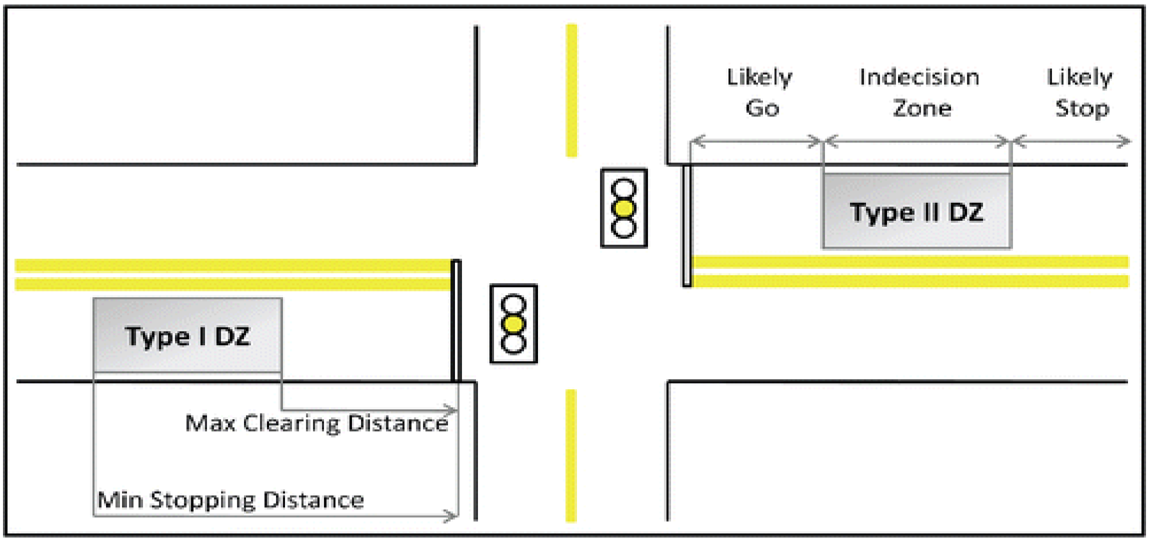


Figure 2: Type I and II Dilemma Zones

Hurwitz et al. (2011a) used field observations of over 1000 vehicles to perform a comparison of the two most common Type-II dilemma zone definitions. The authors found that there was a statistically significant difference between the classification of vehicles as either downstream, within, or upstream of the dilemma zone when using the two definitions. Specifically, it was found that the decision to stop definition classified far more vehicles as 'within' the dilemma zone than the TTSL definition, which classified many more vehicles as 'downstream' of the dilemma zone. This work illustrates the potential for a new model to more accurately and consistently identify the dilemma zone for each individual approaching vehicle.

Various factors which are the reasons for dilemma zone, driver behaviour, and decision making process at the onset of yellow traffic light have been the focus of numerous research in the literature (Amer, Rakha et al. 2012, Wortman and Matthias 1983, Konecni, Ebbeson et al. 1976, Papaioannou 2007). These factors include driver's decision making qualities, intersection characteristics and condition, signal control settings, subject vehicle characteristics, and traffic flow characteristics.

Drivers play a major role in safety issues related to dilemma zone since driver error is considered as the main factor in occurrence of vehicle crashes (Wierwille, Hanowski et al. 2002). Because of the uncertain decision in the dilemma zone, red light running violation is also a major effect due to the dilemma zone. Using a video-based system, Elmitiny et al. (2010) associated drivers' stop or go decision and red light running violation with the vehicle's yellow onset distance, operating speed, and position in the traffic flow. The study suggests that lowering the drivers' approaching speed to the intersection may reduce the possibility of red light running violations. However, Elmitiny et al. found that the following vehicles are more likely to make go decisions and run the red light than the leading vehicles. This means that rear-end accidents are more probable and is actually similar to what other research papers have observed. It can be seen that many researches agreed that the dilemma zone is the primary cause to the danger of signalized intersection, which leads to other researchers to propose yellow light settings that can eliminate the conflict from the dilemma zone.

In order to eliminate the dilemma zone at the onset of yellow light and to reduce incidents such as the rear-end crashes and red light violations, Zimmerman et al. (2004) suggested that the number of vehicles in the dilemma zone indicates the frequency that drivers make an uncertain decision of whether to go or to stop at the end of a green traffic light, which partly causes the many crashes at intersections. They believed that the number of vehicles in the dilemma zone could be used as a potential intersection safety measure and reducing it can reduce the safety risks that occur at a signalized intersection. Bonneson et al. (2004) studied the before-and-after effect of increasing the yellow light interval and they actually found that even if the drivers adapted to the change, there is still a benefit of reducing the safety risks. In support to this, Liu et al. (1996) actually re-examined the dilemma zone using the methodology given by Gazis et al. in 1960 and suggested a possible solution to eliminate it. By knowing the speed distribution function of the approaching vehicles, it is possible to compute the required yellow timing for them to clear the intersection. As observed from this thesis, knowing the initial speed and the acceleration of the vehicles can also be used to compute the yellow timing. By changing the yellow light duration, it can allow for all the approaching vehicles to clear the intersection.

However, some studies have opposing view toward the extension of the yellow light and believe that changing the yellow light timing alone will not be satisfactory. Liu, Chang, Tao, Hicks, and Tabacek suggested in a 2007 study that it is necessary to have a vehicle detection module and a signal control module in order to minimize the safety issues caused by the different dilemma zones from various intersections. Their proposed modules will acquire the vehicle's speed and position information to analyse whether the vehicle is within the dilemma zone. Then, the signal control module will react accordingly, such as to extend the red clearance time, for the safety of the vehicles. Zimmerman et al. (2012) conducted a more detailed study on a vehicle-specific detection, control, and warning system a few years later. The system reduces the number of vehicles trapped in the dilemma zone by controlling the signal phases and warning the drivers ahead of them that they should probably stop. However, while all of these modern technologies proposed to increase the safety at a signalized intersection are explored, their practical usage in the real-time traffic network is still under study due to the complexities of the dilemma zone.

Amber aspect (which is often of a 3 seconds duration) is provided in order to help drivers clear the intersection before the conflicting traffic stream starts its movement. Many studies have focused on a critical area called the 'Dilemma Zone' upstream from the intersection approach during the amber period. A driver approaching the dilemma zone has to make a decision either to stop or proceed through an intersection area before the onset of red. His/her decision is made based on several factors including distance from the stop line, travelling speed, driver reaction time and intersection geometry. According to Kennedy and Sexton (2009), a driver's incorrect decision at the dilemma zone is a more risky behaviour because he/she might decelerate suddenly resulting in a rear-end collision with the close following vehicle or proceed through the red and cause a collision with the conflicting vehicle at the centre of the intersection.

The frequency of stopping and crossing vehicles and their violations of traffic lights has been the most common measure to indicate the safety level they face with the problem zone and the option zone. Driver's decision in response to the amber light has been studied using different methods: analytical model, statistical model, experimental method, simple comparison tests and before-and-after comparison tests are some research methods used in practice. Given the non-identical samples, research -methods, study sites and traffic conditions, the significant effect of each contributory factor to driver's decision may differ. Some factors were also found to overlap between different studies.

Gates et al. (2006) performed field observations on over 1000 vehicle that were either the first-to-stop or last-to-go at the termination of priority for that approach. In addition to making detailed measurements of brake-response time and deceleration rates, the authors evaluated the effects of several variables on the decision to stop/go, including: approach speed, headway, tailway, action of vehicles in adjacent lanes, distance to the stop line, vehicle type, presence of opposing road users, presence of opposing left-turn vehicles, flow rate, and cycle length. The authors report that the factor with the most influence on driver decision making was the estimated TTSL, with the following conditions associated with a higher probability of stopping: shorter yellow interval, longer cycle lengths, vehicle type, presence of opposing roadway users, and absence of vehicles in adjacent through lanes (Gates et al., 2006).

The most common measure of driver's performance is captured at their position on the road relative to the junction and other road users on transition of green to red signal (Gazis, et. al., 1960; Zegeer and Deen, 1978; Van der Horst and Wilmink, 1986; Prashker and Mahalel, 1989; Maxwell and Wood, 2006; Elmitiny, et. al., 2010). Previous studies have shown that driver's possibility to cross a junction without violating any traffic rules is dependent on their distance from the stop line and their travelling speed (Gazis, et. al., 1960; May, 1968; Van der Horst, 1988; Elmitiny, et. al., 2010); and their decision is an interaction between observation and adjusting their position on the road (Van der Horst and Wilmink, 1986; Koh and Wong, 2007). The magnitude of driver's decision problem requires better understanding of the following vehicle specific factors either individually or as a whole.

2.3 Review of drivers' psychology and modelling research

As the human behaviour is such a significant feature in the majority of safety problems, it is necessary to present the history of traffic psychology studies and factors influencing the drivers' behaviour as well as modelling methods.

Some studies have focused more on human factors and drivers psychology in the decision making process. Generally speaking, decisions are grouped in to three types, namely: certain decisions, risky decisions and uncertain decisions. Decisions of drivers in a dilemma zone fall into the risky decision group, in which the occurrences of diverse future conditions can be suggested by probability. Wu et al. divided the decision making process of drivers at intersections into six processes, including observing problems, ensuring decision objectives, analysing prepared plans and possible results, choosing a plan, implementing the plan, and giving feedback.

One important psychological issue related to red light running and the dilemma zone is aggressive driving. Aggressive driving has been proven to correlate with age and gender. Older drivers and men from the society group are more likely to drive aggressively (Shinar and et. al).

In the earlier years of motorisation in the 20th century, more focus was considered to the drivers and the traffic law enforcement. However, earlier research focused on accidents circumstances and basic analysis of accident statistics (OECD, 1997). After the end of World War II in 1945, a lot of attention was paid to psychology research particularly where it related to road safety, because of the high trend of road accidents and the increasing number of casualties. After that, a considerable interest was given to describe the drivers' perceptive behaviour by many researchers because some drivers have difficulties in coping with the road environment.

In the 1970's and 1980's, drivers' research were becoming more established. Two groups of researchers were recognised at these periods: the first was psychologists groups, mainly coming from Europe, focused on human psychology that drivers are able to behave according to the traffic situation and hence they try to face the level of risk. The second was road safety researchers, many of them from the US, concerned with a certain group of drivers that could be mainly responsible to an expected number of accidents. Their perspectives shifted towards development of vehicles' industry and mechanical development (Hakkert and Gitelman, 2014).

Since the 1990's, several studies were also dealing with traffic psychology, however they focused on the experience of drivers and their ability to resume control in different driving conditions.

Therefore, the decision made by a driver at signal-controlled junctions belongs to the risky decisions because he/she is unable to predict the traffic circumstances at the intersection, for instance the movement of the following and preceding vehicles particularly after the traffic light signal showing an amber indication. Drivers have a tendency to pass through the junction without stopping. However, incorrect decisions before assessing the pros and cons of crossing during the 3 seconds amber may increase the risks of accidents like rear-end collisions or right angle accidents with vehicles moving in the conflict flow (Wu et al., 2009).

According to Garber and Hoel (2009), the driver perception-reaction process to a stimulus can be summarised as follows: perception, identification, handling and reaction. At traffic light junctions, the driver perception happens when observing the amber indication. Following that, the driver will understand or identify the meaning of amber aspect which is '*Continue to cross only if unable to stop safely*'. Then, the handling process starts when a driver analyses the surrounding circumstances including junction layout and movement of other road users and decides what plan to take in response to the amber before executing it. For example, if a driver plans to cross the stop line, he/she has three choices or plans: either accelerating, maintaining speed with the preceding and following vehicles or decelerating. Based on which plan decided, the comparison of both merits and demerits of each plan can identify the implementation process to achieve the objectives. Finally, the driver will execute the plan decided in the handling stage (Wu et al., 2009).

2.3.1 Factors affecting drivers' behaviour

Since drivers are the fundamental component affecting the road network systems, studies have shown that behavioural change of drivers has important impacts. Based on real accident statistics, Wetteland and Lundebye (1997) conducted a comparison study between the UK and US accidents to identify the most significant contributory factors. They found that human errors were a major factor in 73% of crashes in the UK. This percent was 6% higher than that of the US. Factors that influence drivers' behaviour can be categorised as in the following subsections.

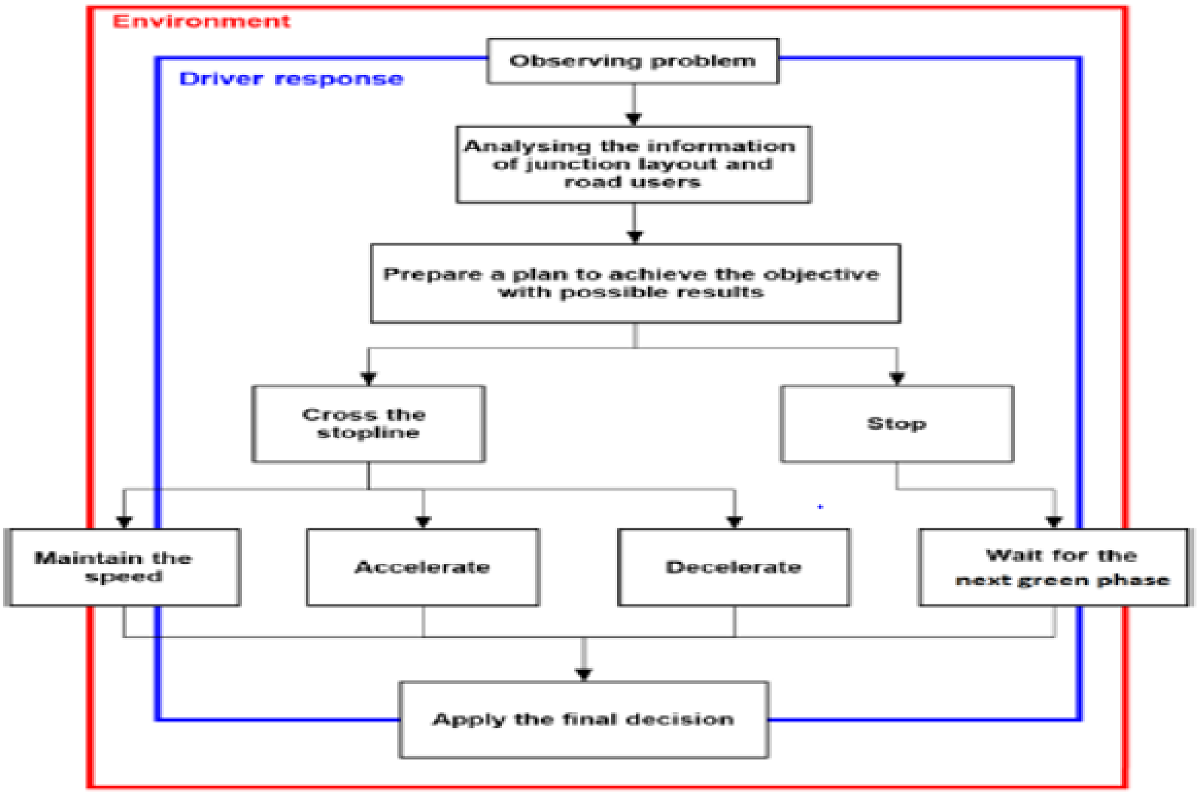


Figure 3: Strategy of driver's decision making at a traffic signal-controlled junction (adapted from Wu et at. (2009)).

