EXPLORATORY APPLICATIONS OF EPIDEMIOLOGICAL METHODS IN TRANSPORT SAFETY AND MOBILITY

by

EMMANUEL KOFI ADANU

STEVEN JONES, COMMITTEE CHAIR
JAY LINDLY
ALEXANDER HAINEN
SETH APPIAH-OPOKU
JOSEPH WALSH

A DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Civil, Construction & Environmental Engineering
in the Graduate School of
The University of Alabama

TUSCALOOSA, ALABAMA

2017

ABSTRACT

Evident similarities and links between the outcomes of traffic crashes and stranded (or constrained) mobility have been identified and are reported in this research. Generally, a high level of travel activities is an indicator of high crash exposure. However, studies have shown that the highest rates of traffic fatalities occur in low- and middle-income regions, where many citizens experience relatively low levels of motorized travel. This ironic observation reveals serious challenges facing transport mobility systems in the less privileged regions of the world. Studies on traffic crashes and mobility constraints also reveal that they both have individual and regional variations in their occurrence, effects, and severities. Consequently, the outcomes of traffic crashes and constrained mobility are serious public health concerns worldwide.

As public health problems, their study is analogous to the study of diseases and other injuries and thus, suitable for the application of epidemiological techniques. This dissertation therefore explores the use of epidemiological techniques to analyze traffic crashes and mobility/accessibility constraints from a human-centered perspective. The dissertation therefore consists of two major focus areas. The first part of the study applies widely used epidemiology/public health – based statistical tools to analyze traffic crashes with the aim of gaining better understanding of the human-centered causes and factors that influence these causes, and how these ultimately affect the severity of crashes. This part is further divided into two sub-sections. The first sub-section used latent class analysis to identify homogeneous clusters of human-centered crash causal factors and then applied latent class logit and random

parameters logit modeling techniques to investigate the effects of these factors on crash outcomes. The second sub-section of the first part of the dissertation applies multilevel regression analysis to understand the effects of driver residential factors on driver behaviors in an attempt to explain the area-based differences in the severity of road crashes across sub-regions. Both studies are necessary to develop potential human-centered mitigations and interventions and for the effective and targeted implementation of those countermeasures. The second part of the study provides an epidemiological framework for addressing mobility/accessibility constraints with a view to diagnosing symptoms, recommending treatment, and even discussing the idea of transmission of constrained mobility among city dwellers. The medical condition, hypomobility, has been used to connote constrained mobility and accessibility for people in urban areas. In transportation and urban studies, hypomobility can result in a diminished ability to engage in economic opportunities and social activities, hence deepening poverty and social exclusion and increasing transport costs, among other negative outcomes. The condition is especially pronounced in poor urban areas in developing countries. The framework proposed in this study is expected to help identify and address barriers to mobility and accessibility in the rapidly growing cities throughout the developing world, with particular applicability to the rapidly developing cities in Sub-Saharan Africa.

Ultimately, this dissertation explores the application of epidemiological techniques to two major transportation problems: traffic safety and constrained mobility. The techniques presented in this dissertation provide policy makers, agencies, and transport professionals with tools for evidence-based policies and effective implementation of appropriate countermeasures.

DEDICATION

This dissertation is dedicated to my parents Mr. Emmanuel Kofi Adanu (Sr.) and Mrs. Mawunyo Adanu, my siblings, and my cherished friends and loved ones for their support while I completed my Ph.D. program. I hope this achievement seals the trust you had in my abilities and also fulfils the dream you all had for me.

LIST OF ABBREVIATIONS AND SYMBOLS

AIC	Akaike's Information Criterion
BIC	Bayesian Information Criterion
CARE	Critical Accident Reporting Environment
CAPS	Center for Advanced Public Safety
DUI	Driving under influence
GDP	Gross Domestic Product
ICC	Intra-class correlation
IIA	Independence of irrelevant alternatives
IID	Independent and identically distributed
LCA	Latent class analysis
LC	Latent class
LL	Log likelihood
ML	Maximum likelihood
MNL	Multinomial logit
NMT	Non-motorized transport
RPL	Random parameters logit
UT-DAT	Urban transport data analysis tool
VKT	Vehicle-kilometers of travel
WHO	World Health Organization

φ	Vector of parameters of chosen density
β	Coefficients to be determined
θ_g	Set of group parameters
c	Number of latent classes
G	Possible number of groups in latent class analysis
π_g	Mixture proportions in latent class analysis
f	Probability density function
α_c	Latent class specific parameters
η	Log-odds
P	Probability
X	Explanatory variable
γ	Higher level regression coefficient
Z_n	Vector of latent class probabilities
Z	Sub-regional explanatory variables

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my advisor, Dr. Steven Jones, who has been an incredible mentor. He has selflessly provided me with great guidance, valuable advice, ideas, and consistent help throughout this journey. I am very fortunate to have had him share with me his knowledge and expertise in research.

My appreciation goes to all my professors especially my committee members, Dr. Jay Lindly and Dr. Alexander Hainen for the support and knowledge they shared during my academic study. I am also grateful to Dr. Seth Appiah-Opoku and Dr. Joseph Walsh for accepting to serve on my dissertation committee.

Special thanks to Ms. Connie Harris for being very helpful with all the administrative work and travel reimbursements. My appreciations also go to my colleagues, Abhay, Samwel, Sufian, Rimi, Irina, Preston, for the enormous help, support, discussions, and suggestions on my research.

I also recognize the quality time spent with my office mates, members of the UA-Chapter of African Students Association, other colleagues in the University of Alabama, especially Kyeiwaa Asare-Yeboah and Sefadzi Tay-Agbozo, and my Tuscaloosa International Friends host families. Their supports have helped to relief the challenges of studying away from my family.

I would like to thank my family for their continuous encouragement, and support in my academic pursuit; the great love, care, and the motivation I needed to undertake my Ph.D. study. My ultimate thanks go to God Almighty for granting me good health, strength, and wisdom needed to pursue my Ph.D. study.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Overview of Transport Mobility and Traffic Safety

The primary objective of transportation systems is to provide mobility and accessibility for people and goods. The ability of people to move efficiently within, and between cities to access jobs, goods, and services is a crucial driver of the quality of life, and a prerequisite for a balanced socioeconomic functioning and prosperity of society. Modern concepts of time and space have hence stimulated the development of mobility as a means of enhancing access to socioeconomic activities. Access to wide range of dispersed basic needs such as hospitals, shopping centers, and schools, among others require some convenient mode of transport. The availability of transport options, and the way they are delivered, can also present major challenges to the economic growth of a region. In today's world, motorized transport, predominantly automobile transport, has broadened the ability to reach places far away in an easier, faster way than ever before. Consequently, the demand for increased fast, long-distance travel is socioeconomically linked with processes of contemporary globalization (Hall, 2005). Transportation infrastructure investments in many regions of the world have therefore been skewed in favor of fast mobility systems, as these transport modes are considered to be drivers of socioeconomic growth. Most cities today are built around the needs of the automobile and not the people, where roadway geometry has been designed to meet the requirements of vehicles – typically at the highest speeds possible. This practice and general socioeconomic conditions of the region have led to making changes to where

and how people live (Wright, 2005; Kenworthy and Laube, 1996). Individual-level's socioeconomic status and the income level of a region dictate what mode of transport they are likely to use and their level of travel activities in general. As travel becomes faster, cheaper, and easier for those who can afford the faster motorized modes, it consequently becomes more challenging for the poor and other disadvantaged groups. This diminishes the ability of those members of society who depend on slow mobility modes, such as walking, as their primary mode of transport to engage in competitive economic and social activities. This group of road users face many challenges in meeting their daily mobility and accessibility needs. Their reach of basic necessities of life become constrained due to changes in land use pattern and transport infrastructure that favor motorized transport. Over time, the poor, disadvantaged groups, and even entire regions become alienated and may even be socioeconomically excluded, further plunging them into extreme poverty. This phenomenon is especially pronounced in poor urban areas in developing countries, where social and economic inequalities have become prominent features of the development and urbanization processes.

Another major consequence of the rapid motorized mobility paradigm has been increased traffic crashes. The World Health Organization (WHO) estimates that road traffic crashes are responsible for nearly 1.3 million deaths annually, with millions of people sustaining varying degrees of injury (WHO, 2015). Traffic crashes have been observed to exhibit geodemographic differentials in the frequency of occurrence and severities across regions. Studies of the trend of crashes reveal that they occur in clusters at specific sites, along some particular sections of the road, or concentrated in some sub-regions (Roberts and Power, 1996). It is ironic that developing economies in their early stage of the motorization process experience the highest transport-related fatalities, with people who depend on low mobility modes disproportionately represented. The

WHO (2015) further reported that more than 90% of road traffic fatalities occur in low- and middle- income countries, where it is known that many of their citizens rely on non-motorized and often slower mobility modes. Moreover, nearly half of all road traffic fatalities involve pedestrians, cyclists, and motorcyclists, the so- called vulnerable road users. It has been shown that though high- income sub-regions record high numbers of crashes, few fatalities are recorded compared to low- income sub-regions, where relatively lower number of crashes result in high fatality rates (WHO, 2015). Even within high-income countries, people from lower socioeconomic backgrounds are more likely to be involved in fatal road traffic crashes. A strong correlation can therefore be observed between crashes and socioeconomic conditions. According to Traynor (2009), the means by which economic conditions impact crash-injury severity can be grouped into two broad categories as: at regional level - public expenditures on transport infrastructure, traffic law enforcement, and emergency response and the quality of the medical care available to crash victims; and at individual level - decisions regarding vehicle choice, use of protective equipment, and driving behavior. It can therefore be noted that the disproportional distribution of crashes and traffic fatalities among regions can be attributed to a wide range of factors, broadly classified into sub-regional and individual-level characteristics. This means that chances of being involved in or dying from a road traffic crash is a function of location (where the individual involved in the crash lives and/or where the crash occurred) and what mode of transport is being used.

There is evidence of a relationship between traffic crash outcomes and transport mobility within the socioeconomic definition of a region. Extreme constraints on sustainable levels of physical mobility of people and accessibility of place are seen to negatively impact individuals' and regional socioeconomic growth and also strongly correlate with traffic fatalities. Consequently, the outcomes of these two human-centered transportation problems are serious

public health concerns worldwide. As public health problems, their study is analogous to the study of diseases and other injuries and thus, suitable for the application of epidemiological techniques. This dissertation therefore explores the techniques to analyze traffic crashes and mobility/accessibility constraints from epidemiological, etiological, and preventive perspectives. This research explores these two major transport challenges to help policy- and decision- makers develop evidence-based solutions to address them.

1.2 Traffic Safety and Constrained Mobility as Public Health Conditions

1.2.1 Traffic Crashes as a Public Health Condition

Crashes account for a significant proportion of morbidity and mortality and are responsible for more years of life lost than many diseases (Petridou and Moustaki, 2000). Putting the issue in a public health context, the WHO reported that traffic crashes were the ninth leading cause of deaths worldwide behind such killers as: heart disease, stroke respiratory/pulmonary conditions, HIV/AIDS, diarrheal diseases, and diabetes (WHO, 2014). It therefore seems possible that to study traffic crashes as a whole may be akin to studying diseases, where the individuals involved in the crash are “patients” and crash severities representing different outcomes of the disease. Like most diseases, traffic crashes are preventable if the dynamics of their causes and prevalence are fully understood. Health outcomes may vary among patients and also across geographies. This variable health-outcome of diseases feature is also exhibited by traffic crashes as it has been shown that that the number of road traffic crashes as well as severities resulting therefrom, differ in their geographic location and road user type, and possibly the causal circumstances. For instance, in 2013, WHO reported that the African region had the highest road traffic fatality rate, at 26.6 per 100,000 people, while the European region had the lowest rate, at 9.3 per 100,000 people; and

approximately half of all road traffic deaths were among those with the least protection – motorcyclists, cyclists, and pedestrians. Globally, road traffic crashes are the main cause of death among those aged 15-29 years (WHO, 2015). Such variations in the "crash-health" outcome may be linked to individual crash "patients" and or regional characteristics. Understanding the contributing circumstances that lead to these variations require detailed diagnostics of the health problem. Diagnosis of disease on the other hand depends fundamentally on causation. For instance, if it is established that the occurrence of a disease is associated with a place, it can be inferred that factors that increase the risk of the disease are present either in the persons living there or in the environment, or both (CDC, 2012). This information is a necessity in identifying treatment measures and how best to apply them. Causation is, however, not easy to establish in traffic crash analysis. According to Norman (1962), the multiplicity of factors operating in the causation pose a challenge in identifying any single preventive countermeasure adequate enough to achieve effective minimization of traffic crashes. One of the early attempts by researchers to gain in-depth understanding of crash causal factors was the Indiana Tri-Level Study. From this study, Treat et al (1979) observed that human errors and deficiencies were definite or probable causes in over 90% of the crashes examined. Vehicle factors and roadway/environmental characteristics make up 10% of the crashes. The leading direct human causes identified in the study included improper lookout (probable cause in 23% of accidents), excessive speed (17%), inattention (15%), improper evasive action (13%), and internal distraction (9%).

As a public health problem, traffic crashes may best be studied using epidemiological techniques. Methods adopted in public health for the study, control, and prevention of epidemiological conditions provide a useful framework and scientific approach for the study of traffic crashes (Norman, 1962). Identifying factors that are associated with traffic crashes will help

to identify populations at increased risk of crashes. The application of epidemiological techniques to traffic crashes will make possible the assessment of the relative influence of the different contributing factors, since it is a necessity for the application of treatment measures.

1.2.2 Constrained Mobility as a Public Health Condition

As cities get larger and the distances between homes, workplaces, and community services get longer, the use of non-motorized transport modes become less feasible. In order to overcome these long distances, urban mobility is now predominantly motorized with the automobile as the dominant mode in many cities. As a consequence of rapid urbanization, transport systems have come under growing strain, exacerbated by transport- related pollutions, traffic crashes, and an ironic decline in travel speeds in a modern era where transport means achieving fast mobility (Lerner, 2011). Many of the world's cities currently face an unprecedented mobility and accessibility crisis, and are characterized by unsustainable mobility systems. The design of transportation infrastructures and the growth of cities around the automobile have negatively impacted accessibility and mobility and have led to a degraded quality of urban life especially for vulnerable groups. In spite of the rapid growth in motorized transport, some urban dwellers face tremendous difficulties to access many places within cities. While many city dwellers suffer from inability to access basic services, lacking adequate or affordable transport to reach health care, markets, and access to socioeconomic opportunities, equally vast numbers who have access to transport spend their travel time stationary, sitting in congested cities, with degraded air quality.

Class and income disparities have been deeply embedded in the spatial arrangements and mobility challenges of many cities (UN-HABITAT 2013). Some groups in the society enjoy fast travel and the others, while depending on the slower modes, suffer the negative consequences of

the faster modes. Adams (2000) describes the phenomenon as one of the simultaneous existence and asymmetric distribution of an overabundance of mobility, defined by the medical conditions – hypermobility, and its opposite, a shortage of mobility – hypomobility. Hypermobility endangers the quality of life and the ecological sustainability of modern society (Adams, 2001). Hypermobile individuals derive benefits from their fast mobility lifestyle but do not pay the full cost of their travel behaviors. For example, the cost of traffic crashes, property damage, community severance and pollutions resulting principally from the development of high mobility transport systems are absorbed by everybody in the community, the majority of whom depend on slow transport modes, but with the highly mobile individuals deriving the most benefits from the transport system. Hypomobility (or constrained mobility), on the other hand, describes the state of insufficient mobility and reduced accessibility, resulting in usually short and infrequent trips, and consequently loss of opportunities in a world that strives on sufficient amounts of accessibility and mobility (Greico et al. 2008). Constrained mobility and reduced accessibility segregate and alienate the poor from the rest of society. Hypomobility, as a phenomenon, can affect an individual, groups, or even a region. The condition is experienced through the ability or inability of an individual or group (human characteristics) to physically move from place to place and the level of reach/accessibility of basic needs and opportunities within a given region (regional characteristics). Constrained mobility and transport inaccessibility can result in a diminished ability to engage in economic opportunities and social activities, hence deepening poverty, social exclusion, increasing costs of transport, among other negative outcomes. The transport hypomobility epidemic that has engulfed many cities is causing harm to urban dwellers and reducing the economic prosperity and viability of these cities. The condition is practically a public health concern. The condition has been observed to be especially pronounced in poor urban areas

in developing countries. The urban poor and other vulnerable groups are particularly exposed to the condition. By treating hypomobility as an urban ailment, it can be captured in a framework using epidemiological techniques. In doing so, the explicit diagnosis of causes and symptoms can lead to targeted treatments.

1.3 Motivation for the Dissertation Research

Road traffic crashes are a leading cause of deaths and injuries. Though human factors have been shown to dominate the causation of crashes (Tillman and Hobbs, 1949; Treat et al 1979; Hendricks et al 1999), many crash studies have focused mainly on roadway characteristics (e.g. Safety Performance Functions) and environmental factors. This may partly be due to the vagueness of what constitutes human factors in crash causation. Traditionally, human factors have been defined as the immediate chain of actions undertaken by a driver that resulted into the crash. This definition is premised on crash accounts as reported by the victims themselves, witnesses or by professionals trained to investigate and record crashes. Driver demographic characteristics, driving styles, and the sub-regional characteristics of where they live influence their exposure to traffic crashes (Tillman and Hobbs, 1949). It therefore seems appropriate to state that both the human-centered and societal characteristics which influence driving behavior in a way which can affect the chances of crash occurrence constitute human factors in traffic safety. It is arguable that the immediate actions leading to a crash (e.g. speeding, failure to yield, drunk driving etc.) may be the results of driving habits that have been "encouraged" by society. Societal factors such as culture, socioeconomics, and policies influence drivers' lifestyles and driving styles, irrespective of driver age or gender. For instance, some risky driving behaviors, such as failure to use seatbelt, may be normal in societies due to lack of policies or no enforcement of traffic safety laws. These extrinsic

sociocultural factors are typically unaccounted for during the crash reporting process. In effect, the root "cause" of the immediate chain of actions/events leading to traffic crashes are often either ignored or treated as though they have no bearing on the crash event.

While human factors have been limited to the immediate driver errors, crash studies involving human factors have to go beyond human errors to holistically include regional characteristics that influence the driving behaviors that put some individuals or groups among the population at greater risks of getting into road traffic crashes. It is also possible that the variations in safety performance between regions may either be directly due to differences among driving styles of people who live there; or groupings based on regions may arise for reasons more associated with the characteristics of the regions. This implies that regions and their residents can exert influences on each other, suggesting different sources of variations in crash outcomes across regions. As such, it can be argued that driver characteristics that increase the likelihood of being involved in a crash may be explained through the sub-regional characteristics of where he or she lives. Individuals who share common sub-regional characteristics are likely to be more similar than others, to the extent that they may be similar in their exposure to crashes. This means that instead of viewing each crash event as an independent unit, there may be great value in exploring similarities and possible dependencies based on the characteristics of the drivers' residential region. In the conventional crash analysis involving human factors, the influence of these regional characteristics in crash causation is masked by the immediate action leading to the crash. These factors therefore do not show up as immediate and obvious contributors to crash causation. In effect, the underlying "cause" of the human-centered crash causal factors are often either ignored all together in safety analyses, or treated as though they act independently of the crash event or the individual involved in the crash. A move from the conventional approach to traffic safety studies

therefore requires a new understanding of how underlying human characteristics, regional characteristics, and their interactions influence risky driving behaviors in crash causation.

Evident relationship between traffic crash outcomes and the level of travel activities (measured in terms of mobility and accessibility) are well known. Generally, high levels of travel activities is an indicator of high crash exposure. However, studies have shown that the highest rates of traffic fatalities occur in low and middle income regions where many of their citizens experience low levels of motorized travel. This ironic observation reveals serious challenges facing transport mobility systems in the less privileged regions of the world. Similar to crashes, transport mobility challenges vary greatly across the population. Individual and regional level factors can put constraints on the extent of mobility citizens can consume. For instance, the development of overly motorized urban mobility systems as sign of modernity and economic growth, is a driver of hypomobility for those without access to motorized transport. The situation is particularly acute in the cities of the developing world where the urbanization process and growth in motorized transport are occurring so fast that if current trends continue, these cities will soon grind to a halt for lack of adequate infrastructure. Mobility in developing cities is therefore not achieving its purpose of increasing accessibility. Land use decisions and urban transport planning practices have locked cities in extreme conditions of transport hypermobility and hypomobility. While the rich and powerful elite in the society are more likely to be hypermobile, the poor and vulnerable are more likely to be hypomobile. This segregation has seen a decline in the provision and support for mobility modes that the poor depend on. Adverse effects of the growing imbalance in the levels of mobility between the rich and the vulnerable poor city dwellers represent both public security and health concerns.

As public health problems, the study of constrained mobility/accessibility and traffic crashes study is analogous to the study of diseases and other injuries and thus, suitable for the application of epidemiological techniques. Methods adopted in public health for the study, control, and prevention of epidemiological conditions provide a useful framework and scientific approach for the study of these two transport challenges. The multiple circumstantial factors involved in their respective causations make the use of epidemiological techniques appropriate. The work performed in this dissertation therefore explores the use widely used robust epidemiological methods to study these two transportation-based public health problems. The application of epidemiological studies in this research makes possible the assessment of the relative importance of the contributing factors. Identifying factors that are associated with these conditions will help to identify populations at increased risk, so that target countermeasures and treatment measures may be effectively implemented.

