Combined Behavioral and Engineering Approach to Preventing Highway Fatalities

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Research Report

KTC-23-01/SPR21-601-1F

Combined Behavioral and Engineering Approach to Preventing Highway Fatalities

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16. Abstract
Traditional, single-discipline highway safety approaches can be augmented through multidisciplinary approaches that consider both engineering and behavioral interventions (e.g., education, enforcement, public outreach campaigns). Leveraging a systems-based conceptual framework of roadway safety, multiple forms of statistical and geospatial analysis, and SPF modeling and network screening, this report proposes and demonstrates methods for unpacking the influence of behavioral-related factors on crash occurrences and outcomes. The primary focus is on behaviors targeted in the Strategic Highway Safety Plan — aggressive driving, distracted driving, impaired driving, and driving without proper restraint (i.e., seatbelts). Based on application of these methods, the report highlights areas and highway corridors in Kentucky where behavioral-related crashes have been most common. Practitioners can use methods presented in the report to locate areas where behavioral-related crashes are problematic and based on this knowledge design behavioral modification strategies and countermeasures which focus on at-risk populations.

17. Key Words highway safety, vehicle crashes, behavior, spatial analysis, countermeasures	**18. Distribution Statement** Unlimited with approval of the Kentucky Transportation Cabinet

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Executive Summary

This project investigated analytical methods that can be used to determine how best to co-integrate engineering countermeasures with behavioral-oriented strategies (i.e., education, enforcement) to improve highway safety in Kentucky. Drawing on literature from public health and system-based approaches to safety, researchers developed a framework to contextualize behavioral influences on crash outcomes. It emphasizes the ways in which multiple, interconnected, and compounding factors affect driving behaviors and crash probabilities. The factors include latent conditions (e.g., demographics, socioeconomics) and proximate influences (e.g., vehicular and roadway factors) on crashes. Figure E1 illustrates the analytical framework researchers developed for understanding how these factors combine and interact with one another.

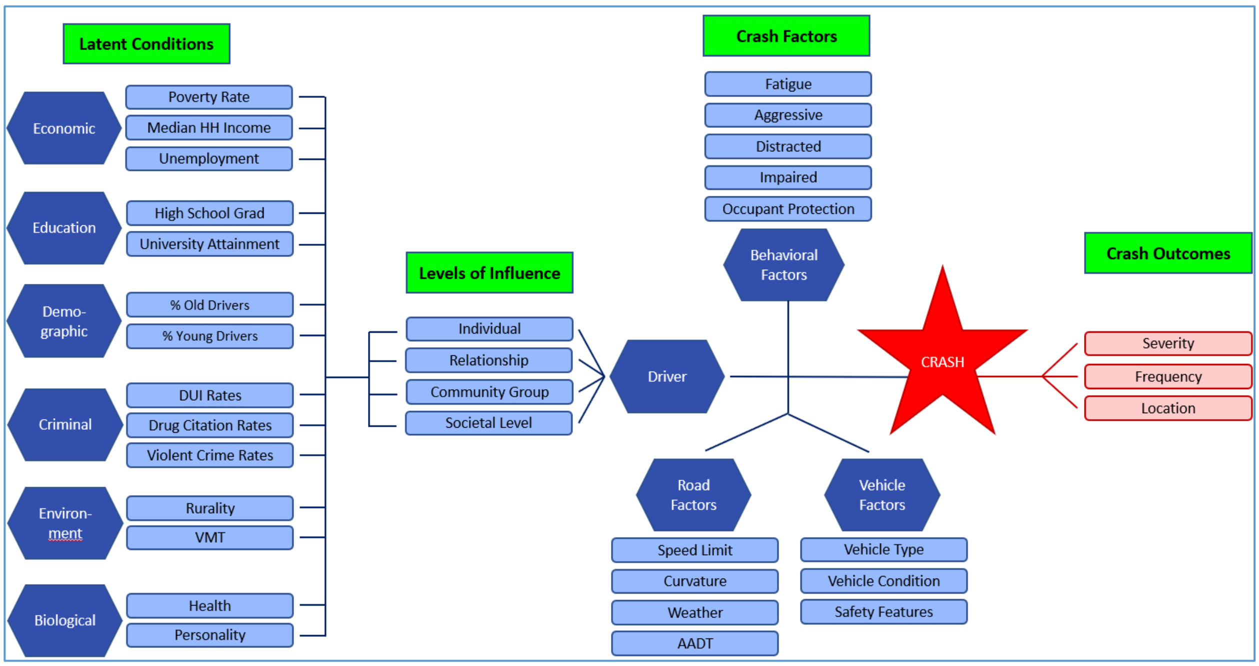

Figure E1 Analytical Framework for Understanding Variables that Influence Crash Occurrences and Outcomes