2.3.1.1 Human factors

According to the National Cooperative Highway Research Program (2003), aggressive drivers are more likely to accelerate near signalised junctions. The majority of accidents were caused by aggressive driving. Aggressive behaviour can be summarised as: following too close to others, braking instantly, overtaking other vehicles or lanes, preventing passage of other vehicles and violating speed limit or changing speed too suddenly for the conditions. In addition, traffic signal violation indicates the noncompliance behaviour of drivers to the traffic signal leading to an increase in the risk of accidents.

Perception-reaction time is another significant factor affecting driver behaviour near signalised intersections. According to Gazis et al. (1960), it is a major factor that affects the Dilemma Zone boundaries and it can be defined as the time travelled after the amber onset but before the driver applies the brakes. Different factors can influence driver Perception-reaction time such as vehicle type, travelling speed, driver gender and age. Finally, a high travelling speed was found to result in lower values of Perception-reaction time (Gates et al., 2007, Rakha et al., 2008). This is reasonable since the mean value of Perception-reaction time might be influenced by the vehicle platooning situations (i.e. the position of vehicle in the queue: leader, follower or drive alone) under different traffic flow conditions. More specifically, the leader's Perception-reaction time was found to be shorter than other situations (Gates et al., 2007, Rakha et al., 2008).

Investigating the psychology of driver behaviour may lead to identifying possible factors associating with speeding. Wang et al. (2009) insisted that there is a positive relationship between the risk of accidents and driving with a speed more than the allowable speed limit in England.

El-Shawarby et al. (2007) concluded that age and gender are important factors affecting driver's decision in the dilemma zone. Their investigation included the impact of distance to the stop line at the onset of amber on driving behaviour. They found that male drivers are more likely to run through the amber than females. Also, elderly people over the age of 65 are more careful to stop compared with other age groups because of driver-learning and experience (Retting and Williams, 1996). It was found that the performance and experience of novice young drivers have been improved in lane keeping, but difficulties have been noticed in tailgating with other vehicles (Summala et al., 1998).

Finally, a view was revealed by Kimber (2005) who suggested to use the term ‘driver’ instead of ‘road system’ for most of the theories in the area of road safety and accident studies. In other words, the interactions between the following and preceding vehicles (the striking and struck vehicles) should be investigated more to find out the probability of road accidents and thereby to identify the level of safety on the road. Therefore, special knowledge is required and more investigations regarding driver behaviour and his/her decisions, particularly after the onset of amber.

2.3.1.2 Other contributory factors

A driver’s decision and response cannot only be influenced by the driver him/herself but also there are other influential factors including vehicle characteristics and junction layout. The effect of vehicle characteristics (such as size and type) on driver’s decision in the DZ was investigated by Sayer et al. (2003), Papaioannou (2007) and Gates and Noyce (2010). They realized that a driver tries to keep a greater following distance with the heavy good vehicles in order to avoid possible collision. This is because they seem to be as obstacle objects that reduce the forward views particularly at sudden changes in speed.

Junction layout such as junction width, number of lanes, lane position and grade are recognized as factors associated with making a decision. Papaioannou (2007) and Yan et al. (2007) stated that an increase in the number of lanes leads to an increase in the probability of signal violations. Finally, the existence of red camera enforcement, pavement marking, location of road signs and signals can improve the safety performance and driver visibility as well as avoiding possible conflicts.

Additionally, driver behaviour can be also influenced by weather and climatic conditions. The results of a questionnaire survey carried out by Kilpelainen and Summala (2007) showed that drivers are likely to be more careful and show lower driving performance during the winter than other seasons particularly in rural areas. Also, the findings indicated that driver behaviour is mostly affected by the prevailing weather conditions instead of traffic-weather forecasts.

2.3.2 Modelling driver’s decision when approaching a signalised junction

Driver behaviour modelling in dilemma zone has mostly focused on the statistical methods. The modelling approach that are taken in the previous research by researchers is to collect data and model some of the driver’s behaviour parameters in dilemma zone such as probability of drivers' stop/go decision based upon the influential factors existing in the collected data set by researchers (Gates, Noyce et al. 2007, Sharma, Bullock et al. 2011, Wu, Juan et al. 2009, Elmitiny, Yan et al. 2010).

Various modelling techniques were used to explain the driver dilemma behaviour which is observed at the signalized intersections. The most commonly used model type was logistic regression model which tries to explain the behaviour (Gates & Noyce, 2010, Pathivada & Perumal, 2018Köll et al., 2004, Papaioannou, 2007). Researchers used fuzzy logic model in order to explain the proportions of variable answers; since, classical logic only carryout yes or no conclusion. (Moore & Hurwitz, 2013; Yang et al., 2014). Decision trees were also used to clearly classify the stop/go driver decision behaviour (Elmitiny et. al, 2010). Agent based models were also found in literature explaining driver decision behaviour (Abbas et al., 2014; Amer et al., 2011).

One of the earlier studies was conducted by Olson and Rothery (1961). They attempted to model the probability of drivers to stop as a function of distance to the stop line. Chang et al. (1985) examined the distance and time to the stop line as well as speed, as factors affecting the percentage of stops and passing vehicles. A modelling method, using data collected from a driving simulator was carried out by Caird et al. (2007) to investigate driver behaviour, including the influence of the amber period and the driver age. Their conclusion was that the driver's STOP/GO decision depends on the time to the stop line, taking into consideration his/her response time. However, the age classification showed no significant differences with respect to response times.

In addition, Gates et al. (2007) used logistic regression analysis to explore the effect of approaching speeds and applied decelerations on the probability of stopping. As a result, it was found that drivers have a tendency to cross with a short time to the stop line and with a longer amber period; other factors were noted, such as whether the vehicle was a bus or heavy truck, the absence of a bus or cycle lane and turning movement lane. Elmitiny et al. (2010) applied classification tree models to predict driver's STOP/GO decision under the following situations: distance to the stop line, vehicle's speed and position in the flow (leading or following). They predicted a RLR model which is strongly dependent on the distance to the stop line (by 99%), position in the platoon (by 25%), speed (by 20%), vehicle type (by 10%), and finally lane position (by 1%) according to the parameter importance.

Wu et al. (2013) developed a driver's decision model by using a binary logistical regression method. For the purpose of their study, loop detectors were located at the stop line and several hundred feet upstream to collect high resolution and signal event data. They attempted to predict driver's STOP/GO decision and RLR events including the effect of the amber period and vehicles' details (e.g. speed, number of amber running and number of red running). The accuracy of the predicted model was 87%. Elhenawy et al. (2015) proposed a measure of the driver aggressiveness (varies from 0= not aggressive to 1= very aggressive) to be included in the model of driver STOP/GO behaviour. Generalized linear models were applied to model the driver response by using historical observations of drivers who decide to proceed when the time to the stop line is greater than the amber interval or travelling at speeds that exceed the speed limit. The authors demonstrated that the accuracy of the model increased significantly after adding the developed driver aggressiveness predictor.

On the other hand, fuzzy inference rules were developed by Kikuchi et al. (1993) for modelling driver's STOP/GO decision based on empirical data. They estimated the degree of anxiety for conservative and aggressive drivers. Another research related to the dilemma zone was carried out by Lin and Kuo (2001). They focused on developing a procedure to estimate the change of a traffic signal and clearance periods using a rule-based fuzzy logic system. Moreover, Tanga et al. (2016) applied a fuzzy approach and binary logic model to investigate the effect of a 3 seconds flashing green (before the 3 seconds amber) on the driver decision-making process, at high speed intersections (in this case the speed limit was 80 kph). They concluded that the results obtained from the fuzzy model were better and more consistent than those produced from the binary logic model. The researchers revealed that the findings can be used to improve the driver STOP/GO decision model in the microscopic simulation software, signal design and dilemma zone protection strategy.

Finally, the dilemma zone still remains a big challenge to all road safety researchers. Despite the fact that many studies have been carried out to find the best prediction model of driver response to the signal change. In addition, the statistical models cannot reflect the situation of interaction between successive vehicles and cannot indicate the effect of changes in the transport system after installing new technologies since this is very complex. More specifically, these models cannot include different drivers' and vehicles' characteristics as in the real world. Therefore, more investigation and micro-simulation research are needed particularly that define the factors affecting drivers' decisions in the dilemma zone. Then, a new microscopic model can be introduced that is more realistic and shows more logic and is capable of representing dynamics of driver behaviour.

Finally, the dilemma zone still remains a big challenge to all road safety researchers. Despite the fact that many studies have been carried out to find the best prediction model of driver response to the signal change. The identification of stop-go decision zones and the modelling of such a dynamic decision making process is not properly defined the situation of interaction between successive vehicles. Therefore, those identifications have important implications, such as the proper design of signal change and clearance intervals, the improvement of stop-go decision models embedded in the microscopic traffic simulation software and the development of effective dilemma protection strategies.

2.4 Summary of literature review

Generally, intersections are the most researched places to study and identify the risky factors affecting traffic movement. Different researchers and transport agencies studied the driver's behaviours in dilemma zone of signalized intersection in different urban and sub-urban area. Based on the result of literature review, the dilemma zone still remains a big challenge to all road safety researchers. Despite the fact that many studies have been carried out to find the best prediction model of driver response to the signal change. The identification of stop-go decision zones and the modelling of such a dynamic decision making process is not properly defined the situation of interaction between successive vehicles. Therefore, those identifications have important implications, such as the proper design of signal change and clearance intervals, the improvement of stop-go decision models embedded in the microscopic traffic simulation software and the development of effective dilemma protection strategies

Chapter Three: Methodology and Data Collection

3.1 Introduction

This chapter presents the methodology that was used to collect field data in order to gain a better understanding of driver behaviour under the effect of dilemma zone (i.e. following the onset of amber) at signalised junctions. The collected data included information about traffic flow, distance from junction and traffic light settings that are needed for providing necessary input parameters in the model development, calibration and validation processes.

3.2. Details of Selected Study Area

Four signalized intersection approaches are selected to collect data for this study in Addis Ababa, Ethiopia. Intersection approaches are selected in such a way that they had different yellow durations, clear visibility up to at least 100m and suitable position to set camera at a higher elevation. The selected approaches have adequate vehicular traffic to allow for collection of driver behaviour data using video graphic survey. These sites were visited two times each to collect real data in good weather conditions so that unbiased results could be obtained. Days affected by special events were disregarded.

3.3. Study Location

The selected intersections which are located in Addis Ababa;

- ✓ Imperial
- ✓ Kadisco
- ✓ Jemo Michael
- ✓ 18 Mazoria

The selection is based on the Criteria's stated below:

- Their relatively high posted speed limit (70 km/hr) since they found on the ring road of Addis Ababa. However, in most of the city's road did not attain this posted speed limit due to congestion.
- They are access controlled so that there will not be a possible obstruction to the vehicles that are approaching at their desired speeds as dilemma behaviour of divers occurs clearly on such roads.

The selected sites have also adequate vehicular traffic, clear visibility up to at least 100m and suitable position to set camera at a higher elevation to allow for collection of driver behaviour data using video graphic survey.

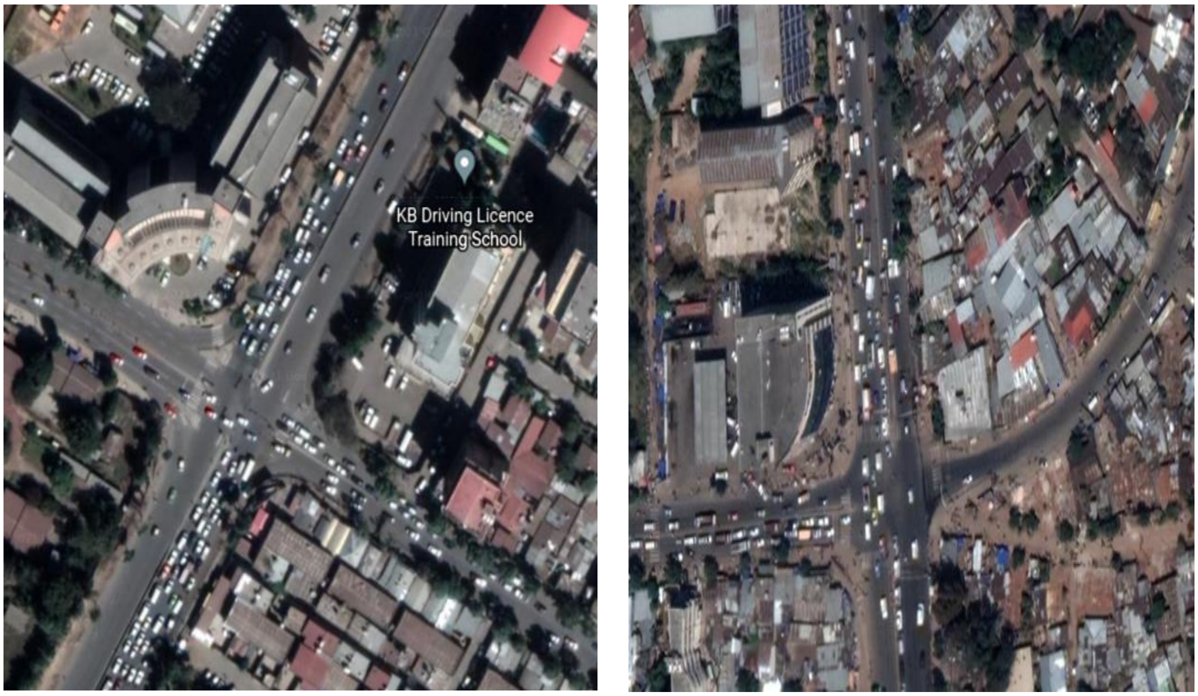


Figure 4: Imperial and 18 Mazoria Intersection Layouts

3.4. Description of Variables

Previous studies have shown that driver's STOP/GO decision at signalized intersection is dependent on their distance from the stop line and their travelling speed (Gazis, et. al., 1960; May, 1968; Van der Horst, 1988; Elmitiny, et. al., 2010). In addition, other factors were noted, such as whether the vehicle was a bus or heavy truck, the absence of a bus or cycle lane and turning movement lane (Gazis, et. al., 1960).