1.4 Structure of the Dissertation

The primary focus of this research is to explore the use of epidemiological techniques to analyze traffic crashes and constrained mobility/accessibility. The dissertation therefore consists of two major focus areas. The first part of the study applies widely used epidemiology/public health – based statistical tools to analyze traffic crashes. This part is further divided into two sub-sections. The first sub-section sought to identify homogeneous clusters of human-related crash causal factors and also investigate the effects of these factors on crash outcomes. The second sub-section investigates the interactive effects of sub-regional and driver characteristics in explaining regional variations in traffic crash outcomes. The ultimate goal of the first part of the dissertation is to provide data-driven evidence necessary to develop potential mitigations and interventions and for

the effective and targeted implementation of human-centered crash countermeasures. The second part of the study focuses on the use of epidemiological research methodology to develop a framework to address the problem of constrained transport mobility and inaccessibility. Each sub-section of the first part and the second part of the research have examined crash causal factors related to drivers and their driving habits. This study attempts to identify homogeneous clusters of human-related crash causal factors and also investigate the effects of these factors on crash outcomes. This is achieved by using latent class analysis to identify segments of drivers based on common crash causal traits, and then developing latent class logit and random parameters logit models to identify how human-centered factors influence injury severity of crashes. Chapter 3 investigates the disparities in road traffic crashes among segments of the population and also among regions. The study applies multilevel regression analysis to understand the effects of driver residential factors on driver behaviors in an attempt to explain the area-based differences in the severity of road crashes across sub-regions. Chapter 4 provides an epidemiological framework for addressing mobility/accessibility constraints with a view to diagnosing symptoms, recommending treatment, and even discuss the idea of transmission. Finally, a summary of the studies and potential future study proposals are presented in Chapter 5.

CHAPTER 2

LATENT CLASS ANALYSIS OF THE EFFECTS OF HUMAN FACTORS ON CRASH-INJURY SEVERITIES

2.1 Introduction

Road traffic crashes occur from a combination of factors related to elements of the transportation system, made up of the road and its environment, vehicles, and road users; with crash outcomes ranging from property damage to death. Some factors contribute to the crash occurrence, while others influence the outcome of the crash, or both. While the effects of some crash causal factors such as speed can be immediately obvious, they may be linked to other unobserved factors, such as sensation seeking nature of the driver, which are not typically accounted for during the crash reporting process. Having a holistic understanding of crash causal factors and how they impact on severities is necessary to develop and target countermeasures.

There is a significant body of road safety literature dedicated to the study of factors affecting crash occurrence and severities. Multiple proposals on countermeasures have ranged from roadway reengineering, improved vehicle safety features, and strategies to influence driver behavior. The development of these proposals or countermeasures have been anchored on understanding the factors that affect the likelihood of crash occurrence and/or circumstances that influence the severity of the crash outcome. A critical component of road traffic crash analyses has been the examination of the driver. Some drivers have habits or choose to drive in ways that increase their likelihood of getting into a crash. For instance, driving styles such as choice of driving speed, threshold for overtaking, headway, and inclination to commit traffic violations have

been strongly linked to certain groups of drivers (Elander et al, 1993). According to Elander et al (1993), while certain groups of drivers may be disproportionately represented in crash statistics, this may be due to reasons not related to their risk of crash. One of the early attempts by researchers to gain in-depth understanding of crash causal factors was the Indiana Tri-Level Study. From this study, Treat et al (1979) observed that human errors and deficiencies were definite or probable cause in over 90% of the crashes examined. The leading direct human causes identified in the study included improper lookout (probable cause in 23% of accidents), excessive speed (17%), inattention (15%), improper evasive action (13%), and internal distraction (9%). In a similar study, Hendricks et al (1999) investigated the specific driver behaviors and unsafe driving acts that lead to crashes. The study further assessed the situational, driver, and vehicle characteristics associated with these behaviors. They found human error to be the most frequently cited contributing factor in 99.2% of crashes, followed by environmental (5.4%) and vehicle factors (0.5%). Thus, most crashes and their associated injuries and fatalities can be linked to some form of unsafe driving habits (Hendricks et al 1999). It is therefore important to examine the causal driver characteristics and also assess their driving behaviors that increase the likelihood of crash occurrence.

Many human-centered crash studies focus on the human errors which result in crash occurrence. In doing so, these errors are treated as the main cause of crashes, while the relationship between these errors and their human-factor catalysts are often not considered. It has therefore become necessary to expand the scope of crash studies to identify the intrinsic and extrinsic human factors that serve as moderators for the manifestation of these “errors” or failures and also investigate how these factors affect driver injury severities. This user-oriented causal analysis embodies a holistic approach where the driver characteristics are studied vis-à-vis driving characteristics in determining how these factors collectively influence crash causation and crash

outcomes. This paper therefore attempts to identify homogeneous clusters of human-related crash causal factors and also investigate the effects of these factors on crash outcomes. This is achieved by using latent class analysis to identify segments of drivers based on common crash causal traits, and then developing latent class logit and random parameters logit models to identify how human-centered factors influence injury severity of crashes.

2.2 Human-Centered Traffic Safety

Driver-related behavioral factors and human errors dominate the causation of traffic crashes (Tillman and Hobbs, 1949; Treat et al 1979; Hendricks et al 1999). Driving behaviors and styles are influenced by external and driver-specific factors. Individual and societal characteristics which influence driving behavior in a way which can affect the chances of crash occurrence collectively constitute human factors in traffic safety. Driver characteristics (e.g. gender, race, age, etc.), attitudes, beliefs, and personality traits (e.g. tolerance, caution, inattentiveness, perception of risk, sensation seeking, etc.) are some human factors that influence driving habits (Donovan, 1993; Yu and Williford, 1993; Elander et al 1993). Societal norms and cultural practices, such as enforcement of traffic rules and regulations, on the other hand, also play important roles in shaping driver attitudes and beliefs. These have impacts on driving styles and can affect traffic safety (NHTSA, 2006; Gaygisiz, 2010; Stanojevic, 2013; AAA Foundation, 2016; Atchley et al. 2014; Schlembach et al. 2016). NHTSA (2006) observed that cultural differences and sensitivities correlate with motor vehicle fatality and injury rates. In the U.S. for instance, racial and ethnic groups are disproportionately killed in traffic crashes compared with the much larger non-Hispanic White population (NHTSA, 2006). This means that with other things being equal, some human-

centered characteristics and behaviors put some groups of the driving population at greater risk of causing traffic crashes.

In an attempt to explore the causal link between human factors and the likelihood of crashes, Petridou and Moustaki (2000) distinguished behavior-related factors into two major categories: those that reduce the capability of a driver to perform driving tasks (e.g. inexperience, accident proneness, alcohol and drug use) and those factors that influence risk taking while driving (e.g. habitual disregard of traffic laws and regulations). Differences in the behavioral factors exist among different demographic groups. For instance, McGwin and Brown (1999) observed that alcohol was less likely to be a factor in traffic crashes involving older drivers, while the primary problems with young drivers are risk-taking and lack of skill. Crashes among young drivers are more likely to involve a single vehicle, one or more driving errors, speed as a factor, or involve alcohol abuse. Moller and Haustein (2013) have also observed that young males are more prone to excessive speeding influenced by peer pressure. Female drivers on the other hand are more prone to driving errors (Shi et al 2010). Other studies have shown that inexperienced drivers are more susceptible to errors and more likely to fail to recover when they get distracted (Groeger, 2006; Shi et al 2010). Gulliver and Begg (2007) conducted a study to examine the effects of personality factors assessed during adolescence on persistent risky driving behavior and traffic crash involvement among young adults. They found that for males, aggression, traditionalism, and alienation were the personality traits most frequently associated with risky driving behavior and crash risk. Willfully flouting driving laws and regulations may be indicative of risk taking behavior. Blows et al (2005) identified that unlicensed drivers were at significantly higher risk of car crash injury than those holding a valid license. Beyond the individual characteristics, certain driving styles and behaviors also affect the severity of the crash. For instance, seat-belt non-use

has been associated with increased risk of injury and death in a crash. NHTSA (2016) estimates reveal that more than half of teen drivers (13-19 years) and adults aged 20-44 years who died in crashes in 2014 were unrestrained at the time of the crash. Faster driving speeds are also known to increase the likelihood of crash occurrence, and also the severity of the crash consequences. Speeding-related fatalities constituted approximately a third of total traffic fatalities across the United States between 2005 and 2014 (NHTSA, 2016). Impairment by alcohol and other drugs, driver distraction and inattention have been cited frequently as contributing factors in crashes and these can also affect the severity of the crash outcome (e.g. Treat et al. 1979; Hendricks et al. 1999; Klauer et al. 2006; NHTSA, 2015).]. Statistics show that alcohol-impaired-driving fatalities accounted for a third of all crash fatalities in the United States in 2014 (NHTSA, 2015). Driver inattention has also been extensively linked to crash occurrence. Nearly 10 percent of fatal crashes, 18 percent of injury crashes, and 16 percent of all police-reported motor vehicle traffic crashes in 2014 were reported be distracted driving related (NHTSA, 2016).

Considering that human factors are responsible for the highest proportion of traffic crashes, countermeasure implementation should largely be human-centered. According to Ogden (1996), crash countermeasures achieve best results when they influence driver behavior. Human-centered countermeasures may take the form of improved driver training and testing, education campaigns aimed at changing driving practices, legislation to control driver behavior, and improvements to the design of road systems and automobiles (Elander et al 1993). Promoting a culture of safe road user behavior is required to achieve sustained reductions in road traffic injuries.

2.3 Crash Injury-Severity Models

The primary emphasis of crash injury-severity studies is to identify factors that influence the severity of crash outcomes. Safety researchers have relied on myriad of statistical modelling techniques, applied to post-crash records and other non-crash specific data, to gain data-driven knowledge and understanding into crash causal circumstances. Mujalli and De Ona (2011) have shown that interest in identifying factors that affect crash injury severity has increased considerably in the last few years; perhaps, due to the availability of data and proliferation of advanced statistical packages. Depending on data characteristics and scope of studies, researchers have the option of choosing from a wide range of statistical tools for crash severity studies.

Discrete-choice (logit and probit) models have been used extensively over the years to analyze crash injury severity due to the classification of the severities into discrete outcomes. These methodologies have been applied to study safety of different roadway facilities, and have included variables that describe the crash circumstances, environmental conditions, roadway, vehicle, and driver characteristics. For instance, Shankar, et al. (1996) used a nested logit formulation to predict crash severity on a section of rural interstate in Washington State. This study investigated the effect of environmental conditions, highway design, crash type, driver characteristics, and vehicle attributes on crash severity. Haleem and Abdel-Aty (2010) and Daniels et al (2010) also applied nested logit techniques to analyze crash severity at un-signalized intersections and at roundabouts respectively. Other logit modelling techniques that have been used in injury severity studies include binary logistic models (Dissanayake, 2004; Savolainen and Mannering, 2007; Peek-Asa et al, 2010; Kononen et al, 2011), ordered logit models (Abdelwahab and Abdel-Aty, 2001; Khattak and Rocha, 2003; Jung et al, 2010; Quddus et al, 2010), (Malyshkina and Mannering, 2009; Schneider et al, 2009), mixed logit (Milton et al, 2008; Morgan

and Mannering, 2011), and heterogeneous models (Quddus et al, 2010). Logit models are however not able to handle random variations and are not applicable to panel data with temporally correlated errors. They also do not allow any pattern of substitution (Train 2009). Probit models address these limitations. Ordered probit model is the most used type of probit models in crash severity analysis (e.g. Xie et al 2009; Wang, 2009; Haleem and Abdel-Aty, 2010; Zhu and Srinivasen, 2011). Khattak et al (2002) used ordered probit modeling techniques to isolate factors that contribute to injuries in older drivers involved in crashes. Abdel-Aty and Keller (2005) analyzed crashes at signalized intersections to determine the expected injury severity level using ordered probit model. Data mining techniques have also been used to analyze traffic crash injury severity. For instance, Council and Stewart (1996) and Chang and Wang (2006) used classification and regression trees and Chen and Jovanis (2000) appliedused Chi-squared automatic interaction detection to crash severities. Other advanced methodologies used in literature include Bayesian networks (e.g. Simoncic, 2004; De Ona et al. 2011), neural networks (e.g. Abdel-Aty and Abdelwahab, 2004; Delen et al. 2006), and linear genetic programming (e.g. Das and Abdel-Aty, 2010). Latent class approach has recently been used for analyzing driver injury severities (Xiong and Mannering, 2013; Chu, 2014; Yasmin et al., 2014).

The fundamental characteristics of crash data and purpose of study result in methodological limitations (Savolainen et al. 2011). Many other methods have been used for crash injury severity studies. This chapter is by no means exhaustive on the subject. Savolainen, et al. (2011) for instance, presents a review of crash injury severity models and methodological approaches. Similarly, Mujalli and De Ona (2011) undertook a meta-analysis and presents a documentation on the characteristics and limitations of different modeling methods for safety researchers.

2.4 Data Description

This study is based on 2011 – 2015 injury-related crash data for the State of Alabama, obtained from the Critical Analysis Reporting Environment (CARE) system developed by the Center for Advanced Public Safety at the University of Alabama. The data was filtered to select crashes that were reported to have human-centered factors as their primary contributing circumstance. These human-centered factors consist of driving styles, decisions, and activities undertaken by the driver, which led to the crash. For each crash event, information on the driver's license status and seatbelt use were obtained. Demographic information of the causal driver was also obtained. Observations with missing values were omitted from the dataset, resulting in a total of 87,326 observations. Table 1 shows the summary statistics of the variables available for model building and analysis.

Two categories of severity were adopted. Serious injury (defined as fatal or incapacitating injury) constituted 30% of the data and minor injury (defined as non-incapacitating injury or possible injury) made up 70% of the crash observations. Crashes involving some form of driver error (defined to include aggressive driving, failure to yield, following too close, ran traffic control device) made up approximately half of injury crashes. About 44% of injury crashes were reported to involve women.

Variable name	Description	Mean (standard deviation)
Crash Severity	Serious injury /Minor injury	0.30/0.70
Driver error	Primary cause: error attributed to driver (1=Yes, 0=No)	0.49 (0.50)
DUI	Primary cause: DUI (1=Yes, 0=No)	0.09 (0.29)
Speed	Primary cause: Speeding (1=Yes, 0=No)	0.11 (0.32)
Distracted	Primary cause: Distracted driving (1=Yes, 0=No)	0.11 (0.31)
Fatigue	Driver condition at time of crash: Fatigued (1=Yes, 0=No)	0.06 (0.23)
Invalid license	License status of causal driver: Invalid license (1=Yes, 0=No)	0.07 (0.26)
No seatbelt	Seatbelt use: No seatbelt (1=Yes, 0=No)	0.11 (0.31)
Female	Driver gender: Female (1=Yes, 0=No)	0.44 (0.50)
Black	Driver race: African American (1=Yes, 0=No)	0.24 (0.43)
Young	Driver age: less than 30 (1=Yes, 0=No)	0.42 (0.49)
Old	Driver age: more than 60 (1=Yes, 0=No)	0.15 (0.36)
Unemployed	Driver employment status: Unemployed (1=Yes, 0=No)	0.30 (0.46)

Table 2.1 Summary statistics of the variables used for model building

A third of the drivers involved in injury crashes were unemployed and about 42% of the drivers were less than 30 years old. Some 9% of the drivers were under the influence of drugs, alcohol, or medication, while 11% involved speeding.

2.5 Methodology

Unobserved heterogeneity is a critical issue in traffic safety research. Ignoring the moderating effect of unobserved variables can lead to biased estimates and incorrect inferences if inappropriate methods are used (Shaheed and Gkitza, 2014; Mannering et al., 2016). Limiting the impact of a variable to its statistical significance in a model can mean eliminating some otherwise risky factors. Ulfarsson and Mannering (2004) observed that an insignificant variable in one model may be due to lack of observations. On the other hand, significance of a variable in an injury severity model is not an automatic indication that it is an important etiologic factor.

The ordinal nature of reporting crash injury severities make ordered probit and logit models appropriate (Zhu and Srinivasan, 2011; Islam and Hernandez, 2013). However, these model forms restrict the way variables influence outcome probabilities, leading to incorrect inferences (Savolainen and Mannering, 2007; Washington et al., 2011). Compared to the traditional ordered probability models, multinomial logit (MNL) models have a flexible structure which allows each severity outcome to have a different function for capturing the probabilities of injury severities (Malyshkina and Mannering, 2008; Jones, et al, 2013; Shaheed and Gkritza, 2014). This notwithstanding, the MNL model is deficient in its application as it is susceptible to correlation of unobserved effects from one crash severity level to the next. Such correlation leads to a violation of the model's independence of irrelevant alternatives (IIA) property (Washington et al., 2011). Also, the assumption that random terms in the crash severity functions in MNL models are independent and identically distributed (IID) is often violated in practice because crash severity functions do not contain a complete list of all contributing factors. Even though nested logit models can capture some unobserved effects shared by some injury severity outcomes, they cannot address unobserved heterogeneity in the data. Random parameters (mixed logit) models and latent class (finite mixture) logit models have the ability to capture the unobserved heterogeneity by allowing parameters to differ across observations (Morgan and Mannering, 2011; Behnood and Mannering, 2015; Mannering et al. 2016). For this study, latent class analysis was first carried out to identify clusters of human-centered causal factors within a large set of heterogeneous crash data. Injury severity analysis was then performed to identify explanatory factors associated with increasing probability of particular injury severities. A traditional MNL injury severity model was first developed to identify how the human-centered variables influence crash outcomes. Random parameters logit (RPL) and latent class (LC) logit models were then estimated to address the

heterogeneity challenges inherent in the MNL model. Estimation results for the RPL and the LC logit models are then compared to select the best fitting alternative model to the MNL model.

2.5.1 Clustering of Human-Centered Factors

Latent class analysis (LCA) is a widely used model-based clustering method for discrete data (Dean and Raftery, 2010). This modeling technique is based on the assumption that each observation of a heterogeneous data comes from one of a number of classes, and models each with its own probability distribution (McLachlan and Peel, 2000; Fraley and Raftery 2002). The overall population therefore follows a finite mixture model, given as:

$$x \sim \sum_{g=1}^{G} \pi_g f\left(x|\theta_g\right) \tag{1}$$

where f is the density for group g, G is the number of groups, π_g are the mixture proportions, $0 < \pi_g < 1, \forall g, \sum_{g=1}^{G} \pi_g = 1$ and θ_g is the set of parameters for the group.

In LCA, the variables are usually assumed to be independent given knowledge of the group an observation came from, an assumption of local independence. Each variable within each group is then modeled with a multinomial density. So, given k variables, the joint group density can be expressed as a product of the individual group densities. Given that $x = (x_1, \dots, x_k)$ the joint group density is expressed as:

$$x|g \sim \prod_{i=1}^{k} \prod_{j=1}^{d_i} p_{ijg}^{1\{x=j\}} \tag{2}$$

where $1\{x = j\}$ is the indicator function equal to 1 if the observation of the ith variable takes value j and 0 otherwise, p_{ijg} is the probability of the variable i taking a value j in group g, and d_i is the number of possible values or categories the ith variable can take. The overall density is then a weighted sum of these individual densities, given by:

$$x \sim \sum_{g=1}^{G} \left(\pi_g \prod_{i=1}^{k} \prod_{j=1}^{d_i} p_{ijg}^{1\{x=j\}}\right) \tag{3}$$

The model parameters p_{ijg} and π_g can be estimated from the data (for a fixed value of G) by maximum likelihood using the EM algorithm or the Newton-Raphson algorithm or a hybrid of the two. The number of classes that gives the best model is selected based on the Bayesian Information Criterion (BIC), which is computed as:

$$BIC = 2 * \log(maximum\ likelihood) - (number\ of\ parameters) * \log(n) \quad (4)$$

where n is the number of observation. Lower BIC values indicate a better model fit. Keribin (1998) showed BIC to be consistent for the choice of the number of components in a mixture model under certain conditions, when all variables are relevant to the grouping. A difference greater than 10 in BIC values is considered strong evidence that the two models are significantly different (Kass and Raftery 1995).

2.5.2 Injury Severity Analysis

2.5.2.1 Random Parameters Logit Model

RPL model allows for heterogeneity within observed crash data by varying the elements of the vector of estimable parameters, β_i . The outcome specific constants and elements of β_i may either be fixed or randomly distributed over all parameters with fixed means. The random parameters logit model formulation is obtained from the standard MNL by introducing random parameters with $f(\beta_i|\varphi)$, where φ is a vector of parameters of the chosen density function (mean and variance) (McFadden and Train, 2000; Train, 2009; Washington et al. 2011) as:

$$P_n(i|\varphi) = \int \frac{exp(\beta_i X_{in})}{\sum_{\forall I} exp(\beta_i X_{in})} f(\beta_i|\varphi) d\beta_i \quad (5)$$

and $P_n(i|\varphi)$ is the probability of injury severity *i* conditional on $f(\beta_i|\varphi)$.

For model estimation, β_i can now account for unobserved heterogeneity of the impact of X on injury-severity outcome probabilities, with the density function $f(\beta|\varphi)$ used to determine β_i. Random parameters logit probabilities are weighted average for some different values of β across observations where some elements of the parameter vector β are fixed parameters and some may be randomly distributed. A continuous distribution relating how parameters vary across crash observations is assumed by the researcher. For this study the normal distribution is assumed for model estimation (Milton et al. 2008).

2.5.2.2 Latent Class Logit Model

LC logit model offers an alternative perspective to the random parameters logit model in terms of accommodating heterogeneity (Greene and Hensher, 2010; Behnood, and Mannering, 2015; Mannering et al., 2016). This model replaces the continuous distribution assumption of random parameter model with a discrete distribution in which unobserved heterogeneity is captured by membership of distinct classes (Greene and Hensher, 2010; Mannering and Bhat, 2014). A latent class logit model allows the driver injury severity to have C different classes so that each of the classes will have their own parameters with the probability given by (Behnood et al., 2014):

$$P_n(c) = \frac{exp(\alpha_c Z_n)}{\sum_{\forall C} exp(\alpha_c Z_n)} \quad (6)$$

where Z_n represents a vector that shows the probabilities of c for crash n, C is the possible classes c, and α_c represents the estimable parameters (class specific parameters). The probability of driver having injury severity i is given by:

$$P_n(i) = \sum_{\forall C} P_n(c) * P_n(i/c) \quad (7)$$

where $P_n(i/c)$ is the probability of drivers to have injury severity level i for crash n in class c. Based on the two equations above, the latent class logit model for class c will be:

$$P_n(i/c) = \frac{exp(\beta_{ic}X_{in})}{\sum_{\forall I} exp(\beta_{ic}X_{in})} \quad (8)$$

where I represents the possible number of injury severity levels and β_{ic} is a class-specific parameter vector that takes a finite set of values.