To understand the influence of these factors, researchers developed statistical models to identify those with the greatest predictive power for crashes involving the risk-taking behaviors targeted in Kentucky's Strategic Highway Safety Plan — aggressive driving, distracted driving, impaired driving, and unrestrained (not wearing seatbelt) driving. The dataset used to generate these models included over 500,000 crashes in Kentucky between 2014 and 2018. Variables evaluated included those pertaining to crashes, along with roadway, vehicle, driver, locational, and socioeconomic characteristics of the U.S. Census block where the Unit 1 driver lived.

Researchers conducted additional statistical modeling using Esri Tapestry® Segmentation data. This geodemographic segmentation data identifies population groups based on demographic, socioeconomic, and geographic characteristics. Commonly used for marketing research, its adoption for this study represents a novel and interdisciplinary approach to highway safety analysis. Model results generated insights into the geodemographic groups most likely to engage in risk-taking driving behaviors. This knowledge can help practitioners develop focused strategies to reach the most at-risk population groups.

While statistical models provided insights into the broader patterns of risk-taking driving behaviors, researchers also identified through network screening highway corridors of concern using safety performance function (SPF) modeling with Empirical Bayes (EB) adjustment. Two methods were developed for incorporating behavioral data into modeling, one that focused exclusively on behavior-involved crashes and one that looked at the contribution of behavior-involved crashes to all crashes. Using these models, researchers identified segments with highest excess expected crashes (EECs) for each of the four behavioral types. Practitioners can easily replicate these techniques to identify roadway segments where risk-taking behaviors result in high crash rates. This in turn can inform the selection of countermeasures.

Chapter 1 Introduction

Kentucky's 2020 Strategic Highway Safety Plan (SHSP) put forth a goal of preventing enough serious crashes such that the average annual number of deaths would fall at or below 500 by 2024. This equates to 200 or more fewer lives lost per year compared to the 2020 five-year rolling average. Since the plan's adoption, however, deaths on Kentucky roadways have not trended as desired in this direction. This can be attributed, in part, to the social and environmental changes that arose with the COVID-19 pandemic. Nonetheless, it is increasingly recognized that applying traditional, single-discipline approaches (e.g., engineering only) will not achieve the sought-after improvements in highway safety.

To address this need, this study developed a more holistic approach to improving highway safety that integrates research and mitigation strategies across the 4 Es of highway safety — Education, Emergency Medical Services (EMS), Enforcement, and Engineering. This multidisciplinary approach is informed by public health and other social behavioral disciplines which argue for a systems approach to addressing highway safety. Such approaches understand crashes as being embedded within overarching societal systems and environments that influence both the likelihood of a crash occurring and the resulting degree of crash severity. While the immediate factors leading to a crash are of great significance, also significant are the multitude of wide-ranging societal influences that act upon drivers and influence driver behavior.

This project sought to identify methods whereby transportation safety could be enhanced through the combination of engineering and behavioral solutions. Of particular interest was identifying both engineering safety countermeasures that could be better informed by behavioral approaches, and concurrently behavioral modification strategies that could be better informed by engineering approaches. To do so, several questions were posed: 1) How do behavioral and engineering factors interact with one another in contributing to a crash? 2) What types of crash data typically used in engineering analysis could be beneficial to behavioral modification strategies, in terms of enforcement and educational campaigns? 3) How can we better understand latent societal conditions that affect driver behavior and then apply that knowledge through behavioral modification strategies? 4) How can behavioral-related crash factors be better identified and deployed through safety engineering methodologies and countermeasures?

The goal of this exploratory project was to identify and develop novel approaches and solutions. This involved taking an interdisciplinary approach in terms of methodology and how the data was analyzed. Key project goals included:

- Perform statistical analysis of behavioral-related crashes using data on roadway characteristics, socioeconomics, and demographics.
- Develop a better understanding of the relationship between behavioral-related crashes and roadway elements — at a systemic level.
- Develop a better understanding of the sociocultural attributes associated with behavioral-related crashes.
- Devise a method practitioners can use to identify communities and corridors where a high-number of behavioral-related crashes occur to facilitate selection of effective safety improvement opportunities.