Table 1: Variables along with their description

Variable	**Variable Type**	**Definition**
Approaching Vehicle Speed (VS)	Independent (Continuous)	Speed of a vehicle when approaching the intersection, (km/hr.)
Distance to Stop Line (DSL)	Independent (Continuous)	Position of the vehicle from the stop line when the traffic light turns to yellow, (m)

Variable	Variable Type	Definition
Vehicle type (VT)	Independent (Categorical)	1 for Small Vehicle; 2 for Medium Vehicle; 3 for Large Vehicle
Duration of Yellow Interval (Y)	Independent (Continuous)	Duration of the yellow signal provided at the selected approach
Driver Response (DR)	Dependent (Categorical)	0 for vehicle crossing at yellow interval; 1 for vehicle stopping at yellow interval

Note that the vehicle type for this study were grouped in to three classes: small vehicle (passenger cars), medium vehicle (minivan and medium buses) and large vehicles (bus and trucks)

3.5. Determination of Sample Size

The sample size was calculated from the following formula which is called the Cochran's formula

$$N = \frac{pqK2}{E2}$$

Where: N is the sample size; p the proportion of vehicles facing a yellow signal that pass; q the proportion of vehicles facing a yellow signal that stop; K the constant corresponding to the desired confidence level; E is the permitted error in the proportion estimate.

For confidence level of 95% (K= 1.96) and permitted error of 5% and assuming that p = q = 0.5, the sample size equals

N= $0.5*0.5*1.96^2/0.05^2$= 384 vehicles

The sample size for assessing the driving behaviour through questionnaire with 95% confidence level and permitted error of 5% and assuming that p = q = 0.5 is as follows;

N= 0.5*0.5*1.962/0.052= 384 persons

3.6. Data Collection Technique and Source

3.6.1. Data Collection Techniques on Selected Signalized Intersection

Video capturing technique is used to collect the data at the selected signalized intersection approaches. It has advantages in that it is reasonably cheap and provides a complete record of the behaviour and traffic activities at any site. Also, it eliminates observer bias and most importantly, it gives a permanent record.

Figure 5: Video recording lay out

The disadvantage of this technique is that it is relatively inflexible in terms of finding a suitable camera position for filming on footways or from a lower level building due to poor visibility either because of trees, an insufficient road section to the stop line or because the traffic light signal cannot be seen by the observer. In addition, working in bad weather conditions can disturb the process of recording.

For data collection, different instruments were employed to obtain different type of data. Linear tape was used to measure stretch length. A video camera was used to recording vehicle movement when traversing the selected stretch length which is 100m. VLC video player was used for extracting type of vehicle, time duration of traversing section and lane position. The driver attitudinal survey (questioners) was randomly distributed for selected drivers in Addis-Ababa after pilot survey. For analysis of data SPSS 22.0 and application software's were also used for documentation.

Video data was collected during the non-peak hours (9 am to 4 pm) of the weekend days (Saturday and Sunday), as dilemma behaviour could not be observed during peak hours due to the queuing. To ensure quality of data, cameras are mounted on nearby building to provide a full view of intersection characteristics which are necessary for the study, traffic signal indication, vehicles which are approaching the intersection, position of the vehicle with respect to the stop line and the driver's decision to stop or pass through the intersection. Only through flow were chosen in this study because the right turning flow was controlled by a different signal setting. Also, vehicles with a lane changing manoeuvre at the onset of amber were not included in this study because of rare events.

Red illuminating tape tapes are placed at 10 m interval on visible objects and illuminating tape will be used to mark the points on the curb of the road side. With the help of red illuminating tape, the extraction was carried out on the transverse movement of vehicles.

Data collection was held for 4 weekend days (Saturday and Sunday) at the non-peak hours (9 am to 4 pm).

3.6.2 Data Collection detail for Driver Attitudinal Survey (Questionnaire)

Questionnaire based driver perception survey was conducted on randomly selected driver in Addis-Ababa. What drivers do when they face to a yellow traffic light analysis was based on the data reported by the driver themselves through structured questioners which contain three parts. The parts are about driver and vehicle Personal questions; driver's general driving questions and yellow traffic light questions. The driver attitude and belief on conditions affects what they do when they see a yellow light questions were answered by using 5 point Likert scale (answered by scales from "strongly agree to strongly dis-agree", which is rating from 1 to 5 respectively) .

The close-ended questionnaire was distributed to randomly selected drivers. The minimum number of sample required for questionaries' was 384 but the totals of 392 samples with pilot survey were distributed for driver so as to obtain reliable data. The vehicle and driver personal questions include (Gender, Age, and Education level): General driving questions (What kind of vehicle do they usually drive, How many times do they drive a motor vehicle, How many times have they been pulled over by the traffic police in the past year, Have they ever been in an accident at an intersection and Do they consider themself a safe driver), driver accident and speeding involvement history in past two years) and yellow traffic light questions. A questionnaire with close-ended items was originally prepared by researchers. It was initially developed in English and then translated into Amharic to collect information from drivers.

3.6.3. Secondary Data

Different studies like dissertations, articles, journals, books and manuals similar to the study are going to be used as secondary data.

3.7. Assurance of Data Quality

The research will strive to do quality of work in collection of data for reliability since more advanced equipment will not be used especially in data extraction.

3.8. Data Extraction Techniques Used for this Thesis

3.8.1 Drivers' compliance and STOP/GO decisions

The video playback technique was used to observe drivers' behaviour approaching the stop line following the onset of amber. Drivers' STOP/GO decisions under the effect of the dilemma zone were detected from the videos and reported in this survey. The number of amber crossing and red light running's were also observed from the records and reported. Three categories of driver compliance were reported: Amber Light Running (ALR), Red Light Running (RLR), and Amber/Red Light Stopping (ARLS). Furthermore, the distance and time to the stop line for each approaching vehicle at the onset of amber was detected in terms of whether the driver's decision was to stop or continue crossing the stop line. These data will be compared with the model results in the calibration and validation processes.

Observations from all the four signalized intersection approaches will be extracted manually with frame by frame analysis of all the video data collected in order to assess driver responses at the onset of yellow. The observations recorded will only for the through traveling vehicles, which have a clear chance to make a stop/go decision immediately when the traffic light turns to yellow. The turning vehicles which will slow down at the intersection and vehicles which are forced to stop because of the following behaviour will not be considered as they do not exhibit dilemma behaviour.

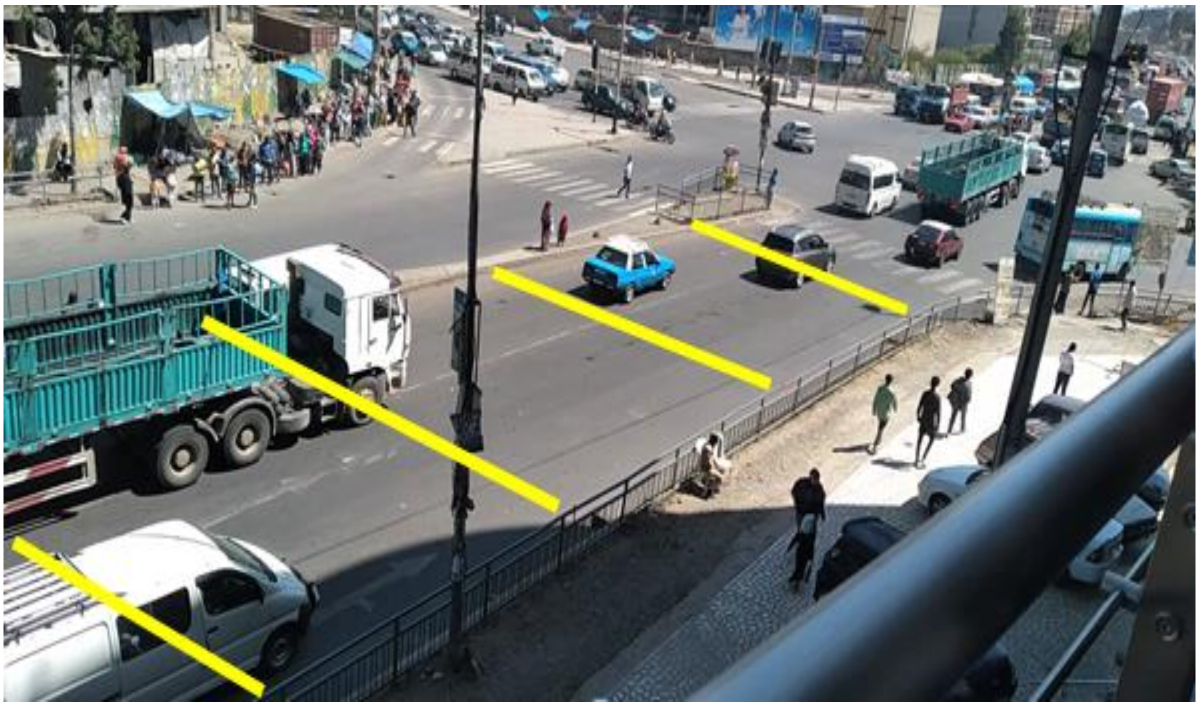


Figure 6: Video playback technique for analysis

After having the available datasets from videos for analysis, the first step in modelling the driver behaviour at the onset of yellow is to characterize the different attributes associated with it. This characterization is carried out in order to serve as an input for the next tasks. The various attributes to be characterized are summarized in the following list.

3.8.2 Red Light Running Behaviour

Many studies were conducted in order to capture the parameters affecting the driver red light running behaviour, as well as to introduce and evaluate different mitigation strategies for the red light running problems.

In study by Porter and England (2000), a forward stepwise logistic regression model was calibrated, based on trained human observer data collected at six intersections located in three cities in Virginia, in order to test explanatory variables of yellow-light versus red-light runners.

The recorder variables were time to green change; signal indication when last vehicle crossed the stop bar, driver sex, use of safe belt, estimated driver age, ethnicity group, direction travelled, and estimated model year; with a total of 5,112 last drivers were collected, of which only 3,785 were observed entering on yellow or red. The model showed that city, time, safety belt use and ethnicity were the most significant variables; i.e. unbuckled and non-Caucasian drivers were more likely to run red lights.

The stopping probabilities of the drivers in the datasets is investigated, and then the analysis investigates the running behaviour of the drivers who decided to proceed through the intersection at the onset of yellow. Some of these drivers were able to hit the stop line before the end of the yellow and those are the yellow time runners, whereas those drivers who failed to cross the stop line before the start of red indication are the red light runners.

The driver yellow/red light running behaviour is characterized first by comparing the distributions of the stopping/running probabilities based on different surrounding variables, and then by empirical investigations of the running behaviour of the different drivers either before or after the end of the yellow indication.

3.9. Data Analysis Techniques

This section describes the overall data analysis methodology of the research. For this study logistic regression and factor analysis would be employed for two different cases. Binary logistic regression has been developed for driver stop/go decision when they see yellow traffic light. Factor analysis was also employed to identify conditions affects what they do when they see a yellow light questions.

3.9.1 Factor Analysis

Factor analysis is a statistical technique for identifying which underlying factors are measured by a (much larger) number of observed variables. Factor analysis is data reduction method used to re-express multi-variate data with fewer dimension (Kim & Mueller, 1978). It allows researchers to investigate concepts they cannot measure directly. It does this by using a large number of variables to estimate a few interpretable underlying factors.

In every factor analysis, there are one fewer factors than there are variables. Each factor captures a certain amount of the overall variance in the observed variables, and the factors are always listed in order of how much variation they explain. The eigenvalue is a measure of how much of the common variance of the observed variables a factor explains. Any factor with an eigenvalue ≥1 explains more variance than a single observed variable. So if the condition which affects driver's decision had an eigenvalue of 2.3 it would explain as much variance as 2.3 of the three variables. This factor, which captures most of the variance in those three variables, could then be used in other analyses. The factors that explain the least amount of variance are generally discarded. Deciding how many factors are useful to retain will be the subject of another post.

The goal of this analysis was used to summarize fewer factors from original reasons to stop when drivers see yellow traffic light that capture maximum possible information from 14 original reasons to stop when the drivers see yellow traffic light which was listed in questionnaire. This method of analysis had been accomplished through factor rotation followed by factor extraction.

Factor extraction is nothing but making choice few number of factors from more factors. This few factors were based on trade-off between simplicity and completeness. It was determined using Kaiser Criterion based on the Eigen value of greater than 1 (Kaiser, 1974). Factor rotation is done to making simple structure for grouping each variable and understandable (Ford, et al., 1986) and (Thurstone , 1947). The rotation of extracted factor was done using orthogonal rotation which used to make factors uncorrelated to each other and easy to understand (Ford, et al., 1986).

The first step for factor analysis was checking sample adequacy and correlation between conditions which affects the decision to cross or stop when the drivers see yellow light. The adequacy of the sample size is based on the ratio of 10 responses per reason. The Kaiser-Meyer-Olkin (KMO) measure should be greater than .70 and is inadequate if less than .50. The Kaiser-Meyer-Olkin (KMO) test tells us whether or not enough items are predicted by each factor. The Bartlett test should be significant (i.e., a significance value of less than .05). On the other hand Kaiser-Mayer –Olkin can measure the adequacy of data's for the application of factor analysis in which it should be above 0.8 (Kaiser, 1974). Bartlett's' test of sphericity was used to check the correlation between items (Bartlet, 1950) and the result should show the presence of at least one significant correlation between conditions which affects the decision to cross or stop when the drivers see yellow light. After assured the adequacy of the sample and the correlation between conditions which affects the decision to cross or stop when the drivers see yellow light, factorial extraction was conducted.

Factor rotation is done to make simple structure for grouping each variable and understandable (Ford, et al., 1986) and (Thurstone , 1947). The rotation of extracted factor was done using orthogonal rotation which is used to make factors uncorrelated to each other and easy to understand (Ford, et al., 1986).