The latent class logit model can be estimated with maximum likelihood procedures (Greene and Hensher, 2003). The latent class method however does not account for the possibility of variation within a class since it assumes homogeneous characteristics of the within-class observations (Mannering and Bhat, 2014). Greene and Hensher (2013) and Bujosa et al. (2010) present the random parameter latent class model as an extension of the latent class logit model to capture interactions with observed contextual effects within the latent classes.

Marginal effects are typically computed to reveal the relative impact of explanatory variables on the dependent variable. Marginal effect in a latent class logit model is computed for each class as the difference in the estimated probabilities with the indicator changing from zero to one, while keeping all the other variables at their means. Greene (2007) has shown that the direct and cross-marginal effects can be computed respectively as follows:

$$\frac{\partial P_{ni}}{\partial x_{nik}} = \beta_{ik}P_{ni}(1 - P_{ni}) \quad (9)$$

$$\frac{\partial P_{nq}}{\partial x_{nik}} = -\beta_{ik}P_{ni}P_{nq} \quad (10)$$

The direct marginal effect shows the effect of a unit change in x_{nik} on the probability, P_{ni}, for crash n to result in severity i. The cross-marginal effect shows the impact of a unit change in variable k of alternative i ($i \neq q$) on the probability P_{nq} for crash n to result in outcome q. According to Greene (2007) and Xie et al. (2012), the final marginal effect of an explanatory

variable is the sum of the marginal effects for each class weighted by their posterior latent class probabilities.

2.6 Estimation Results

The objective of the first part of the study was to identify classes of human-centered causal factors contributing to injury crashes. LCA was applied to identify seven distinct classes as summarized by the fit statistics reported in Table 2. The classes organized around specific driving-related actions (speeding, not wearing a seat belt, etc.) and included demographic information to provide additional context underlying the exhibited behaviors. No significant improvement was observed beyond seven classes. The seven class model also exhibited good separation among classes as indicated by the entropy criterion (McLachlan and Peel, 2000), where entropy criterion of one (1) indicates perfect classification.

Table 3 shows the probabilities of the various human causal factors contributing to each class (parameters with class membership probability less than 0.3 were not included). The classes in table 3 were named to capture the primary human aspects defining each class. For example, Class 1, which accounted for roughly 2% of injury crashes was named *risk takers*. All drivers in this class were driving without a valid license, 77% percent were under the influence of drugs or alcohol, and with 48% probability of no seatbelt use at the time of the crash. The majority (63%) of *risk takers* were unemployed and a third were African American. It can also be inferred that the majority of *risk takers* were men as the probability of being female was less than 0.3.

Speed seekers (Class 2) were involved in about 11% of injury crashes. This group too showed a significant contribution by unemployed drivers but the largest contribution came from younger drivers. Interestingly, women were shown to be a significant proportion of *speed seekers*

– a finding that is interesting given recent evidence of increased rates of aggressive driving among females (e.g., Hennessy and Wiesenthal, 2001; Romano et al., 2008).

Class 3 was termed *reckless drivers* and comprised some 10% of injury crashes. The *reckless drivers* class was similar to the *risk takers* expect it did not include a significant portion of drivers without valid licenses. It did, however, exhibit significant probabilities of DUI and not wearing seat belts and indicated that younger and unemployed drivers were an important component of the *reckless driver* class.

The *improper drivers* class (4) accounted for 31% of injury crashes and was named such due to the high probability of driver error being the main contributing factor. Again, unemployed drivers were seen to be an important contributor to injury crashes and Class 4 indicates that women, younger drivers, and African Americans were significant to the *improper drivers* class.

Class 5 captured injury crashes attributable to *fatigued drivers* and illustrated the importance of women and young people in relation to crashes caused by tired and drowsy drivers. Class 6 indicates that some 29% of injury crashes are attributable to driver error and that *erring drivers* are mostly men (although women were found to contribute significantly to this class). Finally, distracted driving (Class 7) accounted for 12% of injury crashes. Table 3 shows that women and young people both represented half of *distracted drivers*.

Examination of the classes of human-centered factors among injury crashes revealed interesting information on what behaviors contribute to injury crashes and, to some extent, what types of drivers commit them. In order to develop a more nuanced understanding of how human-centered factors affected crash severity, series of analyses were conducted to examine the extent to which the various parameters are useful in estimating crash injury severity. A total of 12 variables were used for model building. Table 4 shows the estimation results for the RPL and the

LC logit models. Since the RPL and LC logit models are improved extensions of the standard MNL model, results for the MNL model has also been shown to confirm this.

The MNL model reveals that crashes involving fatigue, drivers with invalid license, no seatbelt use, old and unemployed drivers were more likely to result into serious injury while driver error, DUI-, speed-, and distracted driving- related crashes were more likely to be lead to minor injuries. The MNL model also shows that female drivers, young drivers, and African American drivers were more likely be involved in minor injury crashes. The effects of the parameters in the MNL model are fixed across severity levels. This implies that variables are assumed to influence either minor injuries or serious injuries, not both. The RPL model, however, reveals that driver error, speeding, distracted driving, no seatbelt use, and young driver indicators were random variables. The random variables significantly contributed to both serious and minor injury crashes. This means that some proportion of crashes involving a random variable, for instance driver error, resulted in serious injuries and some proportion resulted in minor injuries.

Two distinct classes with homogeneous attributes were identified to be significant for the LC logit model; latent class 1 (LC 1) with probability of 0.72 and latent class 2 (LC 2) with probability of 0.28. An inspection of the constant term defined for the serious injury function indicates that a crash in LC 1 is more likely to result in serious injury than a crash in LC 2. One interesting observation was that old drivers had high chance of being involved in serious injury crashes regardless of the latent class. Driver error, driver error, DUI-, speed-, and distracted driving- related crashes were likely to be lead to minor injuries in LC 2, but more likely to result in minor injury in LC 1. Similarly, crashes involving females, African American, and young drivers were likely to result in serious injury in LC 2 and minor injury in LC 1. Unemployed drivers

were more likely to be involved in serious injury crashes in LC 1 but less likely to be involved in same in LC 2.

The marginal effects (Table 5) show that old drivers and crashes involving no seatbelt use respectively had 0.73% and 1.89% higher likelihood of resulting into serious injury. This outcome is interesting as it points to a high possibility of low seatbelt usage among older drivers. Injury crashes involving unemployed drivers, drivers with invalid license, and fatigued driving respectively had 4.19%, 0.32%, and 0.05% higher chance of lead to serious injury outcome. This results also indicate that drivers with no employment have high likelihood to drive with invalid license. Another interesting result from this study is that though a high proportion of the injury crashes were attributed to driver error, DUI, and speeding, their outcomes were more likely to be minor injury.

A comparison of the fit statistics (e.g. McFadden pseudo R^2 = 0.069, 0.183, 0.193 for MNL, RPL and LC logit models respectively) suggest a stronger support for the LC logit model over the MNL and RPL models. Similar conclusions have been reported by other researchers (e.g. see Greene and Hensher, 2003; Shen, 2009; Xie et al., 2012; Wen et al., 2012). An attempt was made to develop LC random parameters logit model for this study. However, none of the random parameters had statistically significant standard deviations. There was also no significant improvement in model fit statistics when compared with the LC logit model.

2.7 Conclusion

In this paper, latent class analysis was performed to identify seven distinct classes of human-related crash causal factors. A latent class logit model and random parameters model were further developed as alternatives to the traditional multinomial logit model for crash injury severity

analysis to account for unobserved heterogeneity. The study was based on 2011 – 2015 injury-related crash data, for the State of Alabama, and considered only crashes that had human-related primary causal factors. Two crash injury outcomes were examined: serious injury (fatal and incapacitating injury) and minor injury (non-incapacitating and possible injuries). Twelve variables were used to build the models.

The latent class analysis results show that about 2% of the injury crashes involved drivers believed to be risk takers. This group consisted of male unemployed drivers with no valid driver's license and also engaged in drunk driving with no seatbelt. African Americans made up 33% of this group. Female drivers were observed to be involved in mostly crashes attributed to driver error. DUI- and speeding- related injury crashes involved high proportion of young male drivers. Fatigue related crashes involved 35% and 40% of female drivers and young drivers respectively. About half of the distracted driving-related injury crashes involved younger drivers and women.

Injury-severity analysis involved developing a random parameters model and a two-class latent class logit model. The random parameter showed that driver error, speeding, distracted driving, no seatbelt use, and young driver indicator variables had varying effects on serious and minor injuries. Serious injury crashes were more likely to involve unemployed drivers, crashes involving no seatbelt use, old drivers, fatigue driving, and drivers with no valid driver's license. Model estimation results point to high possibility of low seatbelt usage among older drivers. The results also indicate that drivers with no employment have high likelihood to drive with no license or invalid driver's license. In view of these results, recommendations can be made on targeted public awareness and education, backed by comprehensive enforcement programs especially among the identified risk takers group of drivers.

Comparison of fit statistics show that the two-class latent class logit model outperformed the random parameters model, as an alternative to the traditional MNL model. This result is generally in line with past studies in this area. An attempt was made to identify random parameters for the LC logit model. However, none of the random parameters had statistically significant standard deviations. There was also no significant improvement in model fit statistics when compared with the LC logit model. Further research, including more data and variables, may be required to explore the strengths of the LC random parameters model for injury severity analysis.

2.8 References

Abdel-Aty, M., Abdelwahab, H., 2004. Modeling rear-end collisions including the role of driver's visibility and light truck vehicles using a nested logit structure. Accident Analysis and Prevention 36 (3), 447–456.

Abdel-Aty, M., Keller, J., 2005. Exploring the overall and specific crash severity levels at signalized intersections. Accident Analysis and Prevention 37 (3), 417–425.

Abdelwahab, H.T., Abdel-Aty, M.A., 2001. Development of artificial neural network models to predict driver injury severity in traffic accidents at signalized inter-sections. Transportation Research Record 1746, 6–13.

American Automobile Association, 2016. 2015 Traffic Safety Culture Index. AAA Foundation for Traffic Safety, Washington, DC.

Atchley P., Shi J., Yamamoto T. (2014). Cultural foundations of safety culture: A comparison of traffic safety culture in China, Japan and the United States. Transportation Research Part F No. 26, pp. 317-325.

Bhat, C. 2003. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. Transportation Research Part A. 32, 495-507.

Bujosa, A., Riera, A., Hicks, R. 2010. Combining discrete and continuous representation of preference heterogeneity: latent class approach. Environmental and Resource Economics 47(4), 477–493.

Behnood, A., Roshandeh, A., Mannering, F. 2014. Latent class analysis of the effects of age, gender, and alcohol consumption on driver-injury severities. Analytic Methods in Accident Research, 3-4, 56- 91.

Behnood, A., Mannering, F. 2015. The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: some empirical evidence. Analytic Methods in Accident Research, 8, 7- 32.

Blows, S., Ivers, R. Q., Conner, J., Ameratunga, S., Woodward, M., Noton, R. 2005. Unlicensed drivers and car crash injury. Traffic Injury Prevention, 6(3), 230-234.

Chang, L.-Y., Wang, H., 2006. Analysis of traffic injury severity: an application of non-parametric classification tree techniques. Accident Analysis and Prevention 38 (5), 1019–1027.

Chen, W., Jovanis, P., 2000. Method for identifying factors contributing to driver-injury severity in traffic crashes. Transportation Research Record 1707, 1–9.

Chu, H.C., 2014. Assessing factors causing severe injuries in crashes of high-deck buses in long-distance driving on freeways. Accident Analysis and Prevention 62,130–136.

Council, F., Stewart, J. 1996. Severity indexes for roadside objects. Transportation Reseach Record 1528, 87-96.

Daniels, S., Brijs, T., Nuyts, E., Wets, G. 2010. Externality of risk and crash severity at roundabouts. Accident Analysis and Prevention, 42(6), 1966-1973.

Das, A., Abdel-Aty, M. 2010. A generic programming approach to explore the crash severity on multi-lane roads. Accident Analysis and Prevention, 42(2), 548-557.

Dean, N., Raftery, A. E. 2010. Latent class analysis variable selection. Ann Inst Stat Math 62, 11-35.

Delen, D., Sharda, R., Bessonov, M., 2006. Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks. Accident Analysis and Prevention 38 (3), 434–444.

De Ona, J., Mujalli, R. O., Calvo, F. J. 2011. Analysis of traffic accident injury severity on Spanish rural highways using Bayesian networks. Accident Analysis and Prevention 43(1), 402-411.

Dissanayake, S. 2004. Comparison of severity affecting factors between young and old drivers in single vehicle crashes. IATSS Reseach 28(2), 48-54.

Donovan, D. M. 1993. Young adult drinking-driving: Behavioral and psychological correlates. Journal of Studies on Alcohol, 54, 600-613.

Elander, J., West, R., French, D. 1993. Behavioral correlates of individual differences in road traffic crashes: An examination of methodology and findings. Psychological Bulletin, 113, 279-294.

Fraley, C., Raftery, A.E., 2002. Model-based clustering, Discriminant Analysis, and Density Estimation. Journal of the American Statistical Association 97 (458), 611-631.

Gaygisiz, E. 2010. Cultural values and governance quality as correlates of road traffic fatalities: A national level analysis. Accident Analysis and Prevention 42(6), 1894-1901.

Greene, W.H. and Hensher, D.A. 2003. A latest class model for discrete choice analysis: contrasts with mixed logit. Transportation Research Part B, 37, 681-698.

Greene, W.H., 2007. NLOGIT Version 4.0 Reference Guide. Econometric Software, Inc., Plainview, NY.

Greene, W. H., Henshar, D. A. 2013. Revealing additional dimensions of preference heterogeneity in a latent class mixed multinomial logit model. Applied Economics, 45(14), 1897-1902.

Groeger J.A. (1997). Youthfulness, inexperience, and sleep loss: the problem young drivers face and those they pose for us. Inj. Prev. Suppl 1: 19-24.

Gulliver P, Begg D. 2007. Personality factors as predictors of persistent risky driving behavior and crash involvement among young adults. Injury prevention. Journal of the International Society for Child and Adolescent Injury Prevention. 13(6):376-81.

Haleem, K., Abdel-Aty, M., 2010. Examining traffic crash injury severity at unsignalized intersections. Journal of Safety Research, doi:10.1016/j.jsr. 2010.04.006.

Hendricks, D. L., Fell, J. C. and Freedman, M. 1999. The Relative Frequency of Unsafe Driving Acts in Serious Traffic Crashes. NHTSA. DTNH22-94-C- 05020.

Hennessy, A. A., Wiesenthal, D. L. 2001. Gender, driver aggression, and driver violence: An applied evaluation. Sex Roles, 44 (11), 661-676

Islam, M., and Hernandez, S. 2013. Large- truck involved crashes: exploratory injury severity analysis. Journal of Transportation Engineering, 596- 604.

Jones, S., Gurupackiam, S., Walsh, J. 2013. Factors influencing the severity of crashes caused by motorcyclists: analysis of data from Alabama. Journal of Transportation Engineering, 139, 949 – 956.

Jung, S., Qin, X., Noyce, D., 2010. Rainfall effect on single-vehicle crash severities using polychotomous response models. Accident Analysis and Prevention 42 (1), 213–224.

Kass, R., Raftery, A. E. 1995. Bayes Factors, Journal of the American Statistical Association, 90, 773-795.

Keribin, C. (1998). Consistent estimate of the order of mixture models. Comptes Rendues de l'Academie des Sciences, Série I-Mathématiques, 326, 243–248.

Khattak, A., Pawlovich, M., Souleyrette, R., Hallmark, S., 2002. Factors related to more severe older driver traffic crash injuries. Journal of Transportation Engineering 128 (3), 243–249.

Khattak, A., Rocha, M., 2003. Are SUVs 'Supremely Unsafe Vehicles'? Analysis of rollovers and injuries with sport utility vehicles. Transportation Research Record 1840, 167–177.

Klauer, S. G., Sudweeks, J., Hickman, J. S., Neale, V. L. 2006. How risky is it? An assessment of the relative risk of engaging in potentially unsafe driving behaviors. Prepared for AAA Foundation for Traffic Safety. https://www.aaafoundation.org/sites/default/files/RiskyDrivingReport.pdf (Last accessed: May 26, 2017)

Kononen, D.W., Flannagan, C.A.C., Wang, S.C., 2011. Identification and validation of a logistic regression model for predicting serious injuries associated with motor vehicle crashes. Accident Analysis and Prevention 43 (1), 112–122.

Malyshkina, N. Mannering, F. 2008. Effects of increases in speed limit on severities of injuries in accidents. Transportation Research Record, 2083, 122-127.

Malyshkina, N., Mannering, F., 2009. Markov switching multinomial logit model: an application to accident-injury severities. Accident Analysis and Prevention 41 (4), 829–838.

Mannering, F., Bhat, C. 2014. Analytic methods in accident research: Methodological frontier and future directions. Analytic Methods in Accident Research 1, 1-22.

Mannering, F., Shankar, V., Bhat, C. 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Analytic Methods in Accident Research 11, 1-16.

McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. Journal of Applied Econometrics 15 (5), 447–470.

McGwin, G., Brown, D. B. 1999. Characteristics of traffic crashes among young, middle-aged, and older drivers. Accident Analysis and Prevention 31(3), 181-198.

McLachlan, G., Peel, D. 2000. Finite mixture models. Wiley series in probability and statistics.

Milton, J., Shankar, V., Mannering, F. 2008. Highway accident severities and the mixed logit model: an exploratory empirical analysis. Accident Analysis and Prevention 40 (1), 260–266.

Moller M, Haustein S. 2013. Peer influence on speeding behaviour among male drivers aged 18 and 28. Accident; analysis and prevention. 64C:92-9

Morgan, A., Mannering, F., 2011. The effects of road-surface conditions, age, and gender on driver-injury severities. Accident Analysis and Prevention 43 (5), 1852–1863.

Mujalli, R. O., De Ona, J. 2011. Injury severity models for motor vehicle accidents: a review. Proceedings of the Institution of Civil Engineers. http://dx.doi.org/10.1680/tran.11.00026

National Center for Statistics and Analysis, Distracted Driving: 2013 Data, in Traffic Safety Research Notes. DOT HS 812 132. April 2015, National Highway Traffic Safety Administration: Washington, D.C.

National Highway Traffic Safety Administration, 2015. Traffic Safety Facts: Alcohol-impaired driving. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812231 (Last accessed: May 26, 2017)

National Highway Traffic Safety Administration, 2016. Traffic Safety Facts: 2014 Data – Occupant Protection. Washington, DC: Available at https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812262 (Last accessed: May 26, 2017)

National Highway Traffic Safety Administration, 2016. Traffic Safety Facts: Speeding. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812021 (Last accessed: May 26, 2017)

National Highway Traffic Safety Administration, 2006. Race and ethnicity in fatal motor vehicle traffic crashes 1999-2004. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809956 (Last accessed: May 26, 2017)

Ogden, K. W. 1996. Safer roads: a guide to road safety engineering. Melbourne, Ashgate Publishing Ltd.

Peek-Asa, C., Britton, C., Young, T., Pawlovich, M., Falb, S., 2010. Teenage driver crash incidence and factors influencing crash injury by rurality. Journal of Safety Research 41 (6), 487–492.

Petridou E., and Moustaki M., 2000. Human factors in the causation of road traffic crashes. European Journal of Epidemiology 16: 819-826.

Romano, E., Keley-Baker, T., Voas, R. 2008. Female involvement in fatal crashes: Increasingly riskier or increasingly exposed? Accident Analysis and Prevention, 40, 1781-1788.

Quddus, M. A., Wang, C., Ison, G. G. 2010. Road traffic congestion and crash severity: econometric analysis using ordered response models. Journal of Transportation Engineering, 136(5), 424-435.

Savolainen, P., Mannering, F. 2007. Probabilistic models of motorcyclists' injury severities in single- and multi- vehicle crashes. Accident Analysis and Prevention, 39, 955- 963.

Savolainen, P., Mannering, F., Lord, D., Quddus, M. 2011. The statistical analysis of crash-injury severities: a review and assessment of methodological alternatives. Accident Analysis and Prevention, 43, 1666- 1676.

Schlembach, C., Furian, G., Brandstatter, C. 2016. Traffic (safety) culture and alcohol use: cultural patterns in the light of results of the SARTRE 4 study. European Transport Research Review, 8:7. doi:10.1007/s12544-016-0194-8

Schneider, W. H., Savolainen, P. T., Zimmerman, K. 2009. Driver injury severity resulting from single-vehicle crashes along horizontal curves on rural two-lane highways. Transportation Research Record 2012, 85-92.

Shaheed, M. S., Gkritza, K. 2014. A latent class analysis of single-vehicle motorcycle crash severity outcomes. Analytic Method in Accident Research. Vol. 2, 30-38.

Shankar, V., Mannering, F., 1996. An exploratory multinomial logit analysis of single-vehicle motorcycle accident severity. Journal of Safety Research 27 (3), 183–194.

Shen, J. 2009. Latent class model or mixed logit model? A comparison by transport mode choice data Applied Economics, 41, 2915–2924.

Shi J, Bai Y, Ying X, Atchley P. 2010. Aberrant driving behaviors: a study of drivers in Beijing. Accident; analysis and prevention. 42(4):1031-40.

Simoncic, M. 2004. A Bayesian network model of two-car accidents. Journal of Transportation Statistics, 7(2-3), 13-25.

Stanojevic P, Jovanovic D, Lajunen T. 2013. Influence of traffic enforcement on the attitudes and behavior of drivers. Accident; analysis and prevention. 52:29-38.