Chapter 2 Literature Review

2.1 Public Health Approach to Highway Safety
Models from public health have been successfully applied to traffic safety policy and planning. More widespread adoption and implementation of these models should prevent crash fatalities and injuries. Such models rely on a systems-based approach that looks at safety more holistically than traditional cause-and-effect analyses.[1] In systems analysis, causality is understood as being rooted in the entirety of a situation rather than in discrete parts.[2] A broader perspective offers a deeper and more comprehensive understanding of the dynamics that contribute to crashes.[3] Systems analyses are "comprehensive, rigorous, founded in theory and proven in practice."[4] Figure 2.1 diagrams the Ecological Systems Framework and captures the nested relationships and embedded nature of driver, vehicle, and roadway characteristics within geography type.[5]

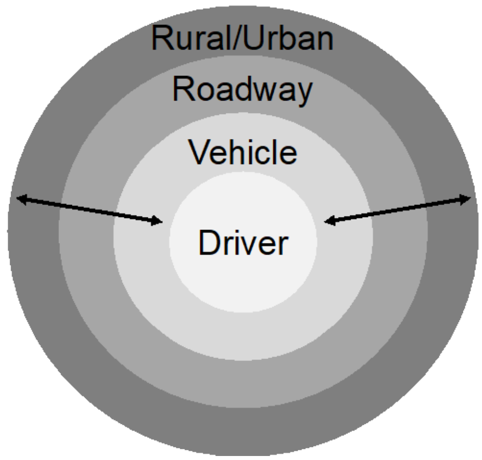

Figure 2.1 Ecological Systems Framework

Dumbaugh et al. presented an example of the systems analysis approach, *Safe Systems*.[6] They identified and described the development and implementation of Safe Systems internationally and discussed opportunities to apply the approach in the United States (U.S.). Rather than viewing crashes as the result of random driver error, the Safe Systems framework sees crashes as occurring within systems of organized complexity comprised of the physical environment — the vehicle, road, and surrounding environment — and the social environment — the behaviors and actions of system users. Latent conditions within these systems can influence the likelihood of risky driving behaviors. Humans exhibit patterns of predictable behavior in response to such conditions. To the extent that latent conditions can be identified and diagnosed, crashes can be treated as predictable, with countermeasures targeted to improve those conditions. Highway designers and traffic safety professionals share responsibility for eliminating latent conditions and minimizing the consequences of crashes. This requires knowledge of the broader societal conditions in which a crash takes place rather than focusing exclusively on events immediately preceding a crash. These conditions may relate to laws, policies, social norms, land development practices, and other cultural factors. Safe Systems adheres to four guiding principles:

- The human body has a known and limited ability to tolerate crash forces
- People make mistakes that lead to crashes
- System designers share a responsibility with road users for crash prevention
- All elements of the system should be strengthened to multiply their effects

The Safe States Alliance provides another example of public health theory being applied to highway safety.[7] It argues that highway deaths and serious injuries can be prevented by widely adopting and implementing public health strategies that address risky driving behaviors (i.e., *aggressive driving*, *impaired driving*, *distracted driving*, *drowsy driving*, *seatbelt non-usage*). The Safe States Alliance operates using a framework of risk factors ("any attribute,

[1] Hughes et al., "A Review of Models Relevant to Road Safety."
[2] Underwood and Waterson, "Systems Thinking, the Swiss Cheese Model and Accident Analysis."
[3] Underwood and Waterson, "Systemic Accident Analysis."
[4] Hughes et al., "A Review of Models Relevant to Road Safety."
[5] Nurse and Edmondson-Jones, "A Framework for the Delivery of Public Health."
[6] Dumbaugh et al., "Implementing Safe Systems in the United States: Guiding Principles and Lessons from International Practice."
[7] Safe States Alliance, "Strategies to Address Shared Risk and Protective Factors for Driver Safety."

characteristic, or exposure at the biological, psychological, family, community, or cultural level that precedes and is associated with a higher likelihood of negative outcomes") and protective factors ("any attribute, characteristic or influence at the biological, psychological, family, community, or cultural level that precedes and is associated with a higher likelihood of positive outcomes and lessens the likelihood of negative consequences"). These factors apply at multiple, interconnected levels, including the:

- Individual level (e.g., biological and personal history factors)
- Relationship level (e.g., a person's social circle)
- Community level (e.g., the settings within which social relationships exist (school, work, neighborhood))
- Societal level (e.g., social and cultural norms, structures, and policies)

Risk and protective factors operating at individual levels of the system have a cumulative impact on risky driving behaviors. Targeting only one layer or dimension is unlikely to be successful, or at least not the most cost-effective or efficient solution. A comprehensive, coordinated approach is needed to bring about real and lasting change. The Safe States Alliance report catalogues proven public health strategies and interventions for addressing risky driving behaviors and situates each within the social ecological framework of risk and protective factors.