For the analysis, we will use an orthogonal rotation (varimax). This means that the final factors will be at right angles with each other. As a result, we can assume that the information explained by one factor is independent of the information in the other factors. Note that if we create scales by summing or averaging items with high loadings from each factor, these scales will not necessarily be uncorrelated; it is the best-fit vectors (factors) that are orthogonal. After factors were extracted, representative name for the extracted factor was given based on the group of correlated variables.

3.9.2 Binary Logistics Regression

Logistic regression is non-linear analysis for estimating categorical dependent variable. Logistic linear regression models are calibrated to the driver stopping probability versus the different surrounding variables. The logistic regression models are then used to carry out sensitivity analysis of the different explanatory variables.

The objective of the model is to be able to predict the driver's probability of passing or stopping at a given situation. The driver will have two choices either to pass or to stop when he/she face a yellow signal while approaching the intersection. The driver's decision to make is statistically related to the attributes of various factors influencing their decision. The probability of a driver, i stopping at the intersection is given by:

$$P_{i\ (Stop)} = \frac{1}{(1+\exp(-Ui))}$$

The utility function of an alternative can be expressed as:

$U_{ji} = \beta_o + \beta_{j1}x_{j1} + \beta_{j2}x_{j2} + \ldots\ldots + \beta_{jn}x_{jn}$

Where: U_{ji} = Utility of driver I choosing alternative j;

j = Alternative to make which is a Stop or Go;

n = Number of independent variable;

β = Model coefficients.

Various possible combinations of discrete and continuous variables affecting the driver behaviour at the time of yellow onset will tried and the final combinations of all the variables used on the study were decided based on p-value at 5% level of significance.

Logistic regression forms a best fitting equation or function using the maximum likelihood (ML) method, which maximizes the probability of classifying the observed data into the appropriate category given the regression coefficients. Like multiple regression, logistic regression provides a coefficient 'b', which measures each independent variable's partial contribution to variations in the dependent variable.

The goal is to correctly predict the category of outcome for individual cases using the most parsimonious model; to find the best fitting, simplest model, to understand the relationship between the Y and the X's, and to be able to reach appropriate statistical conclusions. Not only does binary logistic regression allow you to assess how well your set of variables predicts your categorical dependent variable and determine the "goodness-of-fit" of your model as does regular linear regression, but also it provides a summary of the accuracy of the classification of cases, which helps you determine the percent of predictions made from this model/equation that will be correct. To accomplish this goal, a model (i.e. an equation) is created that includes all predictor variables that are useful in predicting the response variable.

The Purpose of Binary Logistic Regression

1. The logistic regression predicts group membership
   - ✓ Since logistic regression calculates the probability of success over the probability of failure, the results of the analysis are in the form of an odds ratio.
   - ✓ Logistic regression determines the impact of multiple independent variables presented simultaneously to predict membership of one or other of the two dependent variable categories.
2. The logistic regression also provides the relationships and strengths among the variables (Assumptions of (Binary) Logistic Regression)
   - ✓ Logistic regression does not assume a linear relationship between the dependent and independent variables. Logistic regression assumes linearity of independent variables and log odds of dependent variable.

- ✓ The independent variables need not be interval, nor normally distributed, nor linearly related, nor of equal variance within each group. Homoscedasticity is not required. The error terms (residuals) do not need to be normally distributed.
- ✓ The dependent variable in logistic regression is not measured on an interval or ratio scale. The dependent variable must be a dichotomous (2 categories) for the binary logistic regression.
- ✓ The categories (groups) as a dependent variable must be mutually exclusive and exhaustive; a case can only be in one group and every case must be a member of one of the groups.

Chapter Four: Results and Discussion

4.1. Driver Speeding Attitudinal Survey Analysis

In this part, factor analysis was conducted using driver attitudinal survey data by following descriptive statistics.

4.1.1. Descriptive Statistics

Demographic characteristics of driver who participated on the attitudinal survey conducted to see their understanding on yellow traffic light were presented as follow in table below.

As we have seen below in table, male drivers participated in attitudinal survey was contributed 86.9 percent and mostly participated age group were from (25 to 35 year) which was contributed 53.3%.

Table 2: Frequency and Percentage of drivers' gender

Gender	Frequency	Percent
Male	341	86.9
Female	51	13.1

Table 3: Frequency and Percentage of drivers' age category

Age (year)	Frequency	Percent
18-24	41	10.4
25-35	209	53.3
36-60	128	32.7
>60	14	3.6

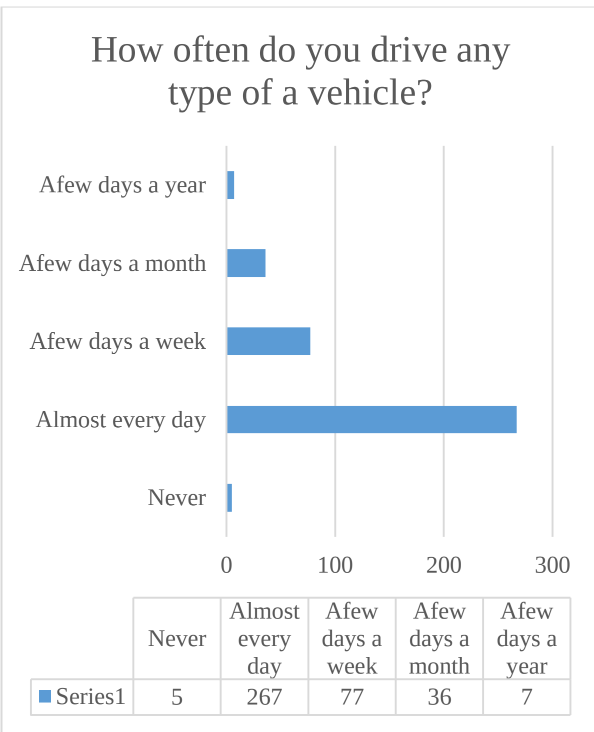
Table 4: Frequency and Percentage of drivers' education category

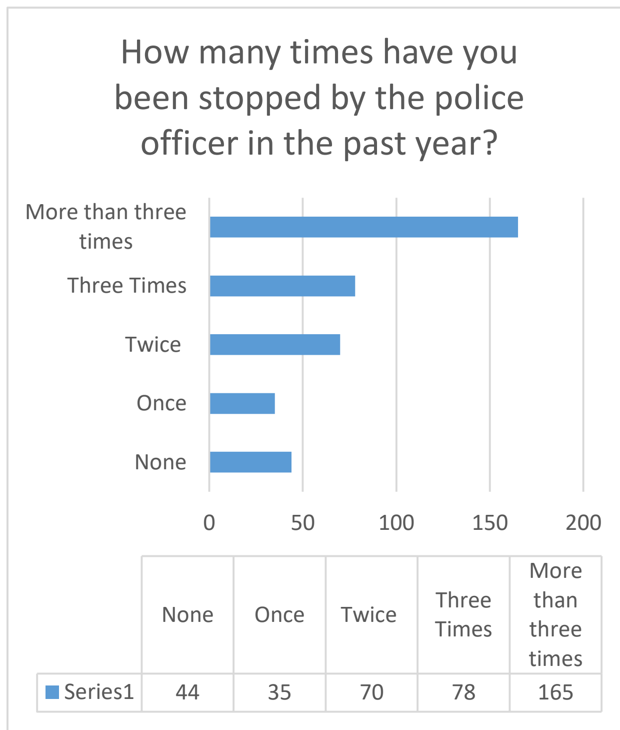
Education level	frequency	percent
High School	137	34.9
TVET Training	82	20.9
Diploma	112	28.6
Degree	49	12.5
Masters and above	12	3.1

General Driving Questions

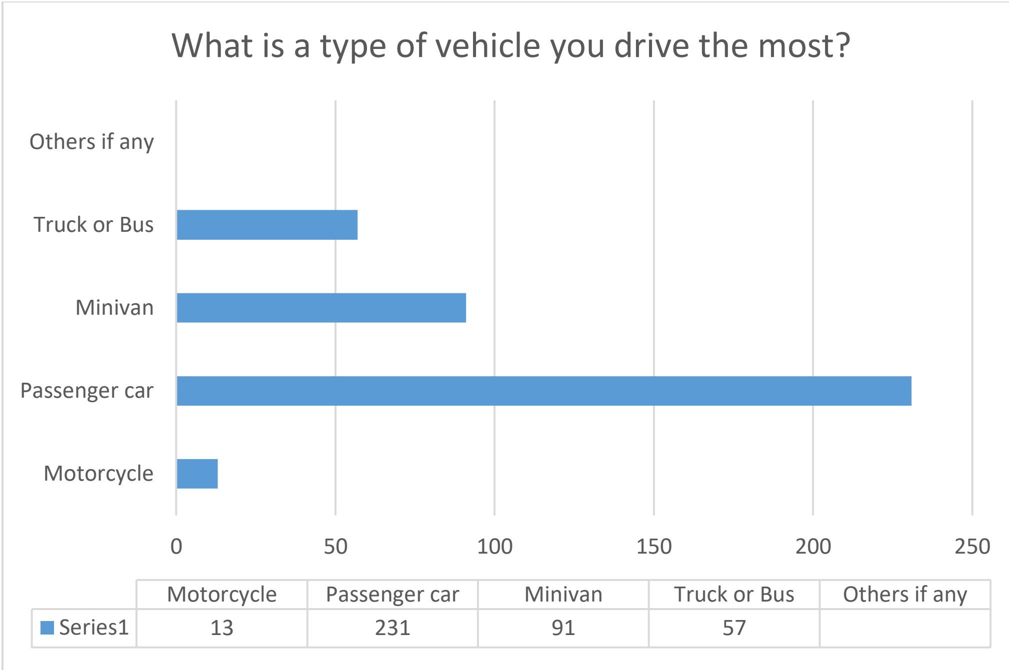
As we can see in the bar charts of three questions of "How often do you drive any type of a vehicle?", "How many times have you been stopped by the police officer in the past year?", and "What is a type of vehicle you drive the most?" respectively. Numbers shown on each choice of answers on the table below each bar chart indicate corresponding categories count. The majority of the responders drive a car almost every day, and the kind of vehicle they drive is a passenger car.

As shown in the bar chart C, 42.1% of drivers have been pulled over by the police more than three times in the past year. This indicates that almost half of the drivers have been pulled over by a police more than three times in the past year based on the report of them.





A) **B)**



C)

Figure 7: Distribution of a) how often participants drive; b) how many times being pulled over by the police; and c) Type of Vehicle.

According to the results of another question from the questionnaire, 32.4% have been involved in an accident at an intersection in the past. On this result, Note that this does not mean they are surely at fault in the occurrence of the accident.

In answering the question, “Do you see yourself as a good driver (safe driver)?”, only 76.3% of drivers consider themselves safe drivers, and also there is a small group, 6.9%, didn’t consider themselves as safe drivers and 16.8% of them do not know if they are safe drivers or not which is interesting.

Traffic Light Questions

As described in the section above, the last part of the questionnaire includes questions directly related to the occurrence of dilemma driver behaviour at yellow traffic light. Figure below shows the choice each respondent given to the question asking ‘How many times do you try to go through amber light and end up running through a red light?’ According to this figure the majority of drivers rarely do this, yet there is almost a large group; 27.3%, who sometimes try to catch the yellow light and end up running a red light.

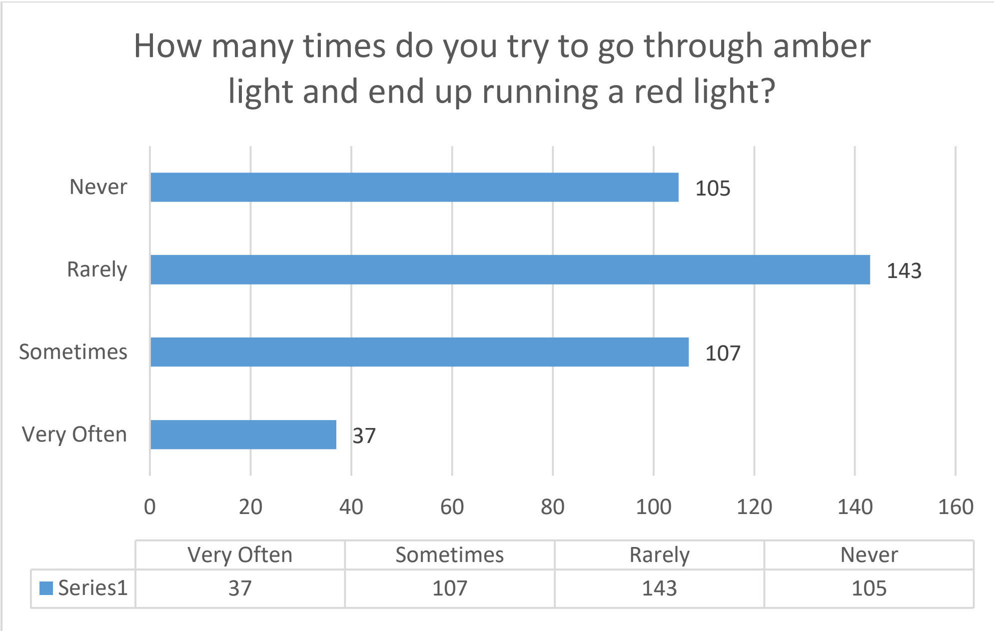


Figure 8: Yellow light catching frequency;

The figure below shows the distribution of what drivers who filled the questioner normally do when they face a yellow traffic light. Forms the result, most drivers decide based on the condition they come into during the yellow traffic light, and 30.9% of them slow down.