Train, K., 2009. Discrete Choice Methods with Simulation. Cambridge University Press, New York, NY.

Treat J. R., Tumbas N. S., McDonald S. T., Shinar D., Hume R. D., Mayer R. E., Stansifer R. L., and Catellan N. J. (1979). Tri-level study of the causes of traffic accidents: Final report, vol.1: Causal factor tabulations and assessments. DOT HS-805 085. Indiana University: Institute for Research in Public Safety.

Ulfarsson, G., Mannering, F. 2004. Differences in male and female injury severities in sport-utility vehicle, minivan, pickup and passenger car accidents. Accident Analysis and Prevention 36 (2), 135–147.

Wang, Z., Chen, H., Lu, J., 2009. Exploring impacts of factors contributing to injury severity at freeway diverge areas. Transportation Research Record 2102, 43–52.

Washington, S., Karlaftis, M., Mannering, F. 2011. Statistical and econometric methods for transportation data analysis (2nd ed.). Boca Raton, FL: Chapman and Hall/ CRC.

Wen, C.H., Wang, W.C., Fu, C. 2012. Latent class nested logit model for analyzing high-speed rail access mode choice. Transportation Research Part E 48 (2), 545–554.

Xie, Y., Zhang, Y., Liang, F., 2009. Crash injury severity analysis using Bayesian ordered probit models. Journal of Transportation Engineering 135 (1), 18–25.

Xie, Y., Zhao, K., Huynh, N., 2012. Analysis of driver injury severity in rural single-vehicle crashes. Accident Analysis and Prevention 47, 36–44.

Xiong, Y., Mannering, F. L., 2013. The heterogeneous effects of guardian supervision on adolescent driver-injury severities: a finite-mixture random parameters approach. Transportation Research Part B 49(1), 39–54.

Yasmin, S., Eluru, N., Bhat, C.R., Tay, R., 2014. A latent segmentation based generalized ordered logit model to examine factors influencing driver injury severity. Analytic Methods in Accident Research 1, 23–38.

Yu, J., Willford, W. R. 1993. Alcohol and risk/sensation seeking: Specifying a causal model of high risk driving. Journal of Addictive Diseases, 12, 79-96.

Zhu, X., Srinivasan, S., 2011. A comprehensive analysis of factors influencing the injury-severity of large-truck crashes. Accident Analysis and Prevention 43 (1), 49–57.

	Number of classes					
Fit statistics	2	3	4	5	6	7
Log-likelihood	-422683.30	-416732.11	-412901.8	-411805.47	-411342.48	-411089.35
G-squared	27955.01	16052.63	8391.92	6199.34	5273.36	4767.12
AIC	28001.01	16122.63	8485.92	6317.34	5415.36	4933.12
BIC	28216.69	16450.84	8926.66	6870.61	6081.16	5711.44
CAIC	28239.69	16485.84	8973.66	6929.61	61852.16	5794.44
Entropy	1.00	0.99	0.87	0.73	0.71	0.74

Table 2.2. Criteria for class number selection

Variable	Class 1 (2%): risk takers	Class 2 (11%): speed seekers	Class 3 (10%): reckless drivers	Class 4 (31%): improper drivers	Class 5 (5%): fatigued drivers	Class 6 (29%): erring drivers	Class 7 (12%): distracted drivers
Driver error				0.81		0.76	
DUI	0.77		0.78				
Speed		0.95					
Distracted							0.67
Fatigue					1.00		
Invalid license	1.00						
No seatbelt	0.48		0.37				
Female		0.42		0.59	0.35	0.37	0.50
Black	0.33			0.31			
Young		0.56	0.38	0.51	0.40		0.48
Unemployed	0.63	0.38	0.42	0.50			

Table 2.3. Classes of human causal factors and their class probabilities

	MNL		RPL		LC 1		LC 2	
Variable	Serious injury	Minor injury	Serious injury	Minor injury	Serious injury	Minor injury	Serious injury	Minor injury
Constant	-0.26 (-13.23)		-0.12 (-4.45)		0.69 (11.94)		-20.67 (-0.06)	
Driver error		0.95 (50.05)		2.19 (7.61) [rp]		1.64 (23.24)		-17.71 (-0.05)
DUI		0.26 (8.99)		0.43 (9.43)		1.26 (8.40)		-19.83 (-0.06)
Speed		0.39 (14.93)		0.94 (4.13) [rp]		0.83 (11.60)		-16.92 (-0.05)
Distracted		1.26 (41.57)		6.10 (5.74) [rp]		2.48 (29.16)		-9.81 (-0.53)
Fatigue	0.14 (4.35)		0.02 (0.47)		-2.19 (-12.81)		47.11 (0.00)	
Invalid license	0.10 (3.44)		0.13 (2.71)		0.09 (1.41)		0.35 (1.21)	
No seatbelt	1.01 (41.70)		2.46 (8.71) [rp]		1.59 (21.19)		-1.64 (-3.52)	
Female		0.17 (10.90)		0.26 (9.09)		0.26 (8.10)		-0.28 (-1.50)
Black		0.12 (6.77)		0.17 (5.89)		0.18 (5.29)		-0.04 (-0.21)
Young		0.23 (13.38)		0.55 (6.58) [rp]		0.43 (10.21)		-1.16 (-4.19)
Old	0.11 (4.77)		0.11 (3.42)		0.11 (2.11)		0.50 (1.34)	
Unemployed	0.22 (12.74)		0.38 (11.56)		0.40 (10.85)		-0.60 (-2.55)	
Latent Class Probability					0.72 (74.94)		0.28 (29.71)	
Log-likelihood at zero			-60529.77			-60529.77		
Log-likelihood at convergence	-49584.82		-49451.9			-48868.27		
McFadden Pseudo R^2	0.069		0.183			0.193		

Halton draw of 200 was used for the RPL model (Bhat 2003). The random parameters found in the RPL model (indicated by rp superscripts) were assumed to be normally distributed (see Milton et al., 2008) and had statistically significant standard deviations at 0.05 significance level.

Table 2.4. Model Estimation Results

	Driver error	DUI	Speed	Distracted	Fatigue	Invalid license	No seatbelt	Female	Black	Young	Old	Unemployed
Serious injury	-13.18%	-1.50%	-1.28%	-0.88%	0.05%	0.32%	1.89%	-4.93%	-1.73%	-1.99%	0.73%	4.19%
Minor injury	3.80%	0.94%	0.78%	0.37%	-0.03%	-0.18%	-1.73%	1.95%	0.69%	1.17%	-0.35%	-2.24%

Table 2.5. Marginal Effects of the variables on probabilities of the severity outcomes (%)

CHAPTER 3

MULTILEVEL ANALYSIS OF THE ROLE OF HUMAN FACTORS IN SUB-REGIONAL DISPARITIES IN CRASH OUTCOMES

3.1 Introduction

Road safety is both a public health and socioeconomic concern. The World Health Organization (WHO) estimates that about 1.25 million deaths occur annually through road traffic crashes, with millions of people sustaining various degrees of injury (WHO, 2013). Globally, road traffic crashes are the main cause of death among those aged 15-29 years (WHO, 2015). To be able to improve traffic safety, there is the need to understand the underlying causes and prevalence of crashes. In an attempt to understand the general distribution of crashes by causal factors, Treat et al. (1979) categorized the relationship among three groups of risk factors contributing to road crashes: human factors, roadway factors, and vehicle-related factors (Treat et al., 1979). The study cited human factors as the probable cause of about 93% of crashes. A growing body of research has examined the disparities in road traffic safety among population groups and among geographic regions (e.g., Abdalla et al., 1997; Ameratunga et al., 2006; Factor et al., 2008; Anderson, 2010; Sehat et al., 2012). These studies reveal disparities in crash outcomes that exist between people and regions with different socioeconomic status and have overwhelmingly observed the disproportionately high fatalities in low income regions (e.g., Nantulya and Reich, 2003; Traynor 2009; Chen et al., 2010; Harper et al., 2015; WHO, 2015).

Humans play major roles, directly or indirectly, in crash causation. Human factors-focused traffic safety analyses, however, often focus on issues that directly contribute to crashes such as

driver error (e.g., failure to yield) and risky actions (e.g., speeding or overtaking) discerned during the crash reporting process. There are, however, complex relationships between traffic safety and the broader social, economic, and environmental context of the humans involved (Tillman and Hobbs, 1949; Abdalla et al., 1997; Lu et al., 2000; Kim et al., 2006; Choudhry et al., 2007; Factor et al., 2008; Traynor 2009; Anderson, 2010; Lee et al., 2014). Indeed, considerable work has been done to define and explore how safety behavior relates to deeper cultural currents (AAA, 2007; Rakauskas et al., 2009; Lund and Rundmo, 2009; Albrecht et al., 2013; Edwards et al., 2014; Atchley et al., 2014; Nordfjaern et al., 2014; AAA, 2015).

Understanding the influence of both direct and indirect factors is particularly relevant to crash studies involving human elements as it has long been established that people are influenced by the sociocultural and economic conditions of where they live; people sharing the same context are more likely to be similar (Hox, 2010). The net effect of these factors on traffic safety require some in-depth analysis of historical crash data by considering the bigger social network of the people involved.

Quantitative crash studies are undertaken to uncover hidden patterns in crash data or to predict the safety performance of facilities. Studies are carried out to investigate relationships between crash occurrence and various potentially contributing factors. Such crash prediction models (e.g., Safety Performance Functions) are popular techniques to predict crash frequency for a particular facility or location type (e.g. Jones et al., 1991; Miaou and Lum, 1993; AASHTO, 2010; Brimley et al., 2012, Mehta et al., 2015). For other purposes, crash studies may be concerned with identifying factors that affect severities of crash outcomes (e.g. Shankar and Mannering, 1996; Al-Ghamdi, 2002; Quddus et al., 2002; Abdel-Aty and Keller, 2005). Crash models have evolved with the development of sophisticated statistical methods to improve the accuracy of crash

prediction. Crash prediction and analytical studies generally involve exploring multiple years of crash records. These studies generally lead to understanding the dynamics of crash causes, usually limited to the factors gathered at the time of the crash or factors believed to be directly linked to the crash occurrence. If it is established, for instance, that a high proportion of a type of crash occurs at a particular location, it can be inferred that the factors that contribute to this trend may be attributable to the characteristics of the people involved or to the location characteristics, or some interaction between both. Similarly, if crash analyses reveal an overrepresentation of certain groups of the population in crashes, then further investigations may be required to understand why such trends exist.

Human behaviors may be influenced by external local characteristics of where they live. Drivers from different regions are therefore likely exhibit different driving characteristics. As such, behaviors that expose drivers to crashes may indirectly be traceable to where they live or come from. This paper explores human-related crash causal factors and is premised on the common assumption that sub-regional (local) factors interact with driver characteristics to influence the occurrence and severity of crashes. The clustering of crashes within regions introduces multilevel correlation among observations and this can have implications for crash model parameter estimates. For this reason, the study applies multilevel regression analysis to investigate the associations between area of residence of a driver and their crash – injury severities. Exploring these underlying relationships can bring clearer understanding of the fundamental effects of regional characteristics on the direct human-centered causes of traffic crashes, with the aim of reforming the implementation of countermeasures to achieve the desired results.

3.2 Multilevel Regression in Traffic Safety Analysis

Understanding the human-centered elements that lead to disparities in crash outcomes among regions requires investigating the relationship between individuals and the segment(s) of society in which the live. Individuals are influenced by the social groups to which they belong and the groups are in turn influenced by the individuals who make up that group (Jencks and Mayer, 1990; Jones and Duncan, 1995; Kreft and De Leeuw, 1998; Wilkinson, 1999; Snijders and Bosker, 1999; Raudenbush and Bryk, 2002; O'Connell and McCoach, 2008). Social groups may be categorized based on the characteristics of the population which constitute the group. A category of social groups can be defined based on similarities (e.g. risk taking behaviors, beliefs, socioeconomic characteristics) of the people. It is therefore possible to define a category to contain social groups that are widely separated. Individuals and their societies may hence be viewed as a hierarchical system of individuals nested within societies (Hox, 2010). Since human errors are responsible for over 90% of road traffic crashes, it is possible that disparities in crash frequencies and consequent severities between regions may either be due to the driving characteristics of the people (direct human factors) in those regions. On the other hand, clusters of crashes may arise for reasons less strongly associated with the people who live in the regions (indirect human factors). This implies that regions and their residents can exert influences on each other in crash causation, suggesting different sources of variation in crash outcomes. Due to this nested structure, the odds of an individual getting into a crash are not truly independent because individuals who share common sub-regional characteristics (e.g. driving regulations, land use pattern, social networks, socioeconomic characteristics, roadway features) may be similar in their exposure and involvement in crashes. In effect, the characteristics of crashes (measured through severity, type and causes) involving drivers from the same sub-region would be correlated. This means that

instead of viewing each crash victim as an independent unit, there is value in exploring similarities and possible dependencies based on the social groups to which they belong. This presents crash data in a hierarchical structure where crash victims are nested within regions (or contexts).

The general idea that there exists bidirectional influential effects between individuals and the social contexts or groups to which they belong, and that the individuals and the social groups are conceptualized as a hierarchical system of individuals nested within groups is the sine qua non of multilevel research. Individuals from the same geographical area are seen to be more similar to each other than are individuals from different geographical areas as this spatial proximity tends to influence/reflect social grouping (Hox, 2010). Samples of individuals from different geographical areas are therefore not completely independent. The average correlation, expressed as intraclass correlation (ICC), between variables measured on individuals from the same geographical area would therefore be expected to be higher than the average correlation between variables measured on individuals from different geographical areas (Hox, 2010). ICC is an indication of the proportion of the variance explained by the grouping structure in the population. The partition of variance at different levels of the hierarchical structure improves statistical estimation (Merlo, 2003). Standard statistical tests are based on the assumption of independence of the observations. If this assumption is violated, which is always the case for hierarchical data, the estimates of the standard errors of conventional statistical tests may be wrong and possibly lead to an overstatement of statistical significance.

The use of multilevel analysis allows for the exploration of causal heterogeneity (Western, 1998). Specifying cross-level interactions makes it possible to determine whether causal effect of lower-level predictors is influenced by higher-level predictors (Steenbergen and Jones, 2002). Multilevel modeling allows simultaneous study of ecological (or regional) and individual-level

risk factors, which is particularly useful in understanding how sub-regional factors translate into differences in individual-level risk (Bryk and Raudenbush, 1992; DiPrete and Forristal, 1994; Huttner and Eeden, 1995; O'Campo et al., 1997; Gelman and Hill, 2007). Multilevel analysis eliminates potential confounding of individual-level explanatory models caused by the omission of higher-level factors. Conducting an analysis at any of these levels while ignoring the lower levels (e.g., individuals) or contextual levels (e.g., sub-regions) can lead to erroneous conclusions. Studies have shown that ignoring a level of nesting in data can impact estimated variances and power to detect covariate effects (Julian, 2001; Shadish et al., 2002; Moerbeek, 2004), can also inflate Type I error rates (Wampold and Serlin, 2000), and may lead to significant errors among regression estimates (Rodriguez and Goldman, 1995; Goldstein, 2003) and consequently in the interpretation of results (Nich and Carroll, 1997; Snijders and Bosker, 1999). Multilevel models have been developed to properly account for the hierarchical (correlated) nesting of data (Heck and Thomas, 2000; Klein and Kozlowski, 2000; Raudenbush and Bryk, 2002; Goldstein, 2003) and are frequently used for research in a variety of disciplines such as education, sociology, political science, and public health. Increasing number of public health studies apply multilevel regression analysis to investigate the associations between area of residence and individual health outcomes (Diez-Roux, 2000; Kawachi and Berkman, 2003), with many of these studies focusing on traditional measures of association such as fixed effects using regression models to find the relationship between neighborhood characteristics and individual health (Merlo, 2003). Even though multilevel techniques have been successfully used in a wide range fields, the traffic safety community has been slow in embracing it.

Traffic crash data also exhibit hierarchical structure due to the data collection and clustering process (Huang and Abdel-Aty, 2010). The inclusion of site-specific random effects and time

factors to improve the explanatory power of crash models by Shankar et al. (1998) was the first attempt in using hierarchical models for studying traffic crashes. Since then other traffic safety researchers have explored the use of modeling techniques to account for the potential cross-group heterogeneity arising from hierarchical crash data structure (e.g. Chin and Quddus, 2003; Jones and Jorgensen, 2003; Lenguerrand et al., 2006; Mitra and Washington, 2007; Huang et al., 2008; Huang and Abdel-Aty, 2010). Some safety researchers have also adopted random parameter modeling techniques similar to multilevel models in which parameters are allowed to have varying effects among crash locations (e.g, Li et al., 2008; Huang et al., 2009; El-Basyouny and Sayed, 2009). Recognizing the hierarchical structure in crash data ensures that the varying relationships between crash count/severities and exposure across locations are appropriately accounted for in crash studies.

3.3 Multilevel Logistic Analysis

Logistic regression techniques have been applied to understand the effects of selected predictor variables on crash-injury severities, especially in studies where specific injury categories are of interest. Considering the disparity in local safety performance within a region, different regression models may be developed for each locality or a single model may be developed for the entire region by ignoring the disparity, as is done in many cases. If the crash data can be organized into a hierarchical structure with clusters of crashes in some defined categories, then the appropriate approach for data analysis should be based on nested sources of variability – arising from different levels of the hierarchy. In that case, developing a single regional level logistic regression model for the analysis of crash-injury severities without accounting for the sub-regional disparities may lead to inaccurate inferences. Multilevel logistic regression models recognize the

hierarchical structure in data and also provide information to compute the amount of variability in the data attributable to each level of the hierarchy. While traditional logistic regression assumes independence of crash observations, multilevel logistic regression takes into consideration dependency of observations in defined groups.

As an illustration of the use of multilevel regression in crash analysis, consider that a researcher wants to investigate the effect of some characteristics of a driver's region of residence on the outcome of a crash. Specifically, the researcher may be interested in understanding the likelihood of individual drivers (level 1) from different sub-regions (level 2) getting involved in a fatal crash. So a binary response variable is created in terms of "fatal crash", defined as Y=1 if the severity of the crash is fatal and 0 otherwise.

First, each group of n_j drivers within j sub-regions is assumed to follow a sub-region specific logistic regression. For a crash involving *i*th driver from the *j*th sub-region, observe a binary response,

$$Y_{ij} = \begin{cases} 1 & \text{for a fatal crash,} \\ 0 & \text{for non fatal crash} \end{cases}$$

$Y_{ij}|p_{ij} \sim$ Bernouilli (p_{ij}), where $p_{ij} = \Pr(Y_{ij} = 1)$.

The probability, p_{ij} of driver *i*, from sub-region *j*, getting into a fatal crash, given one parameter measured on the driver, X_i (e.g. age) is then given by equation 1.

$$\text{logit}(p_{ij}) = \eta_{ij} = \beta_{0j} + \beta_{1j}X_{ij} \qquad (1)$$

where η_{ij} is the log odds of driver *i* in sub-region *j* getting into a fatal crash for, β_{0j} is the intercept or the average log odds of getting into a fatal crash specific to sub-region *j*, X_{ij} is a driver level predictor for driver *i* in sub-region *j*, and β_{1j} is the slope, showing the relationship between the driver level variable and the log odds of getting into a fatal crash. It must be noted that unlike hierarchical linear models where error variance is included at level 1, the variance in a multilevel

model is a function of the population mean and is directly determined by this mean for hierarchical generalized linear models with binary outcomes (Luke, 2004). The difference between Equation 1 and the traditional regression model is the assumption that each sub-region has a different intercept coefficient β_{0j} and may have different slope coefficient β_{1j}.

The next step in the hierarchical regression model is to explain the variation of the regression coefficients, and introducing explanatory variables at the sub-regional level. This means assuming that both the intercept and the slope (effect of the level 1 variable) from Equation 1 are not fixed across sub-regions but vary depending on some sub-regional variable Z_j (e.g. average household income) then:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j} \qquad (2)$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}Z_j + u_{1j} \qquad (3)$$

where γ_{00} provides the log odds of getting into a fatal crash at a typical sub-region, Z_j is a sub-regional explanatory variable for sub-region *j*, γ_{01} is the slope associated with this predictor, u_{0j} and u_{1j} are the sub-regional level error terms showing unique effects associated with sub-region *j*, γ_{10} is the average effect of the driver-level predictor, and γ_{11} is the slope showing the relationship between the sub-region predictor and fatal crash rate in sub-region *j*.

The combined level 1 and level 2 model is then created by substituting the values of β_{0j} and β_{1j} into equation 1 as:

$$\eta_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{11}X_{ij}Z_j + \gamma_{01}Z_j + u_{1j}X_{ij} + u_{0j} \qquad (4)$$

In the case where the effect of the driver level predictor is modeled as fixed across sub-regions (i.e. equation 3 is not substituted into equation 1), then Equation 4 represents a random intercept-only model. Suppressing the sub-region errors so that Equation 4 becomes a fixed effects model and amenable to standard regression requires assuming that driver-level effects are the same

across sub-regions. The equation represents a random intercepts random slopes model if driver level predictors are also allowed to vary across sub-regions (nesting).

For the random intercept-only model, the log odds of driver *i* from sub-region *j* getting into a fatal crash η_{ij}, is hence determined by combining the log odds of getting into a fatal crash by a typical driver from a typical sub-region (γ_{00}), the effects of the driver-level ($\gamma_{10}X_{ij}$) and sub-regional level ($\gamma_{01}Z_j$) predictors, and the sub-regional level error $[u_{0j}, u_{0j} \sim N(0, \tau_{00})]$. An additional effect due to nesting driver-level parameters in sub-regions ($\gamma_{11}X_{ij}Z_j$) and $u_{1j}X_{ij}$ are included for the random intercept random slopes model.