2.2 Behavioral Approaches

Munnich et al. argued that to be effective public policies aimed at reducing deaths on rural highways must have (1) demonstrable evidence to prove their effectiveness and (2) enough public support for politicians to enact them as policy.[8] However, some effective policies perceived and/or presented as controversial may not be so. To explore this issue, the authors surveyed the public to gauge their attitudes toward six proven behavioral countermeasures often seen as controversial. By a large margin, respondents believed each strategy would improve highway safety. A large majority were also very supportive or somewhat supportive of implementing all six countermeasures. The six practices are listed in order from most to least supported below.

1) Graduated driver's license requirements
2) Breathalyzer-based ignition interlocks
3) Sobriety checkpoints
4) Motorcycle helmet mandates
5) Primary enforcement of seat belt laws
6) Automated speed enforcement

Even countermeasures with the least support garnered the support of more than half of survey participants.

Banks et al. looked at employee perceptions of fleet safety interventions among selected Australian organizations.[9] They surveyed several hundred employees to assess the safety cultures of their organizations, identify strategies believed to be effective at improving safety, and determine if perceptions of safety climate and crash history were correlated. Survey results indicated that strategies combining behavioral and engineering countermeasures were regarded as the most effective, while those focused exclusively on improving safety culture were seen as the least effective.

A National Highway Transportation Safety Administration (NHTSA) report presented an effective program for improving highway safety culture among teen drivers.[10] The program stresses a peer-to-peer approach that empowers teens to (1) identify a highway safety problem of importance to their community; (2) develop and deliver a program in which they educate fellow teen drivers about the problem and identify strategies to address it; and (3) evaluate how successful their delivery of the program has been and how effective their program has been at improving highway safety. The peer-to-peer program is situated within a broader understanding of how teens communicate and influence one another in either positive or negative ways (e.g., peer pressure, group norms, behavioral modeling, situational opportunities). The program places teens in the conversation about highway safety and helps them adopt effective methods to improve safety culture.

Juarez identified lack of seat belt usage as a primary factor in traffic deaths and serious injuries among young drivers.[11] Seat belt usage is lower than average among teen drivers, particularly for males. However, usage rates

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[8] Munnich and Loveland, "Do Americans Oppose Controversial Evidence-Based Road Safety Policies?"
[9] Banks, Freeman, and Davey, "An Engineering or Behavioural Approach?"
[10] Fischer, "Peer-to-Peer Teen Traffic Safety Program Guide."
[11] Juarez, "A Conceptual Framework for Reducing Risky Teen Driving Behaviors among Minority Youth."

vary; reasons for these variations differ between demographic and socioeconomic clusters. Juarez established a framework to develop messaging on seat belt usage targeted at teen drivers that can be customized based on age, gender, race, and urban/rural regional differences. Rooted in ecological theory, the framework understands teen driving behaviors as being influenced through multiple and compounding social levels. Juarez argued traffic safety interventions should be applied at multiple social levels, including health education, public media campaigns, community messaging, and traffic enforcement.

2.2 International Approaches

Brüde and Elvik's historical analysis of crash fatalities across multiple countries identified an inflection point at which deaths stopped climbing and began to fall.[12] For four countries — Denmark, Great Britain, Norway, and the U.S. — this occurred around 1970, corresponding to the enactment of transportation safety policies. The authors stress that traffic deaths around the world will not passively decline and will require ongoing policy interventions.

Using data from 56 countries, Sauerzapf examined relationships between crash fatality rates and economic development, public health expenditures, roadway design characteristics, and vehicle traits.[13] Obtaining reliable and consistent crash data was challenging, but similar trends across countries were identified. Factors correlated with higher fatality rates included greater road energy usage (i.e., distance travelled by time), higher percentages of two- or three-wheeled vehicles, higher rates of per capital alcohol consumption, and higher percentages of the driving population in the 15–24 year-old age group. National spending on health care negatively correlated with fatality rates.

A recent study of driver behavior in China focused on crash rates among delivery drivers.[14] With online commerce becoming ubiquitous, delivery drivers represent an increasing share of road users. Zheng et al. found that high workloads, fatigue, and risk-taking behaviors directly impacted the likelihood of a driver being involved in a crash, while time pressures and work-related stress played an indirect role by influencing fatigue and driving behaviors. These findings underscore the importance of not depending on a simple cause-and-effect framework to analyze crashes and to explore broader conditions that underly risk-taking behaviors.