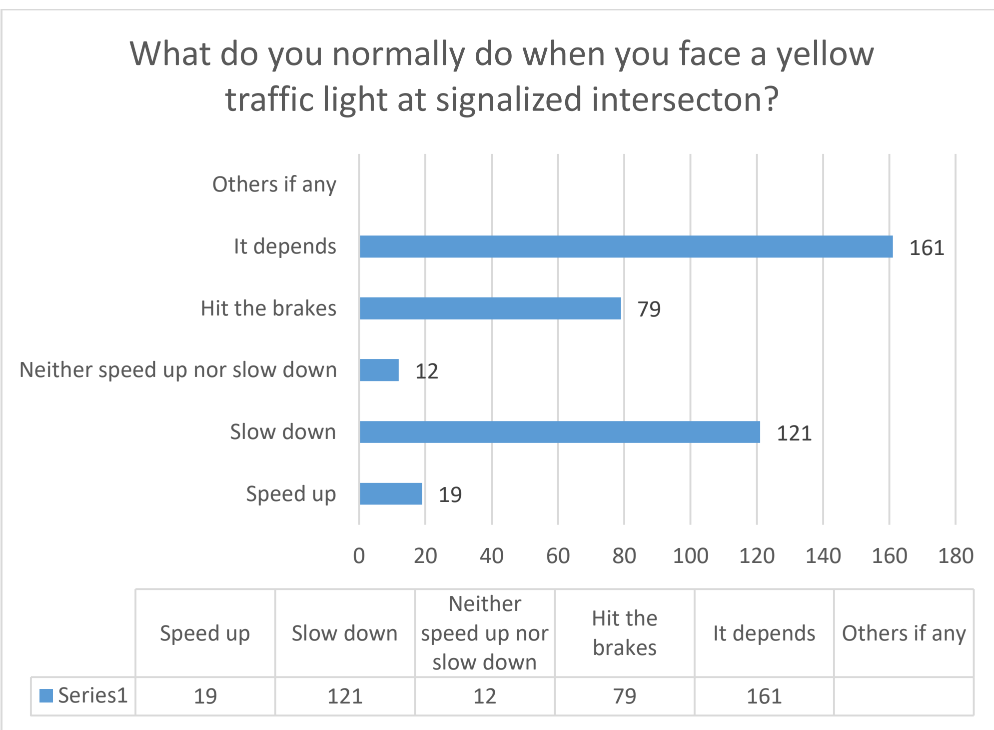


Figure 9: Distribution of responder's reaction while encountering a yellow light.

Among the respondents, 37.2% of them assume that yellow light duration is 3 seconds during responding the question of how long the responders will usually think yellow light usually lasts. However, looking at the next question, from the results it indicates that the majority of the responders (55.4%) have seen that some yellow lights are longer or shorter than others.

From the following conditions which will affect your decision when you face a yellow traffic light at signalized intersection?

The conditions that affect the drivers decision to cross or stop on the intersection when they saw a yellow light was used 5 point Likert scale (always=1, most time=2, sometime=3, rarely=4 and never =5). Individual drivers had their own opinions towards the factors affecting their decision that can be driver behaviour, vehicle characteristics and road way condition. The percent mean and standard deviation for each condition that affects the driver's decision making when they see yellow traffic light presented in table as follows.

Table 5: Descriptive statistics of conditions that affects mostly the drivers' decision making on yellow traffic light

Which of the following conditions affects the decision to cross or stop when the drivers see yellow light?	Mean	Stad.dev.
R1: Your speed.	1.38	0.516
R2: Your distance to intersection.	2.21	0.728
R3: Presence of passengers in the car.	3.99	0.886
R4: Existence of yellow flashing traffic light.	2.93	0.788
R5: Whether you are in conversation through the phone.	4.60	0.562
R6: Whether it is a day time or at night.	3.00	0.888
R7: Presence of police officer.	3.29	0.563
R8: Presence of a vehicle in front of you.	2.64	0.804
R9: Presence of a bicycle, pedestrian or vehicle in the side-street.	2.13	0.871
R10: Whether the next traffic light is timed.	2.93	0.801
R11: Whether you are tired, angry, or sad.	3.98	0.879
R12: Whether you are familiar with the intersection.	2.92	0.813

Which of the following conditions affects the decision to cross or stop when the drivers see yellow light?	Mean	Stad.dev.
R13: Whether it is a safe intersection.	2.22	0.756
R14: Whether you are successfully pass at yellow light before turning to red light.	2.93	0.948

The median and the mean both measure central tendency. But unusual values, called outliers, affect the median less than they affect the mean. In this study, we use the mean to describe the sample with a single value that represents the centre of the data. Many statistical analyses use the mean as a standard measure of the centre of the distribution of the data. To calculate the above mean we add up the observed values and divide by the number of them.

$$\textbf{Mean} = \frac{\text{Sum of all observations}}{\text{Number of observations}} = \bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$$

Where: x is the sample mean, x_i is the i^{th} observation, n is the sample size.

The standard deviation is a statistic that measures the dispersion of a dataset relative to its mean and is calculated as the square root of the variance. The standard deviation is calculated as the square root of variance by determining each data point's deviation relative to the mean.

$$\textbf{Standard deviation} = \text{SD} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

Where: x is the sample mean, x_i is the i^{th} observation, n is the sample size.

Based on the result of the above descriptive analysis from the above possible reasons which affects the decision to cross or stop when the drivers see yellow light speed, distance to intersection, presence of a vehicle in front of the driver, Presence of a bicycle on the road, pedestrian or vehicle on the side of the road and whether it is a safe intersection have lower mean values 1.38, 2.21, 2.64, 2.13 and 2.22 respectively. This mean value are lower than the others which indicates the conditions were the most important frequent reasons which affects the decision to cross or stop when the drivers see yellow light.

4.1.2. Factor analysis

Factor analysis is a statistical technique for identifying which underlying factors are measured by a (much larger) number of observed variables. Factor analysis is data reduction method used to re-express multi-variate data with fewer dimension (Kim & Mueller, 1978). It allows researchers to investigate concepts they cannot measure directly. It does this by using a large number of variables to estimate a few interpretable underlying factors.

In every factor analysis, there are one fewer factors than there are variables. Each factor captures a certain amount of the overall variance in the observed variables, and the factors are always listed in order of how much variation they explain. The eigenvalue is a measure of how much of the common variance of the observed variables a factor explains. The factors that explain the least amount of variance are generally discarded. Deciding how many factors are useful to retain will be the subject of another post.

The goal of this analysis was used to summarize fewer factors from original reason that capture maximum possible information from 14 original condition that affects the driver's decision making when they see yellow traffic light which was listed in questionnaire. This method of analysis had been accomplished through factor rotation followed by factor extraction.

4.1.2.1. Factor Extraction

The first step for factor analysis was checking sample adequacy and correlation between conditions which affects the decision to cross or stop when the drivers see yellow light. The Kaiser-Meyer-Olkin (KMO) test tells us whether or not enough items are predicted by each factor. Here it is .810 so that is good. On the other hand Kaiser-Mayer –Olkin can measure the adequacy of data's for the application of factor analysis in which it should be above 0.8 (Kaiser, 1974). For this particular study, it is possible to apply factor analysis, because KMO value were greater than 0.8 as shown in table below.

The Bartlett test should be significant (i.e., a significance value of less than .05); this means that the variables are correlated highly enough to provide a reasonable basis for factor analysis as in this case. The result below shows the significance value of .000 which is less than .05; this means the presence of at least one significant correlation between conditions which affects the decision to cross or stop when the drivers see yellow light.

Table 6: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of the Sampling Adequacy.		.810
Bartlett's Test of the Sphericity	Approx. Chi-Square	999.302
	Df	91
	Sig.	.000

After assured the adequacy of the sample and the correlation between conditions which affects the decision to cross or stop when the drivers see yellow light, factorial extraction was conducted. The factor analysis was conducted on 14 main conditions which affects the decision to cross or stop when the drivers see yellow light. As shown in table below, the variance of each condition which affects the decision to cross or stop when the drivers see yellow light explaining the variance of all factors which is commonly called communality were presented. Communality is the proportion of variance jointly explained one variable and it is indicator of reliability. Communality calculated by summing up factor loadings for all variables. Based on the result of analysis, R1, R7, R9 and R14 have measured large percent of variance for all speeding reasons.

Table 7: Conditions affects the decision to cross or stop when the drivers see yellow light communalities

	Initial	Extraction
R1	1.000	.626
R2	1.000	.519
R3	1.000	.586
R4	1.000	.609
R5	1.000	.549
R6	1.000	.585
R7	1.000	.703
R8	1.000	.602
R9	1.000	.647
R10	1.000	.373
R11	1.000	.592
R12	1.000	.549
R13	1.000	.558
R14	1.000	.840

Extraction Method Used: Principal Component Analysis.

The Total Variance Explained table shows how the variance is divided among the 14 possible factors. Note that five factors have eigenvalues (a measure of explained variance) greater than 1.0, which is a common criterion for a factor to be useful. When the eigenvalue is less than 1.0 the factor explains less information than a single item would have explained. Most researchers would not consider the information gained from such a factor to be sufficient to justify keeping that factor. Thus, if you had not specified otherwise, the computer would have looked for the best four-factor solution by "rotating" four factors.

Eigen value represents the amount of variance of variable explained by factors. It is the sum of all squared loading of principal factors across all variables. Based on the result of the analysis, Five components were extracted which have Eigen value greater than 1 which explained cumulative variance of 59.6 percent as shown in the table below.

Table 8: Factor extraction based on Eigen value

Component	Initial Eigenvalues.			Extraction Sums of Squared Loadings.		
	Total	%of Variance	Cumulative Percentage	Total	% of Variance	Cumulative Percentage
1	3.652	26.085	26.085	3.652	26.085	26.085
2	1.335	9.536	35.620	1.335	9.536	35.620
3	1.254	8.954	44.574	1.254	8.954	44.574
4	1.076	7.683	52.257	1.076	7.683	52.257
5	1.023	7.309	59.565	1.023	7.309	59.565
6	.923	6.589	66.155			
7	.853	6.091	72.246			
8	.742	5.301	77.546			
9	.647	4.622	82.169			
10	.581	4.149	86.317			
11	.545	3.895	90.213			
12	.527	3.762	93.975			
13	.458	3.269	97.244			
14	.386	2.756	100.000			

The Scree Plot shows the initial Eigenvalues. Note that both the scree plot and the eigenvalues support the conclusion that these fourteen variables can be reduced to five components. Note that the scree plot flattens out after the fifth component.

The scree plot suggests that five components can explain 59.56 % variance of 14 original components.

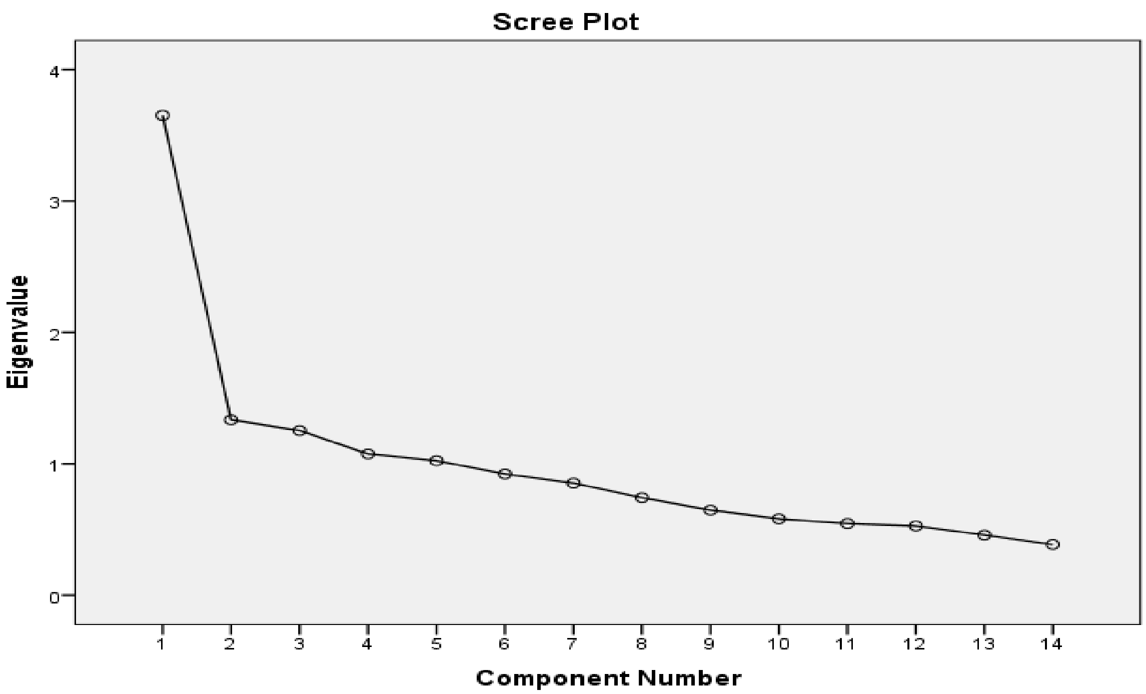


Figure 10: Screen plot of principal component

4.1.2.2. Factor rotation

The rotation of extracted factor was done using orthogonal rotation which is used to make factors uncorrelated to each other and easy to understand. This means that the final factors will be at right angles with each other. The Rotated Factor Matrix table below is key for understanding the results of the analysis.

Table 9: Rotated Component Matrix

Reason	Component				
	1	2	3	4	5
R3	.703				
R11	-.700				

R12	.667				
R1	.560	-.509			
R9		.733			
R4		.725			
R10		.534			
R5		.521			
R13			.679		
R2			.660		
R6			.509		
R8				.743	
R7				.592	
R14					.903
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					

Factors are rotated so that they are easier to interpret. Rotation makes it so that, as much as possible, different items are explained or predicted by different underlying factors, and each factor explains more than one item. This is a condition called simple structure. Although this is the goal of rotation, in reality, this is not always achieved. One thing to look for in the Rotated Matrix of factor loadings is the extent to which simple structure is achieved.

The Rotated Factor Matrix table is key for understanding the results of the analysis. Factors are rotated so that they are easier to interpret. Rotation makes it so that, as much as possible, different items are explained or predicted by different underlying factors, and each factor explains more than one item. This is a condition called simple structure. Although this is the goal of rotation, in reality, this is not always achieved. One thing to look for in the Rotated Matrix of factor loadings is the extent to which simple structure is achieved.

Note that the analysis has sorted the 14 math attitude questions (R1 to R14) into five somewhat overlapping groups of items. The items are sorted so that the items that have the highest loading (not considering whether the correlation is positive or negative) from factor 1 (four items in this analysis) are listed first, and they are sorted from the one with the highest factor weight or loading (i.e., R3, with a loading of .703) to the one with the lowest loading from that first factor

(R1). Actually, every item has some loading from every factor, but we requested for loadings less than |.50| to be excluded from the output, so there are blanks where low loadings exist. (|.50| means the absolute value, or value without considering the sign).

Next, the four items that have their highest loading from factor 2 are listed from highest loading (R9) to lowest (R5). Then the three items that have their highest loading from factor 3 are listed from highest loading (R13) to lowest (R6). Finally, the two items on which factor 4 and one item on factor 5 are listed in order. Loadings resulting from an orthogonal rotation are correlation coefficients between each item and the factor, so they range from −1.0 through 0 to + 1.0. A negative loading just means that the question needs to be interpreted in the opposite direction from the way it is written for that factor.

After factors are extracted and rotated, the next step was naming of new factors which captured most information of original correlated variables. The name of new factor is dependent on the variable mostly explain the retained factors. The renamed reason was presented as follow in table below.