For easy interpretation, the log odds of getting into a fatal crash may be converted into probabilities as:

$$\eta_{ij} = \log\left(\frac{p_{ij}}{1 - p_{ij}}\right) \tag{5}$$

$$p_{ij} = \frac{e^{\eta_{ij}}}{1 + e^{\eta_{ij}}} \tag{6}$$

where p_{ij} is the probability of a driver *i* from sub-region *j* getting into a fatal crash and 1 - p_{ij} is the probability if the crash is not fatal.

3.4 Multilevel Parameter Estimation and Fit Statistics

Multilevel models are generally estimated using maximum likelihood (ML) methods. In multilevel linear modeling, estimating the model parameters via ML estimation allows the researcher to assess model fit by either conducting a likelihood ratio test when examining differences in the deviance or by investigating the change in Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) when the models are either nested or not nested and differ in both fixed and random effects. Given the non-normal nature of the outcome variables in

hierarchical generalized linear models, the use of the traditional ML estimation is not appropriate. However, there are several estimation techniques available for hierarchical generalized linear models that are approximate to ML or are "quasi-likelihood" strategies. These estimation techniques are based on integral approximation or based on linearization methods. Integral approximation methods (such as adaptive Gaussian quadrature, Laplace approximation, and importance sampling) approximate the log likelihood function of the generalized linear mixed models and numerically optimize the approximated function. Linearization proceed on the other hand methods iteratively. The process starts with approximate parameter values that are improved in each successive iteration. For this study, Laplace approximation is adopted because it allows model fit assessment using strategies similar to multilevel linear models. Fit statistics provide the basis to assess and compare models at every stage of the model building process. The models developed for this study are nested, hence model assessment is done by examining the change in AIC, BIC, and the deviance between models. Smaller AIC, BIC, and deviance values indicate better model fit. However, models with more parameters will most likely have lower fit statistics. For this reason, likelihood ratio test is used to investigate whether or not the change in the deviance is statistically significant. This likelihood ratio test is similar to a Chi-square difference test, where $\chi 2$ is equal to the difference in the deviance of the simpler model (i.e., the model with fewer parameters to be estimated) minus the deviance of the more complex model, and with degrees of freedom (df) equal to the difference in the number of parameters between the two nested models. The deviance test between two models is performed as:

$$\chi^2_{diff} = -2 * (LL_{Model\,1} - LL_{Model\,2}) \qquad (7)$$

Raftery (1995 as cited in O'Connell and McCoach, 2008) proposed that differences in BIC between 0-2 provide weak evidence favoring the more complex model; 2-6 provide positive

evidence for favoring the more complex model, 6-10 provide strong evidence; and differences above 10 provide very strong evidence favoring the more complex model. However, researchers are allowed to make the ultimate determination depending on the sensitivity of the study. All fit statistics were examined in the following case study application.

3.5 Multilevel Crash Analysis Case Study

In order to illustrate the potential for crash causation knowledge gained from multilevel analysis, a case study of crash data from the State of Alabama is presented. Specifically, crash data between 2009 and 2013 were obtained from the Critical Analysis Reporting Environment (CARE), developed by the Center for Advanced Public Safety (CAPS) at the University of Alabama (CAPS, 2015). The data was grouped by the postal code (i.e., sub-county level) of the driver who caused the crash. The data was filtered and only the driver demographic characteristics (age, gender, race, and employment status) and proxies for driving behaviors (primary contributing circumstance such as speeding, condition at the time of crash such as intoxicated, validity of driver's license, and safety equipment use) were obtained. After exploring and cleaning the data, a total of 414,806 individual crash records, consisting of 25,830 serious injury (fatal and incapacitating injury) crashes and 388,976 minor injury and property damage only crash observations were available for model estimation. Additionally, socio-demographic and travel behavior data by postal codes were obtained from the U.S. Census Bureau (U.S. Census Bureau, 2010; 2013). Finally, average credit score rating data produced by Experian was obtained for the postal code level as this has been shown to be a reliable measure of general risk taking behavior, including risky driving (Brockett and Golden, 2007; Rivero, 2011). The average VantageScore for each postal code was used.

The primary objective of this case study is to investigate the effects of driver and sub-region (i.e., causal driver's residential postal code) level characteristics on the likelihood of a crashresulting into serious injuries. Hence, using driver characteristics (defined as level 1) and sub-region information (defined as level 2), two-level hierarchical models are developed to understand the relationship between serious injury crash rates and predictor variables at both levels. The specific research questions explored include:

1. What is the serious injury crash rate of Alabama drivers? Do serious injury crash rates vary across sub-regions? (Model 1)
2. How much variance in serious injury crash rates is attributable to the sub-region of a driver's residence? (Model 1)
3. What is the relationship between driver characteristics and the likelihood of getting into a serious injury crash while controlling for sub-regional characteristics? (Model 2)
4. Does the influence of any driver-level predictor vary among sub-regions? (Model 3)
5. What is the relationship between the sub-region and the likelihood of a serious injury crash while controlling for driver characteristics? (Model 4)

To answer the research questions, the model process began with an empty, unconditional model with no predictors. This model only includes a random intercept and provided information to investigate the existence of a possible sub-regional (or contextual) effect on crash outcomes. This model provides an overall estimate of the serious injury crash rate for drivers at a typical sub-region, as well as providing information about the variability in serious injury crash rates between sub-regions. The log odds (or rate), η_{ij} of driver *i*, from sub-region (postal code) *j*, causing a serious injury crash is only function of the sub-region, expressed as:

$$\eta_{ij} = \gamma_{00} + u_{0j} \tag{8}$$

The model estimation results are presented in Table 1 with the fit statistics.

The Model 1 intercept estimate (-2.57) is the log odds of a driver from a typical postal code causing a serious injury crash (where $u_{0j} = 0$). The log odds is then converted into probability for easy interpretation. Substituting the log odds into Equation 6 will help answer the first part of the first research question, in terms of the probability of a serious injury crash involving a typical Alabama driver.

$$Probability_{serious\ injury} = p_{ij} = \frac{e^{-2.57}}{1 + e^{-2.57}} = 0.07$$

$$Probability_{no\ serious\ injury} = 1 - p_{ij} = 0.93$$

Model 1 also shows a statistically significant covariance estimate. This indicates variability in the log odds of a driver causing a serious injury crash across postal codes (as shown in the random intercept), providing response to the second part of the first research question. The unconditional model (Model 1) therefore revealed that the probability of drivers from a typical postal code in Alabama causing a serious injury crash is 0.07 (first part of research question 1). However, the serious injury crash rate for drivers varies significantly across postal codes (second part of research question 1).

	Model 1	Model 2	Model 3	Model 4[a]
Fixed effects				
Intercept	-2.57* (0.02)	-2.97* (0.02)	-2.97* (0.02)	-3.30* (0.08)
Age (ref. age < 30years)		-0.19* (0.01)	-0.19* (0.02)	-0.19* (0.02)
Gender (ref. male)		0.08* (0.01)	0.08* (0.01)	0.08* (0.01)
Employment status (ref. unemployed)		0.29* (0.02)	0.29* (0.02)	0.28* (0.02)
Race (ref. African American)		-0.09* (0.02)	-0.10* (0.02)	-0.11* (0.02)
License status (ref. Invalid)		0.32* (0.02)	0.32* (0.02)	0.32* (0.02)
Seatbelt usage (ref. not used)		1.78* (0.02)	1.78* (0.02)	1.78* (0.02)
Condition at time of crash (ref. DUI)		0.64* (0.02)	0.64* (0.03)	0.64* (0.03)
Primary contributing factor (ref. speed)		0.78* (0.02)	0.78* (0.02)	0.78* (0.02)
Distracted driving (ref. yes)		0.17* (0.05)	0.13* (0.06)	0.13* (0.06)
Postal code average Credit Score				-0.01* (0.01)
Postal code mean travel time to work				0.01* (0.01)
Postal code average population				-0.01* (0.01)
Error Variance				
Intercept	0.26* (0.01)	0.20* (0.01)	0.19* (0.01)	0.15* (0.01)
Age (ref. age < 30years)			0.01* (0.01)	0.01* (0.01)
Employment status (ref. unemployed)			0.04* (0.01)	0.04* (0.01)
Race (ref. African American)			0.02* (0.01)	0.03* (0.01)
Seatbelt usage (ref. not used)			0.04* (0.01)	0.04* (0.01)
Condition at time of crash (ref. DUI)			0.05* (0.02)	0.05* (0.02)
Distracted driving (ref. yes)			0.15* (0.07)	0.15* (0.07)
Model fit				
-2 Log Likelihood	188125.20	175281.90	175196.60	175094.50**
AIC (smaller is better)	188129.20	175303.90	175230.60	175134.50**
BIC (smaller is better)	188138.00	175352.50	175305.70	175222.80**

Note: *p<0.05; ** = significant improvement in Fit statistics. Entries show parameter estimates with standard errors in parentheses; Estimation method = Laplace. [a]Best fitting model

Table 3.1. Multilevel logistic models of serious injury crashes by driver postal codes

From the covariance estimate for Model 1 shown in Table 1, ICC can be computed to answer the second research question. ICC indicates how much of the total variation in the probability of getting into a serious injury crash is accounted for by the postal code of the driver

residence. In hierarchical generalized linear models, there is assumption of no error at level 1, therefore, a slight modification is needed to calculate the ICC. This modification assumes that the binary outcome comes from an unknown latent continuous variable with a level-1 residual that follows a logistic distribution with a mean of 0 and a variance of $\frac{\pi^2}{3}$ (Rasbash et al., 2003; Goldstein, 2003; Enders and Tofighi, 2007). Therefore, 3.29 is used as the level-1 error variance in calculating ICC.

$$ICC = \frac{\tau_{00}}{\tau_{00} + 3.29} = \frac{0.26}{0.26 + 3.29} = 0.073$$

This indicates that 7.30% of the variability in the serious injury crash rate is accounted for by the postal codes of the driver residence, leaving 92.70% of the variability to be accounted for by the drivers or other factors. In other words, elements common to the sub-region (e.g., safety culture, infrastructure condition, emergency response) influence crash severity beyond the immediate driver behavioral (i.e., human) contributing factors.

The model building process progressed by adding the driver level covariates first as fixed effects (Model 2) to answer the third research question, then allowing them to vary across postal codes (Model 3) to answer the fourth research question. Model 3 shows that six out of the nine driver level variables varied significantly across postal codes. The postal code level covariates are added in Model 4 to provide answer to the last research question.

After examining the fit statistics, it was determined that Model 4 is the best fitting model, justifying the usefulness of nesting. It should be noted that for proper interpretation of the intercept values, predictor variables that did not have a “meaningful zero” values were grand-mean centered (Hofmann and Gavin, 1998; Enders and Tofighi, 2007).

3.6 Discussion of Result

The objectives of this paper have been set out in five research questions for which four multilevel models were developed as shown in the preceding section. Model estimation has revealed that postal code of residence account for about 7.3% of the variability in the probability of a driver causing a serious injury crash, regardless of the driver characteristics. It has also been shown that the proportion of serious injury crashes varies with respect to the postal codes of drivers' residence. Some sub-regional characteristics and driver characteristics have been identified to be significant covariates for explaining the occurrence of serious injury crashes. Discussion of the multilevel model estimation results of these factors is grouped under the driver demographics and driving behaviors and sub-regional characteristics.

3.6.1 Driver Demographics and Driving Behavior

The driver-level variables used in this study include demographic information and indicators of risky driving behaviors. Results show that the odds of getting into a serious injury crash increase with drivers' age. Drivers under 30 years old were less likely to be seriously injured in a crash. Males compared to females had a higher chance of being involved in a serious injury crash. This may partly be because more men than women drive on daily basis. The odds of unemployed driver getting into a serious injury crash is 1.32 times higher than employed, self-employed, or retired drivers. Unemployed drivers are likely to drive older cars with fewer safety features and may not be able to withstand the impact of most crashes. Also, unemployed drivers may not be able to keep up with the costs of regular basic vehicle maintenance, hence increasing their exposure to more severe injuries during crashes. African American drivers have 0.47

probability of getting into serious injury crashes compared to Caucasian drivers. This may be attributed to the relatively low vehicle ownership and low African American driver population.

Driving is a complex activity that requires the driver to be alert at all times. Alcohol and other drugs affect a driver's ability to effectively perform driving tasks. Likewise, any form of unwanted distraction to the driver can lead to crashes. Sometimes these distractions may range from objects or persons inside or outside the vehicle to thoughts in the mind of the driver. The causal driver's mental condition and alertness can therefore affect the severity of a crash. From this study, the odds of DUI-related and distracted driving related crashes resulting into serious injuries are 1.89 and 1.14 times higher. These findings confirm existing knowledge from literature that DUI and distracted driving crashes can lead to serious injuries.

Some information recorded by law enforcement officers when crashes occur may be indicative of the driving behaviors and habits of the driver involved. Variables believed to convey information on risky driving habits were obtained from the Alabama crash records and used in model building. Results indicate that the probability of serious injuries were higher for drivers with no, suspended, or invalid license, driving with no seatbelt, and speed-related crashes. The odds of getting into serious injury crash is 5.90 times and 2.17 times higher for drivers who did not use seatbelts and for drivers who were engaged in speeding respectively. It is debatable that these driving habits may not be one-time events for most of the crash victims but are traits that have been developed over time.

The effects of gender, license status of driver, and speeding on the occurrence of serious injury crashes have been found to be fixed across postal codes. However, the study has shown that sub-regional disparities exist in the occurrence of serious injury crashes involving unemployed drivers, young drivers, and African American drivers among postal codes. Some driving habits

have also been found to be significantly common among drivers from some postal codes than others. Study results reveal disparities in the proportions of serious injury crashes involving no seatbelt usage, DUI, and distracted driving. This information reveals the human-centered factors that account for the sub-regional variations in safety performance.

3.6.2. Sub-Regional Characteristics

Local (sub-regional) factors are known to indirectly influence driver behaviors in crash causation. For instance, sub-regional socioeconomic status affect investment in the development, operation, and maintenance of local transportation infrastructure. Similarly, enforcement of driving regulations and quality of emergency response services are both linked to regional socioeconomic characteristics (i.e., availability and quality of services). Lack of enforcement of driving regulations can result in the emergence of bad safety culture in a region and may subsequently affect the local driving behavior of drivers. Also, the nature of the road network, the absence of rapid emergency response service, and well-equipped trauma centers can make a difference in the post-crash injury severity of crash victims. An indirect relation between regional socioeconomic characteristics on one hand and the occurrence of crashes on the other hand is observable.

Sub-regional factors can be a reflection of the aggregate effect of the characteristics of the people who live in the sub-region. Such locality-specific factors may generally be used as proxy for individual characteristics if information is unavailable at the individual level. One such factor used in this study as a sub-regional covariate is the average postal code credit score. Credit score information at the postal code level was used as a measure of the average “riskiness” of residents of that postal code. Model estimation results show that on average, drivers who lived in postal

codes with high credit score had a lower chance of causing serious injury crashes. High credit score is assumed to be an indicator of risk aversion (financial) – a trait that is believed to be exhibited in other aspects of life, including driving. As such, high credit score is assumed to be a reflection of low risky driving behavior. The model results supported the assumption that regions that have high average credit score are likely to have less risky drivers, hence low frequency of serious injury crashes. Using average commute time as a measure of level of travel activities, drivers who lived in postal codes with high mean travel time to work were more likely to be involved in serious injury crashes. The longer amount of time spent traveling on the road is an expression of increased exposure to crashes, predominantly, fatigue related crashes. Drivers from highly populated postal codes have a relatively lower chance of getting into serious injury crashes. Postal code population correlates with other socioeconomic indicators such as median household income. A higher population in a postal code may be indicative of the presence of booming economic activities. High postal code population hence gives a somewhat good socioeconomic outlook though in some cases, high variances may exist among residents. Consequently, it can be argued that different sub-regional characteristics influence the driver characteristics/behaviors that lead to crashes differently. Regional factors may therefore be important in explaining why crash frequencies and severities linked to different driver characteristics and behaviors differ among regions.

3.7 Conclusions and Recommendations

Given the hierarchical structure inherent in crash data, the use of many traditional crash analysis techniques that do not account for data structure can lead to erroneous inferences. Statistical methods such as hierarchical analysis have been developed to take care of the

deficiencies in the traditional approaches. One such method is multilevel modeling. Multilevel modeling incorporates parameters that vary at more than one level and gives a researcher the ability to know the amount of variability in the response variable due to nesting of different levels of data. Even though multilevel techniques have been successfully used in a wide range fields, the traffic safety community has been slow in embracing it.

This study demonstrates the robustness and relative ease of using multilevel modeling approach in human-focused crash studies. Multilevel logistic regression has been used to explore the influence of sub-regional characteristics on human-centered factors in explaining the differential safety performance of sub-regions. The sharing of sub-regional contexts may be reasons for the clustering of risky driving behaviors of drivers which may subsequently be linked to the high occurrence of serious injury crashes in those regions. Model estimation results have shown that on the average, the probability of a driver from a typical postal code in Alabama causing a serious injury crash is 0.07 while the postal code of the causal driver accounts for about 7.3% of the variability in this probability irrespective of the driver characteristics. Some postal code characteristics and driver characteristics have been identified to be significant covariates for explaining the occurrence of serious injury crashes. The study has shown that sub-regional disparities exist in the occurrence of serious injury crashes involving unemployed drivers, young drivers, and African American drivers among postal codes. Postal code credit score, mean travel time to work, and population were also shown to be statistical significant in explaining regional influence on serious injury crash rates. Some driving habits have also been found to be significantly common among drivers from some postal codes than others. Study results reveal disparities in the proportions of serious injury crashes involving no seatbelt usage, DUI, and distracted driving.

These information reveal the human-centered factors and sub-regional characteristics that account for the sub-regional variations in safety performance.

The use of multilevel modeling techniques for traffic crash analysis present decision and policy makers with strong analytical tool to formulate evidence-based policies. The variability in serious injury crash rates observed across sub-regions in this study mean that sub-regions may be targeted for the implementation of specific countermeasures.

3.8 References

Abdalla, I. M., Raeside, R., Barker, D., McGuigan, R.D., 1997. An Investigation into the Relationships between Area Social Characteristics and Road Accident Casualties. Accident Analysis and Prevention 29 (5), 583–593.

Abdel-Aty, M., Keller, J., 2005. Exploring the overall and specific crash severity levels at signalized intersections. Accident Analysis and Prevention 37, 417–425.

Albrecht, C., Li, W., Gkritza, K., 2013. Improving Traffic Safety Culture in Iowa – Phase II. InTrans Report No. 11-398. Center for Transportation Research and Education, Iowa State University, Ames, IA.

Al-Ghamdi, A. S., 2002. Using logistic regression to estimate the influence of accident factors on accident severity. Accident Analysis and Prevention 34, 729–741.

Ameratunga, S., Hijar, M., Norton, R., 2006. Road-traffic injuries; confronting disparities to address a global health problem. Lancet, 367 (9521), 1533-1540.

American Automobile Association, 2007. Improving Traffic Safety Culture in the United States: The Journey Forward. AAA Foundation for Traffic Safety, Washington, DC.

American Automobile Association, 2015. 2014 Traffic Safety Culture Index. AAA Foundation for Traffic Safety, Washington, DC.

Anderson T., 2010. Using geodemographics to measure and explain social and environment differences in road traffic accident risk. Environmental and Planning A. 42(9), 2186-2200.

American Association of State Highway and Transportation Officials, 2009. Highway Safety Manual, Washington DC.

Atchley, P., Shi, J., Yamamoto, T., 2014. Cultural foundations of safety culture: A comparison of traffic safety culture in China, Japan and the United States. Transportation Research Part F No. 26, 317-325.

Brimley, B. K., Saito, M., Schultz, G. G., 2012. Calibration of Highway Safety Manual Safety Performance Function, Development of New Models for Rural Two-Lane Two-Way Highways. Transportation Research Record: Journal of the Transportation Research Board, No. 2279, 82-89.

Brockett, P. L. Golden, L. L., 2007. Biological and psychobehavioral correlates of credit scores and automobile insurance losses: Toward an explication of why credit scoring works. The Journal of Risk and Insurance. Vol. 74, No. 1, 23-63.

Bryk, A. S., Raudenbush, S. W. 1992. Hierarchical linear models. Newbury Park, CA: Sage.

Center for Advanced Public Safety, 2015. Critical Analysis Reporting Environment (CARE). Available at http://care.cs.ua.edu/care.aspx

Chen, H. Y., Ivers, R. Q., Martiniuk, A. L., Boufous, S., Senserrick, T., Woodward, M., Stevenson, M., Norton, R., 2010. Socioeconomic status and risk of car crash injury, independent of place of residence and driving exposure: results from the DRIVE Study. Journal of Epidemiology and Community Health 64 (11), 998-1003.

Chin, H. C., Quddus, M. A., 2003. Applying the random effect negative binomial model to examine traffic accident occurrence at signalized intersections. Accident Analysis and Prevention 35, 253–259.

Choudhry, R., Fang, D., Mohamed, S., 2007. The nature of safety culture: A survey of the state of the art. Safety Science. Vol. 45, 993–1012.

Diez-Roux, A. V., 2000. Multilevel Analysis in Public Health Research. Annual Review of Public Health. No. 21, 171-192.

DiPrete, T. A., Forristal, J. D., 1994. Multilevel models: Methods and substance. Annual Review of Sociology, Vol. 20, 331–357.

Edwards, J., Freeman, J., Soole, D., Watson B., 2014. A framework for conceptualising traffic safety culture. Transportation Research Part F No. 26, 293-302.

El-Basyouny, K., Sayed, T., 2009. Collision prediction models using multivariate Poisson-lognormal regression. Accident Analysis and Prevention 41, 820–828.

Enders, C. K., Tofighi, D., 2007. Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. Psychological Methods, Vol. 12, 121-138.

Factor, R., Mahalel, D., Yair, G., 2008. Inter-group differences in road-traffic crash involvement. Accident Analysis and Prevention, Vol. 40, 2000-2007.

Gelman, A., Hill, J., 2007. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press.

Goldstein, H., Browne, W., Rasbash, J., 2002. Partitioning variation in generalized linear multilevel models. Understanding Statistics. Vol. 1, 223–32.

Goldstein, H., 2003. Multilevel statistical models. 3rd Ed. London: Edward Arnold.

Harper, S., Charters, T. J., Strumpf, E. C., 2015. Trends in Socioeconomic Inequalities in Motor Vehicle Accident Deaths in the United States, 1995-2010. American Journal of Epidemiology182 (7), 606-614.

Heck, R. H., Thomas, S. L., 2000. An introduction to multilevel modeling techniques. Mahwah, NJ: Erlbaum.

Hofmann, D. A., Gavin, M. B., 1998. Centering decisions in hierarchical linear models: Implications for research in organizations. Journal of Management, Vol. 24, 623-641.

Hox, J. J., 2010. Multilevel analysis: techniques and applications. 2nd ed. Routledge, New York, NY.

Huang, H., Chin, H. C., Haque, M. M., 2008. Severity of driver injury and vehicle damage in traffic crashes at intersections: a Bayesian hierarchical analysis. Accident Analysis and Prevention 40, 45–54.

Huang, H., Chin, H. C., Haque, M. M., 2009. Empirical evaluation of alternative approaches in identifying crash hotspots: naive ranking, empirical Bayes and full Bayes. Transportation Research Record 2103, 32–41.

Huang, H., Abdel-Aty, M., 2010. Multilevel data and Bayesian analysis in traffic safety. Accident Analysis and Prevention 42, 1556 – 1565.

Huttner, H., Eeden, P., 1995. The Multilevel Design. Wesport, Conn: Greenwood Press.

Jencks, C., Mayer, S. E., 1990. The social consequences of growing up in a poor neighborhood. In: Jr LL, McGeary M, eds. Inner city poverty in the US. Washington: National Academy Press, 111–86.

Jones, B., Jansen, L., Mannering, F.L., 1991. Analysis of the frequency and duration of the freeway accidents in Seattle. Accident Analysis and Prevention 23, 239–255.

Jones, K., Duncan, C., 1995. Individuals and their ecologies: analysing the geography of chronic illness within a multilevel modelling framework. Health and Place, Vol.1, 27–40

Jones, A. P., Jorgensen, S. H., 2003. The use of multilevel models for the prediction of road accident outcomes. Accident Analysis and Prevention 35, 59–69.

Julian, M., 2001. The consequences of ignoring multilevel data structures in nonhierarchical covariance modeling. Structural Equation Modeling, Vol. 8, 325-352.

Kawachi, I., Berkman, L.F., 2003. Neighborhoods and health. New York, NY: Oxford University Press.

Kim, K., Brunner, I.M., Yamashita, E.Y., 2006. Influence of land use, population, employment, and economic activity on accidents. Transportation Research Record: Journal of the Transportation Research Board 1953, 56-64.

Klein, K.J., Kozlowski, S.W., 2000. Multilevel theory, research, and methods in organizations: Foundations, extensions and new directions. San Francisco: Jossey-Bass.

Kreft, I., De Leeuw, J., 1998. Introducing multilevel modeling. Thousand Oaks, CA: Sage Publications.

Lee, J., Abdel-Aty, M., Choi, K., 2014. Analysis of residence characteristics of at-fault drivers in traffic crashes. Safety Science. Vol. 68, 6-13.

Lenguerrand, E., Martin, J.L., Laumon, B., 2006. Modeling the hierarchical structure of road crash data: application to severity analysis. Accident Analysis and Prevention 38, 43–53.

Li, W., Carriquiry, A., Pawlovich, M.,Welch, T., 2008. The choice of statistical models in road safety countermeasures effectiveness studies in Iowa. Accident Analysis and Prevention 40, 1531–1542

Lu, T., Chou, M., Lee, M., 2000. Regional mortality from the motor vehicle injury: relationships among place-of-occurrence, place-of-death and place-of-residence. Accident Analysis and Prevention 32, 65-69

Luke D. A., 2004. Multilevel modeling. Thousand Oaks, CA: Sage.

Lund, I., Rundmo, T., 2009. Cross-cultural comparisons of traffic safety, risk perception, attitudes and behaviour. Safety Science, Vol. 47, 547-553.

Mehta, G., Li, J., Fields, R. T., Lou, Y., Jones S., 2015. Safety performance function development for analysis of bridges. Journal of Transportation Engineering, Vol. 141, Issue 8

Merlo, J., 2003. Multilevel analytical approaches in social epidemiology: measures of health variation compared with traditional measures of association. Journal of Epidemiology and Community Health, 57 (8), 550-552.

Miaou, S. P., Lum, H., 1993. Modeling vehicle accidents and highway geometric design relationships. Accident Analysis and Prevention 25, 689–709.

Mitra, S., Washington, S., 2007. On the nature of over-dispersion in motor vehicle crash prediction models. Accident Analysis and Prevention 39, 459–468.

Moerbeek, M., 2004. The consequences of ignoring a level of nesting in multilevel analysis. Multivariate Behavioral Research, Vol. 39, 129-149.

Nantulya, V. M., Reich, M. R., 2003. Equity dimensions of road traffic injuries in low- and middle-income countries. International Journal of Injury Control and Safety Promotion. Vol. 10, Issue 1-2, 13-20.

Nordfjaern, T., Simsekoglu, O., Rundmo, T., 2014. Culture related to road traffic safety: A comparison of eight countries using two conceptualizations of culture. Accident Analysis and Prevention, Vol. 62, 319-328.

Nich, C. Carroll, K., 1997. Now you see it, now you don't: A comparison of traditional versus random-effects regression models in the analysis of longitudinal follow-up data from a clinical trial. Journal of Consulting and Clinical Psychology, Vol. 65, 252-261.

O'Campo, P., Xue, X., Wang, M., 1997. Neighborhood risk factors for low birthweight in Baltimore: A multilevel Analysis. American Journal of Public Health. Vol. 87, 1113-1118.

Rakauskas, M. Ward, N., Gerberich, S., 2009. Identification of differences between rural and urban safety cultures. Accident Analysis and Prevention. Vol. 41, 931-937.

Rasbash, J, Steele F, Browne, W., 2003. A user's guide to MLwiN. Version 2.0. Documentation Version 2.1e. London: Centre for Multilevel Modelling Institute of Education University of London.

Raudenbush, S. W. Bryk, A. S., 2002. Hierarchical linear models: Applications and data analysis methods 2nd Ed. Thousand Oaks, CA: Sage.

Rivero, J., 2011. From credit scores to "behavioral scores": What numbers say about you. Forbes Oct 28, 2011. http://www.forbes.com/sites/moneywisewomen/2011/10/28/from-credit-scores-to-behavioral-scores-what-numbers-say-about-you/#250cc9b15afd (last accessed 20 June 2016).

Rodriguez, G., Goldman, N., 1995. An assessment of estimation procedures for multilevel models with binary responses. Journal of the Royal Statistical Society, Series A 158, 73-89.

Sehat, M., Naieni, K. H., Asadi-Lari, M., Foroushani, A. R., & Malek-Afzali, H., 2012. Socioeconomic Status and Incidence of Traffic Accidents in Metropolitan Tehran: A Population-based Study. International Journal of Preventive Medicine, 3(3), 181–190.

Shadish, W., Cook T., Campbell D., 2002. Experimental and quasi-experimental designs for generalized causal inference. Boston, MD: Houghton Mifflin.

Shankar, V. N., Mannering, F., 1996. An exploratory multinomial Logit analysis of single-vehicle motorcycle accident severity. Journal of Safety Research 27 (3), 183–194.

Shankar, V. N., Albin, R. B., Milton, J. C., Mannering, F. L., 1998. Evaluation of median crossover likelihoods with clustered accident counts: an empirical inquiry using the random effect negative binomial model. Transportation Research Record 1635, 44–48.

Snijders, T. A. B. Bosker, R. J., 1999. Multilevel analysis: An Introduction to basic and advanced multilevel modeling. Thousand Oaks, CA: Sage.

Steenbergen, M. R., Jones, B. S., 2002. Modeling multilevel data structures. American Journal of Political Science 46(1), 218–237.

Tillman, W. A., Hobbs, G. E., 1949. The accident prone automobile driver: a study of the psychiatric and social background. American Journal of Psychiatry 106, 321–331.

Traynor, T. L., 2009. The relationship between regional economic conditions and the severity of traffic crashes. Traffic Injury Prevention, Vol. 10, 368-374.

Treat, J. R., Tumbas, N. S., McDonald, S. T., Shinar, D., Hume, R. D., Mayer, R. E., Stansifer, R. L., and Catellan, N. J., 1979. Tri-level study of the causes of traffic accidents: Final report, vol.1: Causal factor tabulations and assessments. DOT HS-805 085. Indiana University: Institute for Research in Public Safety.

O'Connell, A. A. McCoach, D. B., 2008. Multilevel modeling of educational data. Charlotte, NC: Information Age Publishing.

Quddus, M. A., Noland, R. B., Chin, H. C., 2002. An analysis of motorcycle injury and vehicle damage severity using ordered probit models. Journal of Safety Research 33 (4), 445–462.

U.S. Census Bureau, 2013. American Community Survey. Available at https://www.census.gov/programs-surveys/acs/about.html

U.S. Census Bureau, 2010. Census 2010. Available at < http://www.census.gov/2010census/>

Wampold, B. E., Serlin, R. C., 2000. The consequences of ignoring a nested factor on measures of effect size in analysis of variance. Psychological Methods, Vol. 5, 425-433.

Western, B., 1998. Causal heterogeneity in comparative research: A Bayesian hierarchical modeling approach. American Journal of Political Science 42 (4), 1233-1259.

Wilkinson, R. G., 1999. Income inequality, social cohesion, and health: clarifying the theory—a reply to Muntaner and Lynch. International Journal of Health Services, Vol. 29, 525-543.

World Health Organization, 2013. Global Status Report on Road Safety 2013. Available at: http://www.who.int/violence_injury_prevention/road_safety_status/2013/en/

World Health Organization, 2015. Global Status Report on Road Safety.

CHAPTER 4

HYPOMOBILITY – AN EPIDEMIOLOGICAL ANALOGUE FOR VIEWING URBAN TRANSPORT CONDITIONS IN AFRICA AND OTHER DEVELOPING COUNTRIES

4.1 Introduction

It is estimated that by 2030, some 50 percent of the world population will be urban dwellers. The most rapid growth in these new urban dwellers is projected to be in the cities and towns of the developing world (UNS, 2009). Transport plays an important role in the urbanization process, with the associated infrastructure constituting the backbone of urban form (Lyons, 2003). As a consequence of rapid urbanization, transport systems have come under growing strain, exacerbated by transport related pollutions, traffic crashes, and an ironic decline in travel speeds in a modern era where transport means achieving fast mobility (Lerner, 2011; UN-Habitat, 2013). The ability of people to move efficiently within, as well as between cities to access jobs, goods, and services will therefore be a crucial driver of the quality of urban life in the coming decades, and that will be a prerequisite for the balanced socioeconomic functioning and prosperity of cities (Banister, 2000; UN-Habitat, 2013). Urban mobility crisis plagues cities throughout the developing world and is particularly acute in many cities across sub-Saharan Africa (Gwilliam, 2003). This poses a serious challenge in the roadmap of achieving sustainable development.

Urban transport systems and their use continue to change within the evolving socioeconomic context in which they exist and operate. Achieving higher mobility and increased accessibility have been linked with socioeconomic progress (Khisty and Sriraj 1999). This concept of more travel at higher speeds covering longer distances generates economic prosperity is gradually catching up with cities in developing countries, especially those in Africa. As a result of this notion, African cities are experiencing rapid motorization rates that have led to chronic traffic congestions and poor levels of service for public transport due partly to inadequate transport infrastructure (UN-Habitat, 2010). This transformation in mobility trends is having overwhelming social and economic consequences in cities (Adams, 2001; Gwilliam, 2013; UN-Habitat, 2013). The current economic growth, urbanization, and motorization being experienced in the developing world has for the most part exposed the unsustainable nature of their transport systems. According to Peñalosa (2005), in such situations, transport "gets worse rather than better with economic development". This is largely due to the inability of transport systems to absorb the "shocks" that come with human development and rapid economic transformation. This can be seen for instance in the rise in the number of often unregulated informal public transport mini-buses and motorcycles across African cities to meet the rising demand.

Unfortunately, transportation infrastructure investments have heavily been skewed in favor of the car-dependent population. The consequence of this bias is that as travel becomes faster, cheaper and easier for the wealthy it becomes more challenging for the poor and vulnerable road users (pedestrians, cyclists, and motorcyclists). This group of road users face many challenges in meeting their daily mobility needs. The negative externalities (e.g. traffic crashes, pollutions) of the automobile-centric system are also disproportionately borne by the poor and vulnerable

transport system users, though they depend on the slower and environmentally sustainable modes of transport.

A term alluded to in the late 1990's, hypomobility, is used to connote difficulty to achieve sustainable levels of physical mobility and accessibility for people, particularly in urban areas. The term originates as a medical one referring to difficulty in normal movement within human muscular-skeletal systems. In transportation and urban studies, hypomobility can result in a diminished ability to engage in economic opportunities and social activities, hence deepening poverty, social exclusion, increasing costs of transport, among other negative outcomes. The condition is especially pronounced in poor urban areas in developing countries. This study proposes a framework for addressing hypomobility in Africa and other developing country cities from an epidemiological approach with a view to diagnosing symptoms, recommending treatment, and even discuss the idea of transmission.

4.2 The Complexity of Urban Transport

The patterns of, needs for, and impacts of human and goods movement in cities are complex (Cox, 2010). Cities are diverse in terms of their structure, spatial form, economy, wealth, culture, local resources and ecological impact. These features are interlaced and are influenced by the city's transport system, and vice versa. Transport is responsible for personal mobility; provides access to socioeconomic activities, and is integral to the delivery of consumer goods. However, the economic and social benefits derived from transport come with many negative impacts (UN-Habitat, 2011). As transport systems become increasingly motorized, users become vulnerable to traffic-related accidents, congestion, and pollutions, while financially and socially penalizing those who cannot afford or access any motorized mode (UN-Habitat, 2013). In spite of the rapid growth

in motorized transport, majority of urban dwellers face tremendous difficulties to access many places within cities. It has even been argued that while it became possible for man to travel to the moon, it also became impossible, in many cases, to safely walk across the street (Vanderwagen, 1995). Mobility has erroneously been equated to speed.

The inadequacy and inefficiency of urban transport infrastructure and services are major impediments to the socioeconomic growth of cities. Rapid urban growth, which has surpassed the growth of basic services, has given rise to many unplanned poor urban settlements that lack access to transport and other services (Maxwell, 2003). Current urban transport infrastructure and services across most African and other developing countries cities are grossly inadequate to meet the needs of the rapidly growing heterogeneous and spatially dispersed urban population. This is having a negative consequence on countries as studies have shown for instance that about three to six percent of a city's GDP is lost to urban congestion (Kessides, 1993; World Bank, 1994; World Bank, 2002). Even with such overwhelming evidence, remedial measures appear to be very slow, making the quest to achieve transport sustainability increasingly difficult, if not impossible. Cox (2010) identifies that urban characteristics including spatial layout, governance, and the heterogeneous urban dwellers create a complex web that invariably affect the nature, and drives the unsustainability of contemporary urban transport systems. The present state of transport systems has partly been due to the conventional paradigm which favors minimizing travel time and increasing speeds. The consequent impacts on travel distances have however not been part of that debate, notwithstanding that reducing travel distances is central to achieving sustainable transport (Banister, 2011). Cities in the developing world are growing and motorizing at such unprecedented pace that they do not have the time and money to build new infrastructure or capacity to adapt to new technologies.

The transport system is intricately connected with the land-use system, the transport system being one of the prime determinants of the movement and activity of people and goods. The transport-land use system is in turn embedded in the larger socioeconomic and cultural system (Khisty and Ayvalik, 2003). Travel patterns affect land use, the natural and built environments, and the socioeconomic well-being of citizens. Growth in geographic spread is undermining the ability of public transport and non-motorized transport systems to provide the services on which most urban dwellers rely for the bulk of their mobility needs (WBCSD, 2001). It has previously been shown that the physical characteristics of cities are very important in understanding urban travel behaviors. Newman and Kenworthy (1989) and Kenworthy and Laube (1999) have shown that the physical characteristics of cities are very important in understanding urban travel behaviors. In order to overcome the long distances between home and attractions caused by contemporary city forms, urban mobility is now predominantly motorized with the automobile as the dominant mode in many cities. It is now undeniable that this auto-dependent culture of the developed nations that is creeping into the developing nation cities is not sustainable in either economic, environmental or social terms (Kenworthy and Laube, 1996; Vasconcellos, 1997; Vuchic, 1999; Whitelegg and Haq, 2003; Banister, 2000; Bergmann and Sager, 2008; Cox 2010).

4.3 Hypermobility

Modern concepts of time and space have stimulated the development of mobility as a means of enhancing access to socioeconomic activities. Motorized transport has broadened the ability to reach places far away in an easier, faster way than ever before (Bergmann, 2008). Consequently, the demand for increased fast, long-distance travel is socioeconomically linked with processes of contemporary globalization (Hall, 2005). The high speed, long-distance mobility

culture and its attendant problems has prompted the notion of hypermobility (Whitelegg, 1993; van der Stoep and Kee, 1997; Cox, 1997; Khisty and Sriraj, 1999; Adams, 2001; Khisty and Zeitler, 2001; Khisty and Ayvalik, 2003). Hypermobility has been defined as a condition of excessive and imbalanced mobility caused by transport modes that excessively emphasize travel speed and, therefore, distance traveled (Khisty and Zeitler, 2001). Hypermobility endangers the quality of life and the ecological sustainability of modern society (Khisty and Sriraj 1999; Adams 2001; Khisty and Zeitler 2001). It also impinges on the normal functioning of the transportation system. Societies whose members move at high speed and over great distances consume more space, energy and financial resources (Adams, 2001). As evidenced in the research of Appleyard (1981), hypermobile communities have often lost their sociability. In effect, hypermobility ultimately threatens social systems of planning and democracy (Bergmann, 2008). Commentators have described the problem of hypermobility as a situation representative of "The Tragedy of the Commons" – where individual benefits derived from the use of some common public resource outweigh the individual costs (Hardin, 1968). Hypermobile individuals derive benefits from their fast mobility lifestyle but do not pay the full cost of their travel behaviors. For example, the cost of traffic crashes, property damage, community severance and pollutions resulting principally from the development of high mobility transport systems are absorbed by everybody in the community, the majority of whom depend on slow transport modes, but with the highly mobile individuals deriving the most benefits.

4.4 Hypomobility

If hypermobility connotes overemphasis on high speed, long distance travel, then its converse, hypomobility can be defined as the difficulty to move around even small distances with less speed. The Mosby's Medical Dictionary defines hypomobility as a decrease in the *normal* movement of a joint or body part, as may result from an articular surface dysfunction or from disease or injury that affects bone, muscle, or joint. It also describes the condition in which ligaments are tight and movement is restricted. Similar to the human body, certain factors may not allow for the normal movement of people and goods, and the accessibility of services; *normal* movement is constrained. Transport hypomobility therefore describes the state of insufficient mobility and reduced accessibility, resulting in usually short and infrequent trips, and consequently loss of opportunities in a world that strives on sufficient amounts of accessibility and mobility (Adams, 2001; Khisty and Ayvalik, 2003; Grieco and Hine, 2008). In a broader sense, transport hypomobility encompasses the condition in which an individual's ability to move and/or desired level of physical mobility, or accessibility of a place and services is temporarily or otherwise limited beyond the individual's control. Hypomobility sets in when the individual has the ability and is willing to undertake activities that require transport but is constrained. "Stranded mobility" is often used to describe hypomobility. The term, stranded mobility, was a concept developed to define the situation of constrained mobility and poor accessibility experienced by the black townships as a result of policies of apartheid that sought to repress the black population of South Africa (Grieco and Hine, 2008). Many developing nation cities, particularly in Africa have become replicas of the segregated apartheid townships, with the difference being that this time the partition is predominantly along socioeconomic classes. A city that makes it difficult for certain groups to achieve their normal mobility and accessibility needs may be described as hypomobile.

Hypomobility is a feature present in some form in many urban areas and is driven primarily by transport and land use planning decisions. For instance, Grieco and Hine (2008) observed that constrained mobility

> "is to be found on the British peripheral low income housing estates which were developed within a planning logic of low cost regular public transport to city centers and service locations but which now have highly restricted public transport as a consequence of changing economic and policy logics without any corresponding improvement in the provision of locally available facilities and services."

The condition is also found where extreme environmental events and topological features separate poorly resourced populations from their normal range of venues and activities (Grieco and Hine, 2008). Hypomobility can be associated with temporal factors (time of the day, day of the week, season, etc.) and spatial factors (developed versus underdeveloped neighborhoods, zoning, etc.). Hypomobility, as a phenomenon, can affect an individual, groups or even a locality. The condition is experienced through the ability or inability of an individual or group (human characteristics) to physically move from place to place and the level of reach/accessibility of basic needs and opportunities within a given region (regional characteristics). The issue of transport hypomobility becomes complex when many causal factors are involved. For instance, the ability of emergency response team to attend to an incident in a slum development, during morning rush hours may be limited by traffic congestion and the availability of access routes to the slum.

Typically, constrained mobility and accessibility segregate and alienate the poor from the rest of society. Similarly, a dominant automobile society discriminates against certain groups in

the society (Khisty and Ayvalik, 2003). Consequently, class and income disparities are deeply rooted in the spatial arrangements and mobility challenges of many developing country cities (Sandhu and Sandhu, 2007; UN-Habitat, 2013). Inequalities between rural and urban areas and especially within urban areas have been features of the development and urbanization processes (Cohen, 2006). Hypomobility can therefore result in a diminished ability to engage in economic opportunities and social activities, hence deepening poverty, social exclusion, increasing costs of transport, among other negative outcomes. The condition has been observed to be especially pronounced in poor urban areas in developing countries. As such, many cities in the developing world, especially those in Sub-Saharan Africa suffer some form of hypomobility. The urban poor and other vulnerable groups are particularly exposed to the condition.