Table 10: Renamed new factor

Factor	Most correlated reason	New factor name	% explained variance
1	R3: Presence of passengers in the car R11: Whether you are tired, angry, or sad R12: How well you know the intersection R1: Your speed	Emotion and understanding of the driver.	26.085
2	R9: Presence of a pedestrian, bicycle or vehicle in the side-street R4: Existence of yellow flashing traffic light R10: Whether the next traffic light is timed. R5: Whether you are talking on the phone	Roadway and variable control condition	9.536
3	R13: Whether it is a safe intersection R2: Your distance to intersection R6: Whether it is night or day time	Comfort to drive	8.954
4	R8: Presence of a vehicle in front of you	Presence of vehicle	7.683

	R7: Presence of police	and police	
5	R14: Whether you are successfully pass at yellow light before turning to red light.	Past experience of driver	7.309

Based on the result of the analysis, Emotion and understanding of the driver, Roadway and variable control condition, Comfort to drive, Presence of vehicle and police and Past experience of driver were the conditions which will affect the decision to cross or stop when the drivers see yellow light which contributed to explain 59.56 % of variance. Emotion and understanding of the driver found to be the primer ranked factor that affects the driver's decision making when they see yellow traffic light included (Presence of passengers in the car, Whether you are tired, angry, or sad, How well you know the intersection and the drivers speed) which was contributed to 26.1 % all conditions affects the decision to cross or stop when the drivers see yellow light variance. This group of reason had most possible frequent of reason than others which was the conditions affects the decision to cross or stop when the drivers see yellow light.

The second ranked decision factor was Roadway and variable control condition. This new factor includes (Presence of a pedestrian, bicycle or vehicle in the side-street, Existence of yellow flashing traffic light, whether the next traffic light is timed and whether you are talking on the phone). Comfort to drive was the third new factor which explained the variance of 8.9%. This factor includes: (Whether it is a safe intersection, driver's distance to intersection and whether it is night or day time) which were the most variables which were grouped under this category.

Presence of vehicle and police and Past experience of driver was another most important main conditions which affects the decision to cross or stop when the drivers see yellow light. Generally, traffic management office, road safety agency, transport planner and road designer of Addis-Ababa should consider this four grouped factor to create safe and sustainable urban road transport system.

4.2 Binary Logistic Regression

Logistic regression measures the relationship between the categorical target variable and one or more independent variables. It is useful for situations in which the outcome for a target variable can have only two possible types (in other words, it is binary). Binary Logistic Regression Classification makes use of one or more predictor variables that may be either continuous or categorical to predict the target variable classes. This technique helps to identify important factors (Xi) impacting the target variable (Y) and also the nature of the relationship between each of these factors and the dependent variable. Binary logistic regression - determines the impact of multiple independent variables presented simultaneously to predict membership of one or other of the two dependent variable categories.

Since the dependent variable is dichotomous we cannot predict a numerical value for it using logistic regression so the usual regression least squares deviations criteria for best fit approach of minimizing error around the line of best fit is inappropriate. Instead, logistic regression employs binomial probability theory in which there are only two values to predict: that probability (p) is 1 rather than 0, i.e. the event/person belongs to one group rather than the other.

Logistic regression forms a best fitting equation or function using the maximum likelihood (ML) method, which maximizes the probability of classifying the observed data into the appropriate category given the regression coefficients. Like multiple regression, logistic regression provides a coefficient 'b', which measures each independent variable's partial contribution to variations in the dependent variable.

The goal is to correctly predict the category of outcome for individual cases using the most parsimonious model; to find the best fitting, simplest model, to understand the relationship between the Y and the X's, and to be able to reach appropriate statistical conclusions. Not only does binary logistic regression allow you to assess how well your set of variables predicts your categorical dependent variable and determine the "goodness-of-fit" of your model as does regular linear regression, but also it provides a summary of the accuracy of the classification of cases, which helps you determine the percent of predictions made from this model/equation that will be correct. To accomplish this goal, a model (i.e. an equation) is created that includes all predictor variables that are useful in predicting the response variable.

Observations from all the four signalized intersection approaches were extracted manually with frame by frame analysis each of the video data collected on the intersection, which resulted in a total of 397 driver responses at the onset of yellow of signalized intersection. The observations recorded data were carried out only for through moving vehicles, which had a chance to make a stop/go decision at the onset of yellow traffic light at signalized intersection. The responses of the driver are plotted in the figure below for the vehicle approaching speed to a given distance from the stop line at the onset of yellow traffic light at signalized intersection. It can be clearly observed from the figure that that the decision of the drivers overlapping, which shows presence of option zone created at the onset of yellow traffic light at signalized intersection.

The data extracted from the video recording includes response of driver to Stop or Cross the intersection, approach speed of each vehicle in Km/hr., distance to stop line which is extracted in m, and type of subject vehicle (Small Vehicle, Medium Vehicle and Large Vehicle). The sample drivers' responses when they see the yellow traffic light in relation to distance from the stop line and the speed of the vehicle is shown in the figure below:

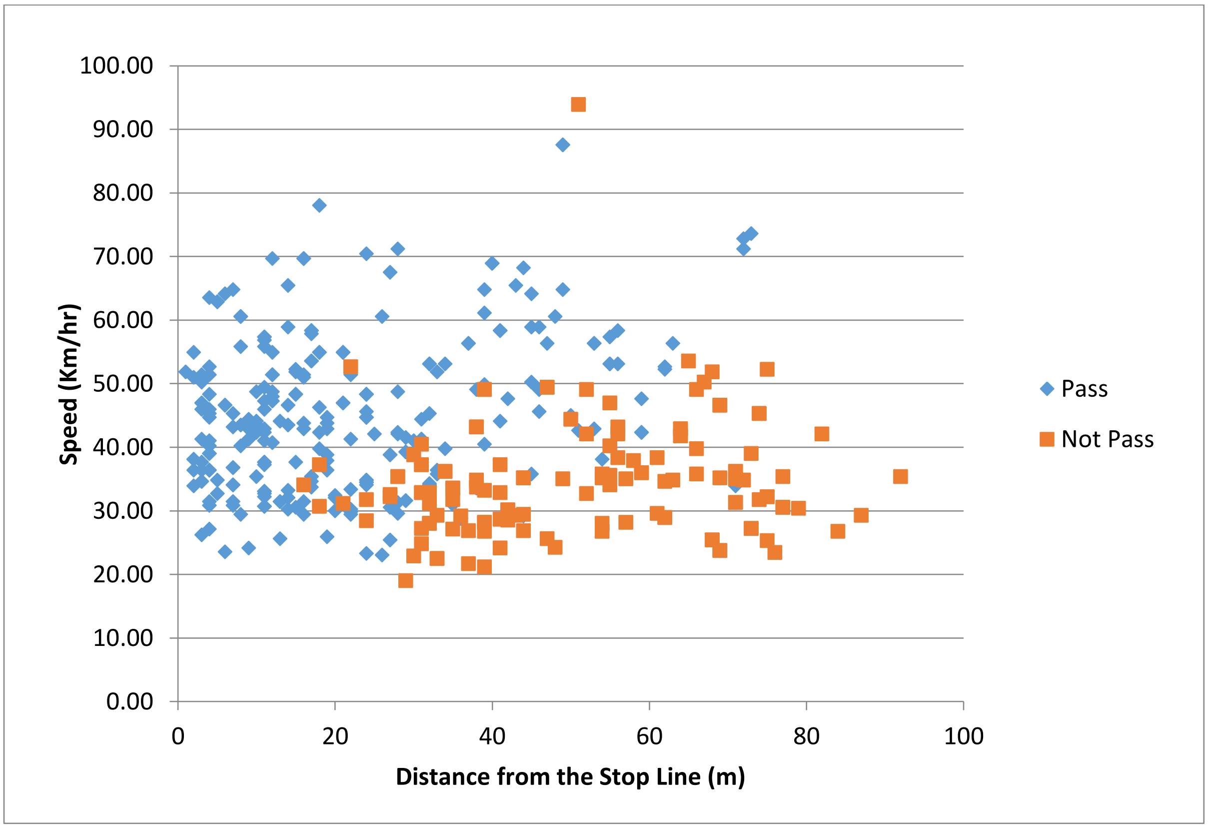


Figure 11: Driver responses at the onset of yellow

SPSS Statistics generates many tables of output when carrying out binomial logistic regression. In this section, only the three main tables required to understand the results from the binomial logistic regression procedure, assuming that no assumptions have been violated.

Variance explained

Statistical analysis on the factors extracted from the video data was performed using the SPSS software. The driver behaviour model was developed using the extracted data i.e., 397 driver responses. All possible combinations of the categorical and continuous variables that affect the driver decision process at the onset of yellow were examined in the construction of the model and the final combination of model variables were shortlisted based on the p-values at 95% confidence interval.

Table 11: SPSS Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	397	100.0
	Missing Cases	0	.0
	Total	397	100.0
Unselected Cases		0	.0
Total		397	100.0
a. If weight is in effect, see classification table for the total number of cases.			

The next 3 tables are the results for the intercept model. That is the Maximum Likelihood model if only the intercept is included without any of the dependent variables in the analysis. This is basically only interesting to calculate the Pseudo R^2 that describe the goodness of fit for the logistic model.

This table informs how the procedure handled the dichotomous dependent variable, which helps to interpret the values of the parameter coefficients. Here, “Pass the Intersection” was coded as a 0, while “Not Pass the Intersection” was coded as a 1.

Table 12: Encoding of Dependent Variable

Original Value	Internal Value
Pass the Intersection	0
Not Pass the Intersection	1

The table below informs the vehicle type as a categorical variable coding which helps in parameter coding for analysis. Here, the vehicle type for this study were grouped in to three classes: small vehicle (passenger cars), medium vehicle (minivan and medium buses) and large vehicles (bus and trucks).

Table 13: Categorical Variables Coding

		Frequency	Parameter coding	
			(1)	(2)
VehicleType	SV	235	.000	.000
	MV	106	1.000	.000
	LV	56	.000	1.000

Table 14: Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 0	Constant	-.630	.105	35.685	1	.000	.533

In the SPSS output of our logistic regression analysis the table below includes the Chi-Square goodness of fit test. It has the null hypothesis that intercept and all coefficients are zero. We can reject this null hypothesis.

The omnibus tests are measures of how well the model performs. The chi-square statistic is the change in the -2 log-likelihood from the previous step, block, or model. If the step was to remove a variable, the exclusion makes sense if the significance of the change is large (i.e., greater than 0.10). If the step was to add a variable, the inclusion makes sense if the significance of the change is small (i.e., less than 0.05). In this case, the change is from Block 0, where no variables are entered.

Table 15: Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	291.865	4	.000
	Block	291.865	4	.000
	Model	291.865	4	.000

In order to understand how much variation in the dependent variable can be explained by the model (the equivalent of R^2 in multiple regression), the table below, "Model Summary" shall be refer:

Table 16: Model Summary which shows R^2

Step	-2 Log likelihood	Cox and Snell R Square	Nagelkerke R Square
1	221.022[a]	.521	.718
a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.			

R-squared is a goodness-of-fit measure for linear regression models. This statistic indicates the percentage of the variance in the dependent variable that the independent variables explain collectively. R-squared measures the strength of the relationship between the model and the dependent variable on a convenient 0 – 100% scale. Larger pseudo r-square statistics indicate that more of the variation is explained by the model, to a maximum of 1.

This table contains the Cox & Snell R Square and Nagelkerke R Square values, which are both methods of calculating the explained variation. These values are sometimes referred to as *pseudo* R^2 values (and will have lower values than in multiple regressions). However, they are interpreted in the same manner, but with more caution. Therefore, the explained variation in the dependent variable based on our model ranges from 52.1% to 71.8%, depending on whether you reference the Cox & Snell R^2 or Nagelkerke R^2 methods, respectively. Nagelkerke R^2 is a modification of Cox & Snell R^2, the latter of which cannot achieve a value of 1. For this reason, it is preferable to report the Nagelkerke R^2 value which is 0.718.

As per the result stated above the R^2 value of 71.8% indicates that 71.8% of the variance of the dependent variable being studied is explained by the variance of the independent variable. Also, the value of the R^2 indicates the better the model fits the data.

Category prediction

Binary logistic regression estimates the probability of an event (in this case, probability to pass an intersection) occurring. If the estimated probability of the event occurring is greater than or equal to 0.5 (better than even chance), SPSS Statistics classifies the event as occurring (e.g., pass the intersection in yellow traffic light). If the probability is less than 0.5, SPSS Statistics classifies the event as not occurring (e.g., not pass the intersection in yellow traffic light). It is very common to use binomial logistic regression to predict whether cases can be correctly classified (i.e., predicted) from the independent variables. Therefore, it becomes necessary to have a method to assess the effectiveness of the predicted classification against the actual classification. There are many methods to assess this with their usefulness often depending on the nature of the study conducted. However, all methods revolve around the observed and predicted classifications, which are presented in the "Classification Table", as shown in table 19 below.

The classification table helps to assess the performance of the model by cross tabulating the observed response categories with the predicted response categories. For each case, the predicted response is the category treated as 1, if that category's predicted probability is greater than the user-specified cut off. Cells on the diagonal are correct predictions.

Firstly, notice that the table has a subscript which states, "The cut value is .500". This means that if the probability of a case being classified into the "yes" category is greater than .500, then that particular case is classified into the "yes" category. Otherwise, the case is classified as in the "no" category (as mentioned previously). Whilst the classification table provides a lot of important information about the binomial logistic regression result, including:

A. The percentage accuracy in classification (PAC), which reflects the percentage of cases that can be correctly classified as "no" Pass the Intersection with the independent variables added (not just the overall model).
B. Sensitivity, which is the percentage of cases that had the observed characteristic (e.g., "yes" for Pass the Intersection) which were correctly predicted by the model (i.e., true positives).
C. Specificity, which is the percentage of cases that did not have the observed characteristic (e.g., "no" for Pass the Intersection) and were also correctly predicted as not having the observed characteristic (i.e., true negatives).
D. The positive predictive value, which is the percentage of correctly predicted cases "with" the observed characteristic compared to the total number of cases predicted as having the characteristic.
E. The negative predictive value, which is the percentage of correctly predicted cases "without" the observed characteristic compared to the total number of cases predicted as not having the characteristic.