4.5 What a City Needs – The Balance Between Hyper – and Hypo – Mobility

It has emerged over the years that a transportation system dependent on a limited choice of modes is unsustainable and more susceptible to inefficiency, disruption and eventual system failure than one with many mobility options (UN-Habitat, 2010). Hirsch (1976) argues that the competitive advantage that is previously gained by using a particular mode of transport is lost when everyone uses it. That is the story of the automobile, with its attendant negative externalities, in many cities particularly in the developing countries. There is now broad and growing recognition that future plans to address urban mobility and accessibility needs cannot rely solely on the expansion of transport infrastructure for only one mode. Decisions made today on transport infrastructure development and urban planning will lock cities into mobility behavior patterns for many years. It is therefore vital that these decisions are shaped to put the city on the path of sustainable urban transport (UN-Habitat, 2010). To achieve this, UNDESA Agenda 21 called upon

> "all countries to integrate land use and transportation planning to encourage development patterns that reduce transport demand; adopt urban transport programs favoring high occupancy, as appropriate; encourage non-motorized modes of transport by providing safe cycle ways and footways in urban and sub-urban centers in countries, as appropriate; devote particular attention to effective traffic management, efficient operation of public transport and maintenance of public infrastructure; promote the exchange of information among countries and representatives of local and metropolitan areas; and reevaluate present consumption and production patterns in order to reduce the use of energy and natural resources" (UNDESA, 1992).

An overall framework for understanding the relationship between transport hyper- and hypo-mobility is proposed in Figure 1. The more mobile society becomes, the more certain groups are excluded from and/or disproportionately impacted by the system (Khisty and Zeitler, 2001; Kenyon et al., 2003). This suggests that to reduce transport induced socioeconomic exclusion, policies should not only be oriented towards the populations that are currently excluded or at risk of exclusion but also on reducing the worsening dynamic of hypermobility and its effects across society as a whole (Urry, 2004). It is early in the motorization process that public policy interventions can have the greatest impact and help preserve the viability of sustainable urban transport modes (Barter and Kenworthy, 1997; Grant, 2014). For mobility to be sustainable, it must improve accessibility while avoiding disruptions that offset the benefits of the improvements (WBCSD, 2001). Public transport and non-motorized transport remain the principal means of mobility for most citizens of the developing world. The challenge for policy-makers is to integrate

all modes of transport in a manner that decreases deficiencies and increases mobility while minimizing other costs to the external environment. This is necessary to balance the transport demands of both the highly mobile wealthy few and those of the majority least mobile dwellers such that all transport users pay appropriate costs for their travel decisions. The hypomobile do not have to suffer the negative impacts of hypermobility, and vice versa. A more integrated transport-land use system, backed with appropriate policies and legislation will create transport systems that will increase the socioeconomic competitiveness of cities. Also, the provision of opportunities and services within the reach of the poor and vulnerable urban dwellers is necessary for the creation of an all-inclusive urban area for shared prosperity.

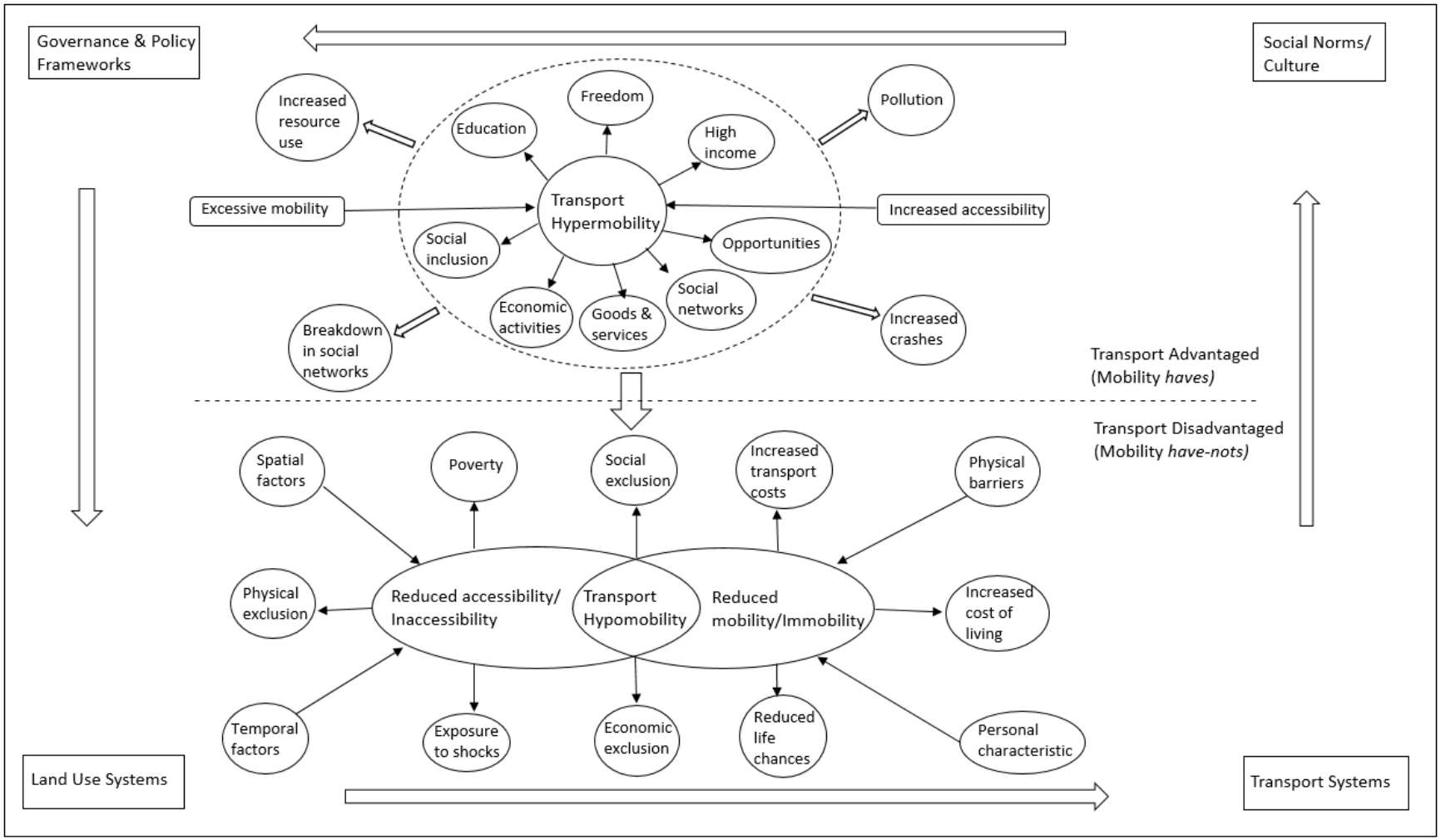

Figure 4.1. Transport hypermobility-hypomobility

4.6 African Context

Transport in urban Africa is quite different from those of industrialized nations. Throughout Africa, travel times are already quite high and continue to increase. There is rapid motorization, with travel demand far exceeding the supply of roadways and related facilities (e.g., signalized intersections and interchanges). Public transit trips account for about 75 percent of urban vehicular trips, and the general mobility concerns demand a viable public transportation system. Privatization has, in many cases throughout Africa, had a negative impact on the quality of transportation and resulting accessibility and mobility. Where public buses exist, their operations are often not sustainable because the vehicles deteriorate quickly due to lack of maintenance exacerbated by poor road conditions (Gakenheimer, 1999; Godard, 2013). Furthermore, low fares and irregular subsidies make providing consistent and high quality services, extremely difficult.

The failure of governments (whether on their own or as a result of privatization) to supply organized and high-occupancy public transportation systems has given way to the proliferation of privately operated minibuses such as: tro-tros in Ghana (Figure 2), matatus in Kenya, danfos in Nigeria, gbakas in Ivory Coast, and sotramas in Mali, etc (Kumar and Barrett, 2008). The minibuses are often operated unprofessionally by private individuals with vehicles usually in substandard and, even, unsafe conditions and the passenger facilities are often informal and chaotic (see Figure 2). Some parts of Africa have seen a rise in informally operated motorcycle taxis (e.g., okadas in Nigeria and currently in Ghana) whose operations have been received with mixed reactions - transportation professionals see such modes as a major public safety concern while many system users view them as a relief for often-stranded commuters. Such conditions render

public transportation unattractive to emerging middle classes. This leads to increased demand for private automobiles and vehicle-kilometers of travel (VKT) on an underdeveloped road system. The net effect for developing countries is premature traffic congestion at lower levels of automobile ownership, deteriorating urban environment, reduced accessibility for the poor, and safety and security concerns due to high incidence of transportation related injuries. Of particular significance is the issue of traffic safety, as about 85 percent of traffic related injuries worldwide occur in developing countries with 75 percent of these occurring in urban areas (Gwilliam, 2003).

Throughout Africa, road construction projects favoring the minority automobile users ignore the majority of the public travelling as pedestrians or other means of non-motorized transportation Ahmed et al., 2008; Freeman, 2009; Obeng-Odoom, 2014). In addition to the provision of roads and public transportation (e.g., buses), Africa requires transportation planning and development that facilitates an equitable provision of safe NMT. Such an approach should recognize the social exclusion of the poor from transportation development and promote infrastructure and operations that facilitate accessibility for all (Riverson and Carapetis, 1991; Porter, 2007).

Nonetheless, many transportation plans and policies in Africa are developed via conventional transportation planning approaches that originate from an automobile-dependent, Western context (Dimitriou, 1992; Feng et al., 2010). These conventional approaches are typically intended to maximize throughput for automobile traffic at the highest achievable levels of service. Much of this Western influence is leftover from colonial times, as the spatial framework and accompanying transport systems of many cities in Africa were laid during the colonial period (Otiso and Owusu, 2008). Such conventional approaches can be rigid and mode-specific, and in many cases do not adequately integrate analyses of the various modes prevalent in Africa, such as

high pedestrian volumes, non-motorized forms of transportation, and reliance on informal public transport (Johnston, 2004; Khisty and Arslan, 2005; Feng et al., 2010; Samberg et al,. 2011; Zheng et al., 2011). Furthermore, the conventional approaches, when applied in developing countries, can be quite weak in public involvement and stakeholder participation. As such, they often do not sufficiently identify local needs and issues that may impact the sustainability of transportation projects, plans and policies. In South Africa for instance, the guidelines are mostly based on American standards that emphasize speed and efficiency (Jennings and Covary, 2008).

Lack of access, costs, and unreliability of mobility services are barriers to the socioeconomic development of African cities and their citizens. While high speed, long-distance travels are experiencing the fastest growth rates, the low speed and environmentally sustainable modes of transport are in steep decline (Cox, 2010). Despite the increasing level of urban mobility, access to goods, places, activities and services has become increasingly difficult for many urban dwellers who do not have access to the high speed mobility lifestyle, hence increasing the gap between the mobility-rich and the mobility-poor residents in cities (Adams, 2001).

Figure 4.2. *Tro-tro* station in Kumasi, Ghana.

4.7 Proposed Approach – Epidemiological Framework of Hypomobility

To the extent that the terms hypermobility and hypomobility both owe their roots to medical science, this paper proposes an epidemiological approach to analyze hypomobility in developing countries, particularly those in Africa, with the aim of understanding its causes, symptoms, transmission, and ultimately, diagnosis and treatment. It is important to understand the patterns of hypomobility in space and time. From the patterns one may infer causes, predict the future and then make preventive, control and treatment decisions for the condition.

It is a common practice to use epidemiological techniques in studies outside public health, and this has successfully been carried out by many researchers. Epidemiological techniques have been applied in studies to investigate the spread of homicides (Zeoli et al., 2012), civil conflict and violence (Galtung, 1996), urban blight (Gilreath, 2013), violence (Huesmann and Taylor, 2006),

invasive species (Drake, 2005), water quality risk assessment (Blumenthal et. al., 2001). Epidemiological studies have also been carried out in the field of transportation: road traffic accidents (e.g. (Mishra et al., 2010; Saadat and Soori, 2011; Jha et al., 2004; Labinjo et al., 2009), drunk driving (Hingson and Winter, 2003), transport noise and cardiovascular risk (Babisch, 2008), and even the relationships between transport, physical activity and public health (Florindo et al., 2009).

The transport hypomobility epidemic that has engulfed many cities is causing harm to urban dwellers and reducing the economic prosperity and viability of these cities. The condition is unfortunately endemic for cities in developing countries. By treating hypomobility as an urban ailment, it can be captured in a framework using epidemiological techniques. In 2011, the World Bank Group released the Urban Transport Data Analysis Tool (UT-DAT) developed by Agarwal et al. (2011). Although not developed explicitly from an epidemiological approach, the UT-DAT is an Excel-based tool for comparing urban transport performance measures among peer cities. It produces a performance report for the study city that, as the developers stated, can generate a "report that would be something like a pathologist's report helping a doctor better identify the patient's ailment". This study proposes an expansion of this basic premise – to explicitly treat transport hypomobility as a "disease". In doing so, the explicit diagnosis of causes and symptoms can, ideally, lead to targeted treatments and other measures that can be applied and repeated in other locations with similar conditions. The basic epidemiological framework being proposed is illustrated in Figure 3.

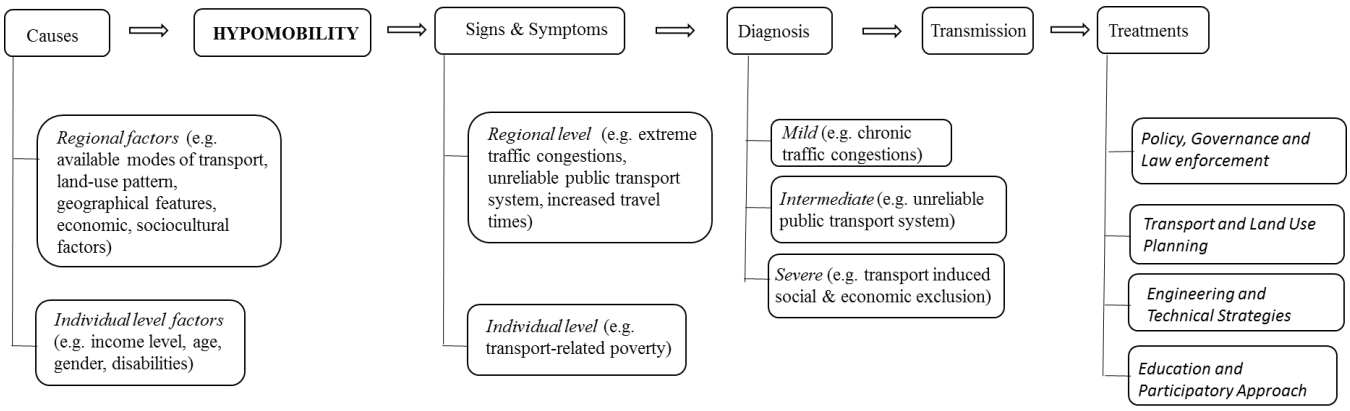

Figure 4.3. Epidemiological Framework for hypomobility

4.8 Causes of Hypomobility

Burchardt et al. (1999) have shown that an individual's mobility and accessibility to socioeconomic activities are affected by range of interconnected factors including: their own personal characteristics; characteristics of the area in which they live; and social, civil and political institutions with which they have to interact. These factors may act alone or in combination to cause hypomobility. This section discusses some of these causes.

4.8.1 Spatial or Geographical Factors

The built environment that makes up the transportation infrastructure can affect the accessibility and mobility of some groups of people. The sociocultural environment influences what modes of transport are suitable. For instance cultural beliefs in some societies forbid women from driving or even riding bikes. So, in the absence of a robust alternative mode of transport, these women may face challenges meeting their daily mobility needs. Topographical barriers such as hills, valleys, water bodies, and other geographical relief features dictate the nature of transport

that may be available (Cox, 2010). With little or no money to build transport systems to overcome these barriers, access to opportunities can be problematic for residents.

The presence of several lanes of highways with heavy and high speed motorized traffic can cause community severance, leading to hypomobility for those who may not be able to cross-over to access their daily needs (Freund and Martin, 1993). Also, the location of services and opportunities far away from home means that access to motorized transport is imperative. This phenomenon is a major driver of urban sprawl. For vulnerable groups in the urban society, urban sprawl and lack of means of transport often leads to socioeconomic isolation/exclusion (Lucas, 2009).

4.8.2 Temporal Factors

Mobility and accessibility may be affected by temporal features such as rush hour delays, seasonal events (e.g. festivals), time of the day (e.g. night). Gaffron et al. (2001) have shown that temporal factors affect people's participation in certain activities. Travel activities using especially NMT and public transport for some vulnerable groups such as women and children may be restricted to day time, due to personal security reasons. Sexual harassments and fear of attacks contribute to constrained access and mobility. Additionally, transport services may not be readily available at all the time. For instance, public transport services to certain suburbs of the city is demand-driven and may only be available at specific times.

Other temporal factors such as natural disasters (e.g. floods, epidemics), curfews imposed due to conflicts and fear of terrorist attacks can affect physical mobility of people and goods. Perennial floods are common phenomena in many African cities (e.g. Accra), as a result of inadequate and poor drainage systems. Also, many African countries have or are still embroiled in

conflicts (e.g. South Sudan, the Boko Haram resurgence in Nigeria), while others such as Liberia and Sierra Leone have in recent times been plagued with the Ebola epidemic. These temporal factors affect patterns of mobility and subsequently have negative impacts on the socioeconomic well-being of citizens.

4.8.3 Personal Factors

Individual characteristics such as age, gender, and disabilities affect people's travel behaviors. Transport facilities can be available but inaccessible because of their nature and the personal characteristics, such as age, of the transport user. Societal factors (such as mobility histories, cultures and belief systems) typically influence these personal characteristics. For instance, racist, sexist or other discriminatory attitudes of transport providers can hinder the use of the available transport facilities by certain groups of people (Lavery et al., 1992). Generally, it has been shown that, women travel shorter distances, closer to home, but make more frequent trips than men. However, women are more sensitive to safety concerns hence limit their movements and activities as much as possible. Also, men usually get access and priority for the use of the faster modes of transport.

In Africa and other developing countries, transport infrastructure are rarely designed to cater for the needs of physically disabled system users. The chaotic nature of the transport system, exacerbated by lack of disability-friendly facilities contribute to the constrained mobility of people living with some form of disability. Children and the elderly are often faced similar challenges.

4.8.4 Economic and Financial Factors

Regional economic conditions affect the nature and health of the transport system. Increase in regional income correlates with transport infrastructure development. Cities across the developing world have seen improvements in their transport infrastructure over the past decades, with a boom in their economies.

Transport costs can be a constraint for people on low incomes, influencing their decision on mode and extent of travel (Church et al., 2000). Due to economic reasons and unavailability of the alternate modes, the poor use NMT for most of their trips and depend on public transport for longer trips (Hook, 2006). Barter (2002) observed that the poor travel shorter distances and make fewer trips, but take more time to do so than the rich. In extreme situations, the poor may not be able to afford any motorized transport, hence drastically reducing their ability to access widely dispersed opportunities and basic needs.

4.9 Signs, Symptoms, and Susceptibility

Preston and Rajé (2007) have identified three criteria that are useful in identifying the degree of transport hypomobility. These include the level of travel in the area as a whole (area mobility), the level of travel made by particular individuals or groups (individual mobility) and the overall accessibility of the area. These criteria are however not exclusively independent. Hypomobility may range from mobility and accessibility constraints caused by traffic congestion to transport-related socioeconomic exclusion. Hypomobility is perceived and experienced differently by different people. Subjective perceptions and experiences of transport users, and objective analysis by experts are therefore significant in diagnosing hypomobility. Personal experiences give the symptoms, while regional characteristics as observed by experts define the

signs of hypomobility. A hypomobile region exhibits low economic competitiveness that naturally leads to citizens migrating to other regions, leaving behind individuals and families that may not have the means or opportunities to move out. Political, institutional, and geographical factors can interplay to form a constraint on mobility and accessibility to basic human needs, to and from a region. These regions tend to be poor neighborhoods often inhabited by low skilled migrants, with poor or no access to basic services. In many developing nations, such settlements (or slums) have become so prominent that resettlement efforts are easily thwarted and in some cases almost fiscally and politically impossible. Land use planning and the spatial distribution of attractions of the region are strong indicators of what forms of transport may be present.

A hypomobile neighborhood in a city center is characterized by withdrawal of local services, collapse of support systems leading to decaying housing stock. While low mobility is good for social interaction, severe transport hypomobility may lead to alienation and segregation as consequences of the inability to engage in economically or socially valued activity. Personal characteristics can be influenced by other factors to cause transport hypomobility. For instance, due to the chaotic transport system, people with disabilities tend to make fewer trips. For the visually impaired and those who walk only with special assistance, the lack of unimpeded and secure sidewalk footing as well as curb ramps may be serious barriers to mobility. Also, street crossings have been planned without consideration of disabled people (insufficient pedestrian crossing time, “talking lights”, etc.).

4.10 Transmission and Treatment

Transport hypomobility can be a spatiotemporal characteristic of a region or characteristic of an individual. As a feature of a region, it can be transmitted to residents. If the ability to move

is not constrained by human characteristics such as disabilities, then transport hypomobility may directly or indirectly "enter" a person or a population through other personal or regional factors. For instance, lack of transport infrastructure linking a community to basic goods and services means that residents of that community are excluded from accessing those needs, even though residents have the ability and desire to do so. Other sociocultural, temporal or even permanent topological, and environmental features of an area such as rivers and hills can induce transport hypomobility into certain individuals of the community. Land use characteristics coupled with transport planning influence the location and accessibility of services. Such factors can prevent residents of certain communities from achieving their needs.

For cities in Africa and the developing world, the decision to emulate Western car dependency or design an alternative urban transport strategy will likely set over the course of the next decades (Wright, 2004). Cities in the early stages of large-scale infrastructure development have a unique opportunity to choose an efficient and sustainable pathway. Since major investments in transport infrastructure are relatively irreversible over the medium term, decisions made by developing nation officials today will likely determine the shape and direction of their future urban form. With regard to urban transport, developing nations could "leap-frog" and move directly to more sustainable options rather than committing to the predominantly auto-based urban form which breeds transport poverty among vulnerable groups of society (Wright, 2004). Instead of reinventing the wheel, African cities can adopt and adapt innovative measures being implemented, in the form of lessons of general experience, technology, and institutional management from the developed world (Godard, 1999).

Treatment measures may be a combination of best practices such as policies, governance and law enforcement, proper integration of land-use planning strategies, engineering and technical

solutions, and other soft strategies as participatory approach to transport planning. This will ensure that cities apply the principle of "planning before development," with a central focus on the future needs of low-income populations (Garau et al., 2006). Otherwise, once policies are oriented towards unsustainable motorization, it will be difficult to return to more sustainable options at a later time. For instance, lessons from the developed world show that, moving commuters away from cars to public transport and non-motorized options is quite difficult and costly. It is early in the transport development process that certain policies and practices can be most effective and sustainably implemented.

4.11 Conclusions

Mobility and accessibility are essential to economic and social development of a city, and by extension, to the overall development of a country. This is particularly true for Africa, where cities have become the symptom and standard of determining development in its entire connotation. With the rapid rates of urbanization and development, cities reflect the socioeconomic dynamics of a country. Urban mobility systems enable people to access economic activities, opportunities and social networks. Although increased mobility yields great benefits, it also generates many negative externalities. The development of overly motorized urban mobility systems as sign of modernity and economic growth, is a driver of hypomobility for those without access to motorized transport. The situation is nowhere more acute than in the cities of the developing world where the urbanization process and growth in motorized transport are occurring so fast that if current trends continue, these cities will soon grind to a halt for lack of adequate infrastructure. Mobility in developing cities is therefore not achieving its purpose of increasing accessibility. Land use decisions and urban transport planning practices have locked cities in the extreme conditions of

transport hypermobility and hypomobility. While the rich and powerful elite in the society are more likely to be hypermobile, the poor and vulnerable are more likely to be hypomobile. This segregation has seen a decline in the provision and support for transport modes that the poor depend on. Integration of policy and technical solutions can help cities balance the challenges of hyper-and hypo-mobility that has characterized transport systems in most cities.

This study has therefore proposed an epidemiological framework that can help transport decision and policy makers to better understand the phenomenon of hypomobility, its impacts on Africa and other developing countries and the potential to counteract them. This framework treats hypomobility as a disease and also captures adequate information about the condition to help identify appropriate treatment measures. Ultimately, it is our expectation that this framework will help in identifying and addressing barriers to mobility and accessibility in the rapidly growing cities throughout the developing world, with particular applicability to the rapidly developing cities in Sub-Saharan Africa.

4.12 References

Adams, John. 2001. The Social Consequences of Hypermobility. In Text of an RSA Lecture, 1–10. http://john-adams.co.uk/wp-content/uploads/2006/hypermobilityforRSA.pdf.

Agarwal, O. P., Gouthami, P., Arutha B., Salvador, P. 2011. Urban Transport Data Analysis Tool (UT-DAT). The World Bank Group. http://www.worldbank.org/en/topic/transport/publication/urban-transport-data-analysis-tool-ut-dat1.

Ahmed, Q.I., H. Lu, and S. Ye. 2008. Urban Transportation and Equity: A Case Study of Beijing and Karachi. Transportation Research A 42: 125–39.

Appleyard, D. 1981. Livable Streets. Berkeley: University of California Press.

Babisch, W. 2008. Road Traffic Noise and Cardiovascular Risk. Noise Health 10: 27–33.

Banister, D. 2000. Sustainable Urban Development and Transport - Eurovision for 2020. Transport Reviews 20 (1): 113–30. doi:10.1080/014416400295365.

Banister, D. 2011. The Trilogy of Distance, Speed and Time. Journal of Transport Geography 19 (4). Elsevier Ltd: 950–59. doi:10.1016/j.jtrangeo.2010.12.004.

Barter, P. A. 2002. An International Comparative Perspective on Urban Transport and Urban Form in Pacific Asia: The Challenge of Rapid Motorisation in Dense Cities. Perth: Murdoch University.

Barter, P., Kenworthy, J. 1997. Urban Transport and Land Use Patterns: Challenges and Opportunities of High Density Cities in East and Southeast Asia. 81. Asia Research Centre.

Bergmann, S., Tore, S. 2008. In between Standstill and Hypermobility - Inttroductory Remarks on a Broader Discourse. In The Ethics of Mobilities. Rethinking Place, Exclusion, Freedom and Environment, edited by Sigurd Bergmann and Tore Sager, 1–24. Burlington, VT: Ashgate Publishing Limited.

Burchardt, T., Le Grand, J., Piauchaud, D. 1999. Social Exclusion in Britain 1991–95. Social Policy and Administration 33 (3): 227–44.

Church, A., Frost, M., Sullivan, K. 2000. Transport and Social Exclusion in London. Transport Policy 7 (3). London, UK: 195–205.

Cohen, B. 2006. Urbanization in Developing Countries: Current Trends, Future Projections, and Key Challenges for Sustainability. Technology in Society 28 (1-2): 63–80. doi:10.1016/j.techsoc.2005.10.005.

Cox, P. 2010. Moving People. Sustainable Transport Development. UCT Press.

Cox, K, R. 1997. Spaces of Globalization: Reasserting the Power of the Local. New York: The Guilford Press.

Diez-Roux, A. V. 2000. Multilevel Analysis in Public Health Research. Annual Review of Public Health 21: 171–92.

Dimitriou, H. 1992. Urban Transport Planning: A Developmental Approach. New York: Routledge.

Drake, J. M. 2005. Risk Analysis for Invasive Species and Emerging Infectious Diseases: Concepts and Applications. American Midland Naturalist 153: 4–19.

Feng, X., Zhang, J., Fujiwara, A., Hayashi, Y., Kato, H. 2010. Improved Feedback Modeling of Transport in Enlarging Urban Areas of Developing Countries. Frontier of Computer Science in China 29 (4): 313–30.

Florindo, A. A., Valente Guimarães, V., Luiz, C., Galvão, C., De Azevedo Barros, B., Cecília, M., Porto, G., Goldbaum, M. 2009. Epidemiology of Leisure, Transportation, Occupational, and Household Physical Activity : Prevalence and Associated Factors. Journal of Physical Activity and Health 6: 625–32.

Freeman, N. P. 2009. Ten Years of World Bank Action in Transport: Evaluation. Journal of Infrastructure Systems, ASCE December.

Freund, P., Martin, G. 1993. The Ecology of the Automobile. Montreal: Black Rose Books.

Gaffron, P., Hine, J., Mitchell, F. 2001. The Role of Transport in Social Exclusion in Urban Scot/and - Literature Review.

Gakenheimer, R. 1999. Urban Mobility in the Developing World. Transportation Research Part A: Policy and Practice 33 (7-8): 671–89. doi:10.1016/S0965-8564(99)00005-1.

Galtung, J. 1996. Peace by Peaceful Means. Peace and Conflict, Development and Civilization. London, UK: SAGE Publications.

Garau, P., Sclar, E. D., Carolini, G. Y. 2006. A Home in the City : UN Millennium Project Report on Improving the Lives of Slum Dwellers. Global Urban Development 2 (1): 1–8.

Gilreath, M. B. 2013. A Model for Quantitatively Defining Urban Blight by Using Assessment Data. Fair & Equitable.

Godard, X. 2013. Comparisons of Urban Transport Sustianability: Lessons from West and North Africa. Research in Transportation Economics 40 (1): 96–103.

Grant, R. 2014. Sustainable African Urban Futures: Stocktaking and Critical Reflection on Proposed Urban Projects. American Behavioral Scientist 59 (3): 294–310. doi:10.1177/0002764214550301.

Grieco, M., Hine, J. 2008. Stranded Mobilities, Human Disasters: The Interaction of Mobility and Social Exclusion in Crisis Circumstances. In The Ethics of Mobilities. Rethinking Place, Exclusion, Freedom and Environment, edited by Sigurd Bergmann and Tore Sager, 65–71. Ashgate Publishing Limited.

Guo, G., Zhao, H. 2000. Multilevel Modeling for Binary Data. Annual Review of Sociology 26: 441–62. http://www.jstor.org/stable/223452.

Gwilliam, K. 2003. Urban Transport in Developing Countries. Transport Reviews 23 (2): 197–216.

Gwilliam, K. 2013. Cities on the Move - Ten Years After. Research in Transportation Economics 40 (1): 3–18.

Hall, C. M. 2005. Tourism: Rethinking the Social Science and Mobility. London, UK: Pearson Education Limited.

Hingson, R., Winter, M. 2003. Epidemiology and Consequences of Drinking and Driving. National Institute on Alcohol Abuse and Alcoholism. http://pubs.niaaa.nih.gov/publications/arh27-1/63-78.htm.

Hirsch, F. 1976. Social Limits to Growth. London, UK: Routledge & Kegan Paul.

Hook, W. 2006. Urban Transport and the Millennium Development Goals. Global Urban Development Magazine, June. http://www.globalurban.org/GUDMag06Vol2Iss1/Hook.htm.

Huesmann, L. R., Taylor, L. D. 2006. The Role of Media Violence in Violent Behavior. Annual Review of Public Health 27: 393–415.

Jennings, L., Covary, N. 2008. A Partnership towards Sustainable Transport: The Urban TRANSIT Model. In Proceedings of the 27th Southern African Transport Conference. SATC.

Jha, N., Srinivasa, D. K., Roy, G., Jagdish, S. 2004. Epidemiological Study of Road Accident Cases: A Study from South India. Indian Journal of Community Medicine 29 (1): 20–24.

Johnston, E. 2004. Women Flee Tokyo Train Gropers. The Guardian, November 24. http://www.guardian.co.uk/.

Kenworthy, J., Laube, F. 1999. An International Sourcebook of Automobile Dependence in Cities, 1960-1990. Boulder: University Press of Colorado.

Kenworthy, J., Laube, F. 1996. Automobile Dependence in Cities: An International Comparison of Urban Transport and Land Use Patterns with Implications for Sustainability. Environmental Impact Assessment Review 16 (4-6): 279–308. doi:10.1016/S0195-9255(96)00023-6.

Kenyon, S, Lyons, G., Gafferty, J. 2003. Social Exclusion and Transport in the UK: A Role for Virtual Accessibility in the Alleviation of Mobility-Related Social Exclusion. Journal of Social Policy 32 (3): 317–38.

Kessides, C. 1993. The Contributions of Infra Structure to Economic Development, A Review of Experience and Policy Implications. Washington, D.C.

Khisty, J., Sriraj, P. 1999. Taming the Problems of Hypermobility through Synergy. In Synergy Matters - Working with Systems in the 21st Century, 1 edition, 271–76. Springer.

Khisty, J., Ayvalik, C. 2003. Automobile Dominance and the Tragedy of the Land-Use / Transport System : Some Critical Issues. Systems Practice & Action Research 16 (1).

Khisty, J., Zeitler, U. 2001. Is Hypermobility a Challenge for Transport Ethics and Systemicity? Systems Practice & Action Research, 597–613.

Khisty, J., Arslan, T. 2005. Possibilities of Steering the Transportation Planning Process in the Face of Bounded Rationality and Unbounded Uncertainty. Transportation Research C 13: 77–92.

Kumar, A., Barrett, F. 2008. Africa Infrastructure Country Diagnostic, Stuck in Traffic: Urban Transport in Africa. Washington, D.C.

Labinjo, M., Juillard, C., Kobusingye, O., Hyder, A. 2009. The Burden of Road Traffic Injuries in Nigeria: Results of a Population-Based Survey. Injury Prevention 15 (3): 157–62.

Lavery, I., Davey, S., McKenna, O. 1992. Transport Deprivation and Marginalisation of People with a Handicap. In Proceedings Seminar F at Planning and Transport, Research and Computation (PTRC) 20th Annual Meeting. London, UK.

Lerner, W. 2011. The Future of Urban Mobility. Towards Networked, Multimodal Cities of 2050.

Lucas, K. 2009. Actual and Perceived Car Dependence: Likely Implications for Enforced Reductions in Car Use for Livelihoods, Lifestyles and Well-Being. Transportation Research Record 21 (18): 8–15.

Lyons, G. 2003. Britain's Transport Crisis. In Getting out of the Jam: Britain's Transport Future. London, UK. http://eprints.uwe.ac.uk/9864/1/9864.pdf.

Maxwell, R. R. 2003. Converting a Large Region to a Multimodal Pulsed-Hub Public Transport Network. Transportation Research Record 1835: 128–36.

Mishra, B., Sinha, N., Sukhla, S., Sinhah, A. 2010. Epidemiological Study of Road Traffic Accident Cases from Western Nepal. Indian Journal of Community Medicine 35 (1): 115–21.

Newman, P., Kenworthy, J. 1989. Cities and Automobile Dependence: A Sourcebook. Aldershot: Avebury Technical.

Obeng-Odoom, F. 2014. Sustainable Urban Development in Africa? The Case of Urban Transport in Sekondi-Takoradi, Ghana. American Behavioral Scientist 59 (3): 424–37. doi:10.1177/0002764214550305.

Otiso, K. M. and Owusu, G. 2008. Comparative urbanization in Ghana and Kenya in time and space. Geo Journal, 71(2): 143-157

Peñalosa, E. 2005. The Role of Transport in Urban Development Policy. Eschborn.

Porter, G. 2007. Progress Report: Transport Planning in Sub-Saharan Africa. Progress in Development Studies 7 (3): 251–57.

Preacher, K., Zyphur, M., Zhang, Z. 2010. A General Multilevel SEM Framework for Assessing Multilevel Mediation. Psychological Methods 15 (3): 209–33.

Preston, J., Rajé, F. 2007. Accessibility, Mobility and Transport-Related Social Exclusion. Journal of Transport Geography 15 (3): 151–60. doi:10.1016/j.jtrangeo.2006.05.002.

Qian, S., Cuffney, T., Alameddine, I., McMahon, G. 2010. On the Application of Multilevel Modeling in Environmental and Ecological Studies. Ecology 91 (2): 355–61.

Riverson, J., Carapetis, S. 1991. Intermediate Means of Transport in Sub-Saharan Africa: Its Potential for Rural Travel and Transport. World Bank. Washington, DC.

Saadat, S., Soori, H. 2011. Epidemiology of Traffic Injuries and Motor Vehicles Utilization in the Capital of Iran: A Population Based Study. BMC Public Health 11 (488): 1–6.

Samberg, S., Bassok, A., Holman, S. 2011. Sustainable Transportation Evaluation Method (STEM): Towards a Comprehensive Approach. In 90th Annual Meeting of the Transportation Research Board. Washington, D.C.

Sandhu, R, Sandhu, J. 2007. Globalizing Cities: Inequality and Segregation in Developing Countries. Jaipur, India: Rawat Publications.

Steenbergen, M. R., Jones, B. S. 2002. Modeling Multilevel Data Structures. American Journal of Political Science 46 (1): 218–37.

UNDESA, (UN Department of Economic and Social Affairs). 1992. Agenda 21. The United Nations Programme of Actions from Rio. http://www.un.org/esa/dsd/agenda21/index.shtml.

UN-Habitat. 2010. A New Perspective - Sustainable Mobility in African Cities. Nairobi, Kenya.

UN-Habitat. 2011. Cities and Climate Change: Global Report on Human Settlements 2011. London, UK. http://www.unhabitat.org/grhs/2011.

UN-Habitat. 2013. Planning and Design for Sustainable Urban Mobility. Global Report on Human Settlement 2013. New York, USA.

UNS, (United Nations Secretariat). 2010. World Urbanization Prospects: The 2009 Revision. Highlights. New York.

Urry, J. 2004. The System of Automobility. Theory, Culture & Society 21 (4-5): 25–39. doi:10.1177/0263276404046059.

Van der Stoep, J., Kee, B. 1997. Hypermobility as a Challenge for Systems Thinking and Government. Syst. Res. Behav. 14: 399–408.

Vanderwagen, J. 1995. Coming down to Earth. In Beyond the Car, edited by S. Zielinski and G Laird, 137–39. Toronto, Canada: Steel Rail Press.

Vasconcellos, E. A. 1997. The Demand for Cars in Developing Countries. Transportation Research A 3 (31): 245–58.

Vuchic, V. R. 1999. Transportation for Livable Cities. New Brunswick, New Jersey: Center for Urban Policy Research.

WBCSD, (World Business Council for Sustainable Development). 2001. World Mobility at the End of the Twentieth Century and Its Sustainability - Mobility 21.

Whitelegg, J., Haq, G. 2003. The Earthscan Reader on World Transport Policy and Practice. London, UK: Earthscan.

Whitelegg, J. 1993. Transport for a Sustainable Future: The Case for Europe. 1st ed. Belhaven Press.

World Bank. 1994. World Development Report. Washington, D.C.

World Bank. 2002. Urban Transport in the Europe and Central Asia Region: World Bank Experience and Strategy, Infrastructure and Energy Services Department, Europe and Central Asia Region. Washington, D.C. http://www.thepep.org/ClearingHouse/docfiles/World.

Wright, L. 2004. Car-Free Development. Eschborn. http://www.sutp.org.

Zeoli, A. M., Pizarro, J. M., Grady, S. C., Melde, C. 2012. Homicide as Infectious Disease : Using Public Health Methods to Investigate the Diffusion of Homicide Homicide as Infectious Disease : Using Public Health Methods to Investigate the Diffusion of Homicide. Justice Quarterly, no. December 2013: 1–24.

Zheng, J., Atkinson-Palombo, C., McCahill, C., O'Hara, R., Garrick, N.W. 2011. Quantifying the Economic Domain of Transportation Sustainability. In Proceedings of the Transportation Research Board 87th Annual Meeting, 19–28. Washington DC USA.

CHAPTER 5

SUMMARY AND FUTURE WORK

5.1 Summary

Providing safe, affordable, and sustainable mobility remains a top priority for many transportation agencies as well as governmental policy makers. However, much of the world faces an unprecedented mobility and accessibility crisis, characterized by unsafe and unsustainable mobility systems. The burden of mobility and its attendant safety crises on citizens have been described as public health problems. Viewing these human-centered transport problems as ailments that can be studied using epidemiological techniques present transportation decision makers with a robust tool to aid in making informed evidence-based decisions concerning promoting safe and equitable mobility to promote socioeconomic growth. The application of widely used epidemiological methods makes possible the assessment of the relative importance of the contributing factors of these problems and also helps identify populations at increased risk, so that target countermeasures and treatment measures may be effectively implemented. The first chapter of the dissertation presents an overview of the current state of constrained mobility and traffic safety as public health conditions and makes the case for a shift from the conventional approach of studying them. A summary of the subsequent chapters of the dissertation and the findings of the studies are detailed as follows:

Chapter 2 examined crash causal factors related to drivers and their driving habits. The study identified homogeneous clusters of human-related crash causal factors and also investigated the effects of these factors on crash outcomes. Homogeneous clustering of human-related crash causal factors was achieved by using latent class analysis to identify seven distinct segments of drivers based on common crash causal traits. A latent class logit model and random parameters model were further developed to understand the effects of the human factors on crash injury severity. The LC logit and RPL models were chosen as alternatives to the traditional multinomial logit model to account for unobserved heterogeneity.

Chapter 3 presented a study on the use of multilevel regression modeling techniques to explore the factors responsible for explaining the area-based differences in the frequency and severity of crashes across the state of Alabama. Unlike many conventional crash studies, this research used only driver characteristics and the characteristics of their place of residence to explain the variability in the occurrence of fatal crashes. With its unique feature of intra-class correlation, the multilevel analysis revealed that the area of residence of a driver accounts for about 7.3% of the variability in the probability of getting into a fatal crash, irrespective of the driver characteristics. This study revealed disparities in human-centered crash causal factors and crash outcomes that exist between people and regions with different characteristics and pointed out disproportionately high fatalities in low income regions. This paper has confirmed previous studies that regional characteristics can be significant correlates in explaining the differences in crash outcomes across regions. The use of multilevel modeling techniques for traffic crash analysis presents decision and policy makers with a strong analytical tool to formulate evidence-based policies.

Chapter 4 proposed an epidemiological framework that can help transport decision and policy makers to better understand the phenomenon of constrained mobility and accessibility, defined as hypomobility. This framework treats hypomobility as a disease afflicting urban areas and captures adequate information about the condition to help identify appropriate treatment measures. Ultimately, this framework is expected to help in identifying and addressing barriers to mobility and accessibility in the rapidly growing cities throughout the developing world, with particular applicability to the rapidly developing cities in Sub-Saharan Africa.

5.2 Future Work

The results of this dissertation present a number of promising directions for future work. Some of the proposed directions follow:

1. The two crash studies focused solely on human-centered causal factors. It is known that road traffic crashes occur from a combination of factors related to the road and its environment, vehicles, and road users. Further research is required to investigate how the other elements of the transportation system affect driving behavior in crash causation.
2. The latent class logit method applied in this study does not account for the possibility of variation within a class since it assumes homogeneous characteristics of the within-class observations. Further research, including more data and variables, may be required to explore the strengths of the LC random parameters model for injury severity analysis.
3. Another potential study area is to apply multilevel analysis techniques to study the effects of crash location characteristics on driver injury severities.

4. All the crash models presented in this study are based on Alabama crash data sets. The proposed models should be evaluated using data sets from other states or nations to see if similar trends may be obtained.
5. Difficulties in acquiring mobility data in developing countries have hindered evidence-based research in that area. One potential area of future research is to use crowd-sourced travel data to quantify mobility constraints.