Table 17: Prediction Success Table for the Developed Model

Observed			Predicted		
			Decision		Percentage Correct
			Pass the Intersection	Not Pass the Intersection	
Step 1	Decision	Pass the Intersection	236	23	91.1
		Not Pass the Intersection	24	114	82.6
	Overall Percentage				88.2
a. The cut value is .500					

For choice given, if the predicted probability which is found from the model is less than 0.5, it is assumed that the model predicts the driver choice to pass and the model predicts that the driver choice to stop if the predicted probability is greater than 0.5. The model validation based on the extracted driver responses is carried out with success prediction table as shown in table above and the overall prediction accuracy was found as 88.2%. As shown from the result the proposed model is strong enough to predict the driver behaviour at the onset of yellow light at signalized intersection.

The table below shows the contribution of each independent variable to the model and its statistical significance.

Table 18: Statistical Parameters for Estimated Model

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Speed	-.156	.021	54.228	1	.000	.856	.821	.892
Distance From Stop Line	.126	.014	83.069	1	.000	1.135	1.104	1.166
Vehicle Type(1)	-.408	.444	.845	1	.358	.665	.279	1.587
Vehicle Type(2)	1.128	.481	5.496	1	.019	3.088	1.203	7.928
Constant	.861	.726	1.405	1	.236	2.366		
a. Variable(s) entered on step 1: Speed, Distance From Stop Line, and Vehicle Type.								

The Wald test ("Wald" column) is used to determine statistical significance for each of the independent variables. The statistical significance of the test is found in the "Sig." column. From these results we can see that speed (p = .000), Distance from the Stop Line (p = .000) and Vehicle Type 2 (Medium Vehicle) (p = .019) added significantly to the model/prediction, but

Vehicle Type 1 (Small Vehicle) (p = .358) did not add significantly to the model. Column Exp (β) in the Table above shows the odds ratio i.e. the percentage change in stopping probability with unit increase in the explanatory variable.

Based on the results presented in the table, the utility equation can be rewritten as:

$U_i = 0.861 - 0.156{*}V + 0.126{*}D - 0.408{*}MV + 1.128{*}LV$

$\text{Logit}(P) = \ln\left(\frac{P}{1-P}\right) = Ui = 0.861 - 0.156{*}V + 0.126{*}D - 0.408{*}MV + 1.128{*}LV$

Where: P represents the probability of a driver's decision to stop

D represents the distance from the vehicle to the stop line at yellow onset

V is the speed of a vehicle at the moment of yellow signal's turning on

MV is medium vehicle passing at the moment of yellow signals turning on and,

LV is large vehicle passing at the moment of yellow signals turning on

The negative sign for the variables speed indicates that the probability of stopping decreases with increase in speed of the same vehicle used for the analysis. The positive sign to the distance variable indicates that the vehicles stopping probability increases with the increase in vehicles distance to the stop line at the start of yellow. It should be recognized that the reference vehicle was taken as small vehicle while developing the model. Stopping probability was also found to be significantly affected by subject vehicle type; large vehicle was more likely to stop compared to medium vehicle. However, it should be noted that the model is developed based on only four intersection approaches (fewer sample size), more approaches should be considered for a sophisticated and generalized driver behaviour model.

4.3 Red-Light-Running

Many studies were conducted in order to capture the parameters affecting the driver red light running behaviour, as well as to introduce and evaluate different mitigation strategies for the red light running problems. At the onset of the yellow indication, drivers who are approaching the intersection must make a quick decision to either stop or cross the intersection. Among all the intersection-related crashes, yellow-phase-related crashes caused by the dilemma zones are of significant concern to transportation engineers. The dilemma zone, which is also known as the 'indecision period', describes the region which begins at the position where most drivers choose to stop and ends at the position where most drivers choose to cross the intersection at the onset of the yellow indication of the signal. The indecision period of the driver may have a negative impact on crash risks. Sometimes, red light runners violations occur because of the drivers' false stop/go judgment, and rear-end crashes happen due to the different drivers' decisions at the yellow duration. Many different types of dilemma zone countermeasures have been proposed, including adding the flashing yellow phases or the pavement marking at upstream of the intersection to help drivers' make better decisions during the yellow interval.

In this study, from 397 driver responses 41 of them which are 10.33% of driver responses at the yellow onset were red light runners. The average red light violation speed was 47.5 km/hr. More than half (53.6%) of the drivers ran the red light at speeds of 50 km/hr or less. The highest posted speed limit on the ring road is 50 km/hr., and only 43.9 percent of the violators ran the red light at speeds higher than that limit.

The table below shows the relationship by those drivers decided to pass, stop or red light runners on their respective distance from stop line and vehicle speed.

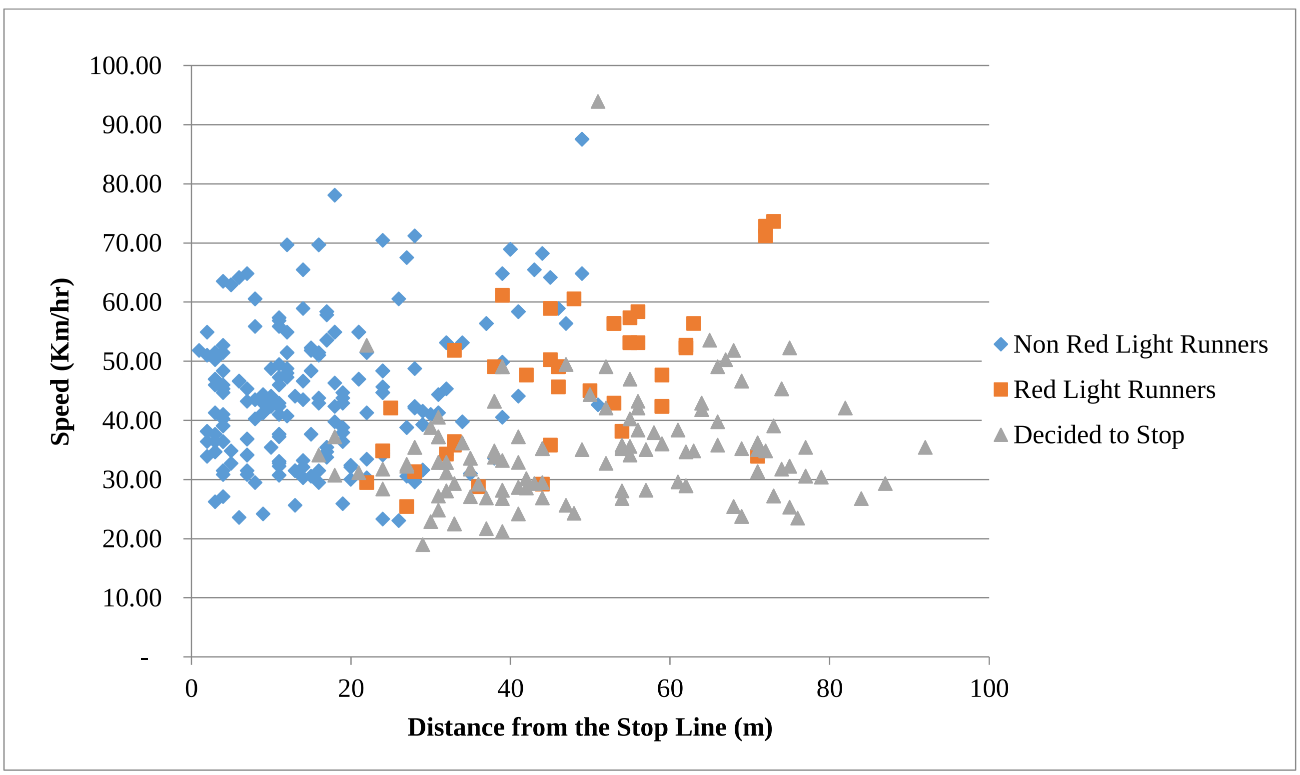


Figure 12: Red light running vehicle Vs. Non red light runners

At the yellow-light duration, drivers' false stop/go decisions can lead to red-light running (RLR) violations. Other studies shows that, no significant difference of probability of RLR violation can be found between the scenario without warning system and the scenario with flashing green. Although the flashing green can provide drivers more time to make stop/go decisions, drivers will still make decisions based on their own judgment and the preference of stop/go decisions should not change significantly for each driver. Thus, the flashing green cannot effectively decrease the percentage of false decisions by drivers.

The following conditions were found to contribute to a greater likelihood of red light running (assuming all other variables are held constant):

- The subject vehicle was a heavy vehicle (i.e., truck, bus);
- Presence of vehicles in adjacent lanes that go through;
- Absence of vehicles, bicycles, and pedestrians waiting on the side street and opposing vehicles waiting to turn left;
- Shorter yellow interval times; and
- High vehicle speed

To examine speeding by the violating vehicles, data from violation records were grouped by individual intersection and posted speed. Overall, about 53% of the violating vehicles were not speeding through the intersections at the time of the violation.

Chapter Five: Conclusion and Recommendation

5.1 Conclusion

In this study, data at four signalized intersection approaches were collected and 397 driver responses at the onset of yellow were recorded using video capturing technique for modelling the driver behaviour at the onset of yellow. The driver has two choices either to pass or stop at the signalized intersection, a binary logistic regression model has been developed to explain this driver behaviour. The application of logistic regression modelling approach to evaluate the factors influencing driver's decision at signalised intersection at the onset of yellow light on either to stop or crosses to clear the intersection. The most important findings from this investigation are summarised as follows:

- It was observed that the probability of stopping the vehicle decreased with the increase in the vehicles approaching speed.
- Driver's distance from the stop line was found to be the major factor influencing the driver's decision at the onset of amber light. Vehicles stopping probability decreased with the increase in their distance from the stop line.
- The other characteristic which has a significant effect on the stopping probability in mixed traffic condition is a type of vehicle. Stopping probability was also found to be significantly affected by subject vehicle type; large vehicle was more likely to stop compared to medium vehicle.
- Findings from this study also suggest that there is a possibility that the red light runners are due to the existence of dilemma zone at the signalized intersection. Thus, the design of a traffic signal control system to regulate traffic movements at an intersection needs to re-evaluate the implication of such a zone in order to reduce the red light running violations and hence improve the level of safety at intersections.

The developed model can be utilized to improve safety and operational performance of the signalized intersections in Addis Ababa by providing a dynamic real time pre-signal or by developing an in-vehicle warning system to eliminate the option zone at the intersections.

The study also done by a detail driver's attitudinal survey which is used to described the output by descriptive statistics. In addition that condition that affects the driver's decision making when they see yellow traffic light at the intersection was carried out by using factor analysis. Based on the result of the analysis, Emotion and understanding of the driver, Roadway and variable control condition, Comfort to drive, Presence of vehicle and police and Past experience of driver were the conditions that affect the drivers decision making process which contributed to explained 59.56 % of variance. The Emotion and understanding of the driver found to be the primer ranked factor that affects the driver's decision making when they see yellow traffic light included (Presence of passengers in the car, Whether you are tired, angry, or sad, How well you know the intersection and the drivers speed) which was contributed to 26.1 % all conditions affects the decision to cross or stop when the drivers see yellow light variance. This group of reason had most possible frequent of reason than others which was the conditions affects the decision to cross or stop when the drivers see yellow light.

5.2 Recommendation

The output of this study can be used as initial guide for transport planner, geometric designer and traffic management agency for evaluation of existing urban intersections and identifying factors which are used for decreasing accidents occurred at the intersection. This study aimed at only investigating the factors influencing the drivers decision making that could be observed from the data obtained from the recorded video on the field and through attitudinal survey. Based on this study, the following recommendations are provided for further enhancement and improvement:

- Efforts should be made in order to investigate other factors which cannot be observed from the field with the help of driving simulator or through a controlled experiment.
- The driver behavior at the intersection are usually influenced by internal and external factors such as intersection geometry, visibility of the signal, distraction due to in-vehicle technology, surrounding land-use, driver's knowledge on the phases, emotional state of the driver, and driver attributes etc. These factors can be considered in the future to enhance the driver decision model.
- Further, dilemma zone boundaries should be explored to establish various countermeasures to improve safety at the signalized intersections.
- In all of the studied intersections the yellow time and all red times on the intersection is 3s. However, the design of a traffic signal control system to regulate traffic movements at an intersection needs to re-evaluate the implication of such a zone in order to reduce the red light running violations and hence improve the level of safety at intersections.

Bibliography

[1] Papaioannou, P. Driver dilemma zone behaviour and safety effects at the urban signalized intersections in Greece, 2007.

[2] Gates, T. and Noyce, D. Dilemma zone driver behaviour as a function of the vehicle type, time of day, and platooning, 2010.

[3] Köll, H., Bader, M. and Axhausen, K. W. Driver behaviour during flashing green before amber: A comparative study, 2004.

[4] Gazis, D., Maradudin, A. and Herman, R. The problem of the amber signal light in traffic flow, 1960.

[5] Rakha, H., Amer, A. and El-Shawarby, I. Modelling driver behaviour within a signalized intersection approach decision-dilemma zone, 2008.

[6] Yang, Z., Tian, X., Wang, W., Zhou, X and Liang, H. Research on the driver behaviour in yellow interval at signalized intersections, 2014.

[7] Abbas, M., Machiani, S. G., Garvey, P. M., Farkas, A. and Lord-Attivor, R. Modelling the Dynamics of Driver's Dilemma Zone Perception by Using Machine Learning Methods for Safer Intersection Control, 2014.

[8] Zhang, Y., Fu, C. and Hu, L. Yellow light dilemma zone researches; A review Journal of the Traffic and Transportation Engineering (English Edition), 2014.

[9] Chang, G.-L., Franz, M. L. and Yang, L. Design and Evaluation of a Dynamic Dilemma Zone System for a High Speed Rural Intersection, 2012.

[10] Elmitiny, N., Yan, X., Radwan, E., Russo, C. and Nashar, D. Classification analysis of drivers stop or go decision on signalized intersection and red-light running violation, Accident Analysis and Prevention, 2010.

[11] Amer, A., Rakha, H. and El-Shawarby, I. Agent based driver's behavioural modelling framework of the driver behaviour at the onset of yellow indication at signalized intersections, 2011.

[12] Long, K., Liu, Y. and Han, L. D. Impact of countdown timer on the vehicles driving manoeuvres after the yellow onset at signalized intersections: An empirical study in Changsha, China, 2013.

[13] Moore, D. and Hurwitz, D. S. Fuzzy logic for improved dilemma zone identification. Transportation Research Record: Journal of the Transportation Research Board, 2013.

[14] Pathivada, B. K. and Perumal, V. Modelling driver behaviour at signalized intersection dilemma zone under mixed traffic conditions Retrieved from. In Transportation Research Board, 2018.

[15] Sharma, A., Bullock, D. and Peeta, S. Estimating dilemma zone hazard function at high speed isolated signalized intersection, 2011.

[16] El-Shawarby, I., Rakha, H., Inman, V. W. and Davis, G. W. Age and gender impact on driver behavior at the onset of a yellow phase on high-speed signalized intersection approaches, 2007.

[17] Savolainen, P. T., Gates, T. J. and Sharmaa, A. Driver decision making in the dilemma zone, Examining the influences of clearance intervals, enforcement cameras and the provision of advance warning through a panel data random parameters probit model, 2016.

[18] Tanga, K., Xua, Y., Wanga, F. and Oguchib, T. Exploring stop/go decision zones at rural high-speed intersections with flashing green signal and insufficient yellow time in China. Accident Analysis and Prevention, 2016.

[19] Elhenawy, M., Jahangiri, A., Rakha, H. A. and El-Shawarby, I. Modelling driver stop/run behavior at the onset of a yellow indication considering driver run tendency and roadway surface conditions, 2015.

[20] J. A. Bonneson and K. H. Zimmerman, Effect of Yellow Interval Timing on the Frequency of Red Light Running Violations at Urban Intersections, Transportation Research Record: Journal of the Transportation Research Board, 2004.

[21] Sharma, A., Bullock, D. and Peeta, S. Estimating dilemma zone hazard function at higher speed isolated intersection, Transportation Research on the Emerging Technologies, 2011.

[22] Kilpelainen, M. and Summala, H. Effects of weather and its forecasts on driver behaviour. Transportation research part F: Traffic psychology and behaviour, 2007.

[23] Retting, R. and Williams, A. Characteristics of red light violators; Results of a field investigation. Journal of Safety Research, 1996.

[24] Kimber, R. Application of fuzzy set theory on the change of intervals at a signalized intersection, 2005. Traffic and accidents: Are the risks too high?

[25] National Cooperative Highway Research Program Volume 1: A Guide for Addressing Aggressive Driving Collisions. USA, 2003.

[26] Yan, X., Guo, D. and Radwan, E. Effects of major-road vehicle speed and driver age and gender on left-turn gap acceptance, 2007.

[27] Rakha, H., El-Shawarby, and Amer, A. Modelling driver behaviour within the signalized intersection approach decision-dilemma zone, 2008.

[28] Sayer, J. R., Huang, R. W. and Mefford, M. L. The effects of lead vehicle size on driver following behaviour, 2003.

[29] Wu, W., Juan, Z. and Jia, H. Drivers' behavioural decision making at signalized intersection with countdown display unit, 2009.

Appendix

Appendix 1: Driver attitudinal survey questionnaire (English Version)

Thank you for taking the time to fill out this survey! Your feedback will help us to learn better about what drivers do when the traffic light turns to yellow at signalized intersection. The survey will take approximately 5 minutes to complete.

Section I: Personal Questions

1) Age:
- ✓ 18-24 years
- ✓ 25-35 years
- ✓ 36-60 years
- ✓ Greater than 60 years

2) Gender:
- ✓ Male
- ✓ Female

3) Education level:
- ✓ Some High School
- ✓ Vocational Training
- ✓ College Diploma or Certificate
- ✓ Bachelor's Degree
- ✓ Graduate Degree
- ✓ Other:………. (please specify)

Section II: General Driving Questions

5) How often do you drive any type of a vehicle?
- ✓ Never
- ✓ Almost every day
- ✓ Few days within a week
- ✓ Few days within a month
- ✓ Few days within a year

6) What is a type of vehicle you drive the most?
- ✓ Motorcycle
- ✓ Car
- ✓ Minibus or Van
- ✓ Bus or Truck
- ✓ Other: …… (please specify if any)

7) How many times have you been stopped by the police officer in the past year?

- ✓ None
- ✓ Once in the past year
- ✓ Twice in the past year
- ✓ Three times in the past year
- ✓ More than three times in the past year

8) Do you have ever been in an accident at signalized intersection?

- ✓ Yes
- ✓ No

9) Do you see yourself as a good driver (safe driver)?

- ✓ Yes, I see myself as a safe driver
- ✓ No, I am not a safe driver
- ✓ Do not know

Section III: Yellow Traffic Signal Light Questions:

10) How many times do you try to go through amber light and end up running through a red light?

- ✓ Very often
- ✓ Sometimes
- ✓ Rarely
- ✓ Never

11) What do you **normally** do when you face a yellow traffic light at signalized intersection?

- ✓ Speed up your vehicle
- ✓ Slow down your vehicle
- ✓ Neither speed up nor slow down your vehicle
- ✓ Hit the brakes
- ✓ It depends on the condition
- ✓ Other:…..(please explain)

12) From the following conditions which will affect your decision when you face a yellow traffic light at signalized intersection?

Your speed	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Your distance from the stop line of an intersection					
Presence of other peoples in the car					
Existence of blinking yellow traffic light					
Whether you are in conversation through the phone					
Whether it is a day time or at night					
Presence of police officer					
Whether there is a vehicle in front of you					
Whether there is a pedestrian, vehicle or bicycle in the side road					
Whether the traffic light is timed					
Whether you are tired, angry, or sad					
Whether you are familiar with the intersection					
Whether it is a **safe** intersection					
Whether you are successfully pass at yellow light before turning to red light					

13) How long do you think the traffic light stay yellow?

- ✓ 1 second
- ✓ 2 seconds
- ✓ 3 seconds
- ✓ 4 seconds
- ✓ 5 seconds
- ✓ Other: ……(please specify if there is any)

14) Is there any difference on the duration of yellow traffic lights of different intersections?

- ✓ Yes, they have difference
- ✓ No, they are all the same
- ✓ I do not know

Thank you very much for your time and cooperation.

Appendix 2: Driver attitudinal survey questionnaire (Amharic Version)

Amharic version survey questionnaire for Assessment and Modeling of Driver Behavior in Dilemma Zone of Signalized Intersection

ይህንን ጥናት የማካሂደው በአዲስ አበባ ዩኒቨርሲቲ፤ የቴክኖሎጂ ኢንስቲትዩት፤ የሲቪል እና ኢንቫይሮንሜንታል ኢንጂነሪንግ ዲፓርትመንት ስር ለማስተርስ ፕሮግራም ማሟያ ሲሆን የጥናቱም ርእስ "**ባለትራፊክ መብራት መስቀለኛ መንገዶች ላይ ዉሳኔ ለመስጠት አሽከርካሪዎች የሚያሳዩት ባህሪ መገምገም እና ሞዴል መስራት**" ነው:: የጽሁፍ ቃለመጠይቁ ከ5 እስከ 10 ደቂቃ ሊፈጅ ይችላል:: ጥያቄዎቹ ስለ ቢጫ የትራፊክ መብራት ያልዎትን ግንዛቤ የትምህርት ዝግጅት እንዲሁም ምን ያህል እንዳሽከረከሩ የሚጠይቁ ናቸው:: በዚህ ጥናት በመሳተፍዎ በቀጥታ የሚያገኙት ጥቅም ላይኖር ይችላል ሆኖም ጥናቱ መንገድ ላይ የሚደርሱ አደጋዎችን ለመቀነስ ላለዉ ጥረት ስለሚረዳ በተዘዋዋሪ እርሶንና ማህበረሰቡን የሚጠቅም ስራ እንደሚሆን ተስፋ አደርጋለሁ:: የሚገኘውን መረጃ በሚስጥር ይጠበቃል:: ስምዎ ተመዝግቦ አይያዝም:: በጥናቱ ያለመሳተፍ ሙሉ መብትዎ የተጠበቀ ነው:ለመሳተፍ ፈቅደው አንዳንድ መረጃዎችን ላለመስጠት ከፈለጉ መረጃውን ያለመስጠት መብትዎ ይከበርልዎታል:: ምናልባት መረጃውን ከሰጡ በኋላ ስለጥናቱ ማወቅ ከፈለጉ የጥናቱን አድራጊ ሰለሞን ጸጋየ በ +251-951-096722 በመደወል መጠየቅ ይችላሉ::

እባክዎ ፈቃደኝነትዎን በፊርማዎ ያረጋግጡል:: ፊርማ____________
በጥናቱ ለመሳተፍ ስላሳዩት በጎ ፈቃደኝነት አስቀድሜ ልባዊ ምስጋናየን በአክብሮት እገልፃለሁ::

ክፍል አንድ: <u>ግላዊ ጥያቄዎች</u>

1.1 *ፆታ* 1. □ ወንድ 2. □ ሴት

1.2 አድሜዎ ስንት ነው

1. □ 18-24 አመት 2. □ 25-35 አመት 3. □ 36-60 አመት 4. □ ከ60 አመት በላይ

1.3 በሞያዎ የደረሱበት ከፍተኛ የት/ም ደረጃ (የተጠናቀቀ)

1. □ ሁለተኛ ደረጃ ትምህርት
2. □ ቴክኒክ እና ሞያ ስልጠና
3. □ ዲፕሎማ
4. □ ዲግሪ
5. □ ማስተርስ
6. □ ሌሎች ካሉ ይጠቀስ _____

ክፍል ሁለት: <u>ጠቅላላ የማሽከርከር ጥያቄዎች</u>

2.1 ምን ያክል ጊዜ ያሽከረክራሉ?

1. □ በፍጹም አሽከርክሬ አላውቅም
2. □ ሁልጊዜ አሽከረክራለሁ
3. □ በሳምንት የተወሰነ ቀናቶች አሽከረክራለሁ
4. □ በወር የተወሰነ ቀናቶች አሽከረክራለሁ
5. □ በአመት የተወሰነ ቀናቶች አሽከረክራለሁ

2.2 ምን አይነት ተሽከርካሪ ነው ብዙ ጊዜ ሚያሽከረክሩት?

1. □ ሞተር ሳይክል
2. □ የቤት መኪና (ፒክ አፕን ያጠቃልላል)
3. □ ሚኒ ባስ
4. □ ከባድ መኪና ወይም ባስ
5. □ ሌላ ካለ ይጠቀስ__________________

1

Amharic version survey questionnaire for Assessment and Modeling of Driver Behavior in Dilemma Zone of Signalized Intersection

2.3 በአንድ አመት ዉስጥ ስንት ጊዜ ትራፊክ አስቁሞሃል/አስቁሞሻል?

1. ☐ ምንም
2. ☐ አንዴ
3. ☐ ሁለቴ
4. ☐ ሶስቴ
5. ☐ ከሶስት ጊዜ በላይ

2.4 መስቀለኛ መንገድ ላይ አደጋ አጋጥሞህ ያዉቃል/አጋጥሞሽ ያዉቃል?

1. ☐ አዎ
2. ☐ አጋጥሞኝ አያዉቅም

2.5 እራስከን እንደ ጠንቃቃ አሽከርካሪ ያያሉ?

1. ☐ አዎ
2. ☐ አላይም
3. ☐ አላዉቅም

ክፍል ሶስት: ከቢጫ የትራፊክ መብራት ጋር የተገናኙ ጥያቄዎች

3.1 ምን ያክል ጊዜ በቢጫ የትራፊክ መብራት ለማለፍ ሞክረህ ቀይ ሲበራብህም አቋርጠው ያውቃሉ?

1. ☐ በተደጋጋሚ
2. ☐ አልፎ አልፎ
3. ☐ ከብዙ ጊዜ አንዴ
4. ☐ አላዉቅም

3.2 እያሽከረከርክ ቢጫ የትራፊክ መብራት ሲበራ ምን ያደርጋሉ?

1. ☐ ፍጥነት እጨምራለሁ
2. ☐ ፍጥነት እቀንሳለሁ
3. ☐ ፍጥነት አልጨምርምም አልቀንስምም
4. ☐ ፍሬን እይዛለሁ
5. ☐ እንደሁኔታው ፍጥነት ልጨምርም ልቀንስም እችላለሁ
6. ☐ ሌሎች ካሉ ይጠቀስ ______________________

2

Amharic version survey questionnaire for Assessment and Modeling of Driver Behavior in Dilemma Zone of Signalized Intersection

3.3 ከሚከተሉት ዉስጥ ቢጫ የትራፊክ መብራት ስታዩ የመቆም ወይም በፍጥነት የማቋረጥ ዉሳኔዎት ላይ ተጽእኖ የሚያሳድርብዎትን ይምረጡ፡

		በፍጹም	አልፎ አልፎ	አንዳንድ ጊዜ	ብዙ ጊዜ	ሁልጊዜ
3.3.1	ፍጥነትዎ					
3.3.2	ከመስቀለኛ መንገድ ያለዎት እርቀት					
3.3.3	ተሳፋሪ አሳፍረው ከሆነ					
3.3.4	እሚበራና ሚጠፋ ቢጫ የትራፊክ መብራት ካለ					
3.3.5	ስልክ እያዎሩ እያሽከረከሩ ከሆነ					
3.3.6	ማታ እና ቀን መሆኑ					
3.3.7	ትራፊክ ፖሊስ መኖሩ					
3.3.8	ከፊት ለፊት መኪና ካለ					
3.3.9	በጎንዎት ብስክሌት፣ እግረኛ ወይንም ተሽከርካሪ መኖሩ					
3.3.10	የትራፊክ መብራቱ ሰአት ሚያሳይ ከሆነ					
3.3.11	ደከሞዎት፣ ተበሳጭተው ወይንም ከፍቶዎት ከሆነ					
3.3.12	መስቀለኛ መንገዱን በፊት ያውቁት ከነበር					
3.3.13	ለማሽከርከር ምቹ መስቀለኛ መንገድ ከሆነ					
3.3.14	ከዚህ በፊት ቀይ የትራፊክ መብራት ሳይበራብወት መስቀለኛ መንገዱን ማቋረጥ ችለው ከሆነ					

3.4 ቢጫ የትራፊክ መብራት ምን ያህል ጊዜ ሚቆይ ይመስሎታል?

1. □ 1 ሴኮንድ
2. □ 2 ሴኮንድ
3. □ 3 ሴኮንድ
4. □ 4 ሴኮንድ
5. □ 5 ሴኮንድ
6. □ ሌሎች ካሉ ይጠቀሱ ______________________

3.5 ቢጫ የትራፊክ መብራቶች የጊዜ ቆየታ አንዱ ከሌላው እንደሚለያይ አስተዉለዉ ያውቃሉ?

1. □ አዎ
2. □ አይ አላውቅም
3. □ አልገባኝም

በጥናቱ ፈቃደኛ ሆነው ስለተሳተፉ ልባዊ ምስጋናዬን እገልጻለሁ!!!

3