Safarpour et al.'s review of traffic safety approaches from multiple countries culminated in a framework that maps how these approaches are organized and relate to one another.[15] Traffic safety approaches were divided into three tiers: traditional approaches, systemic approaches, and Vision Zero approaches. For example, traditional approaches include a road-user approach that treats human error as the primary contributor to crashes. Using this logic, countermeasures should be developed and implemented to prevent behaviors associated with driver error. Also under the traditional approach is the causal approach, which tries to identify factors at work in each crash and identify and deploy strategies to curb driver error and improve highway design. Three systemic approaches were identified: sustainable safety, safe systems, and the UN plan for a decade of action. Rather than focusing on factors that lead to an individual crash, these approaches situate all crashes within a wider net of societal conditions that influence highway safety. They also seek out a comprehensive suite of strategies and countermeasures to address the problem across multiple levels.

2.3 Demographic and Socioeconomic Factors

Researchers have explored the potential connection between crashes, risky driving behaviors, and demographic and socioeconomic factors. Pawlovich et al. presented a conceptual methodology for using GIS and statistical analysis to investigate the relationship between crashes and socioeconomic, demographic, and land use data.[16] Census TIGER data at the block group level were used to determine variables, while GIS was employed to calculate crash rates at the block-group level and assess their relationships with socioeconomic, demographic and land use variables.

Stamatiadis et al. refined this form of analysis to investigate why the Southeast U.S. has higher crash fatality rates than other parts of the country.[17] The Southeast has lower educational attainment and economic disadvantages, leading to older vehicles with fewer safety features — perhaps not properly maintained, — more pickups and sport utility vehicles, and drivers with a propensity to engage in risk-taking behaviors. Stamatiadis et al. highlighted that single-vehicle crashes correlated more closely with socioeconomic factors than multi-vehicle crashes. Similarly, Kumfer et al. found that

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[12] Brüde and Elvik, "The Turning Point in the Number of Traffic Fatalities."
[13] Sauerzapf, "Road Traffic Crash Fatalities: An Examination of National Fatality Rates and Factors Associated with the Variation in Fatality Rates between Nations with Reference to the World Health Organisation Decade of Action for Road Safety 2011 - 2020."
[14] Zheng et al., "Crash Involvement and Risky Riding Behaviors among Delivery Riders in China."
[15] Safarpour, Khorasani-Zavareh, and Mohammadi, "The Common Road Safety Approaches."
[16] Pawlovich, Souleyrette, and Strauss, "A Methodology for Studying Crash Dependence on Demographic and Socioeconomic Data."
[17] Stamatiadis and Puccini, "Fatal Crash Rates in the Southeastern United States."

speeding, alcohol use, distraction, and avoidance maneuvers all increased the likelihood of single-vehicle crashes.[18] Age and race were not correlated with them, however. In a subsequent study focused on crashes in Kentucky, Stamatiadis et al. looked at a larger group of socioeconomic factors, including education level, poverty level, employment, driver age, and the rurality of the area.[19] This analysis confirmed that educational attainment and economic standing were correlated with single-vehicle crashes. Additionally, positive correlations were found between age and crashes, for both younger and older drivers.

In both studies Stamadiatis et al. adopted the quasi-induced exposure methodology to analyze the socioeconomic attributes of the home zip codes of drivers in observed crashes. This methodology was also applied in a study of socioeconomic factors in California crashes.[20] Sharmin et al. extended the methodology by presenting a GIS-based method for aggregating road segments to achieve a sample large enough for statistical analysis. The study focused on the association between age groupings and crash involvement and severity. Young (teenage) drivers were more likely than not to be involved crashes of all types, while older (65+) drivers were more likely to be involved in severe crashes.

Shaon et al.'s work on crash frequency and crash severity used multivariate analysis to explore correlations between crashes and engineering factors and behavioral factors.[21] Their analysis used proxy variables to account for behavioral factors in crash count modeling, including DUI rate, drug related arrest rate, violent crime rate per county, per capita number of alcohol outlets, and liquor licensing rate. They found, on average, that crashes had 70% engineering-related factors and 30% behavioral-related factors, contrary to previous work that placed greater importance on behavioral factors. The authors suggested incorporating more behavioral factors (e.g., speeding, distracted driving, occupant protection) into the model would better reflect this reality. Of the behavioral variables evaluated, drug arrest rate consistently correlated with injury crashes. DUI arrests correlated negatively with crash severity, which may be counterintuitive. The authors speculated that higher presence of enforcement, which led to more DUI arrests, may have mitigated the impact of driving while intoxicated.

Lee et al.'s[22] analysis of FARS data from 1996 to 2000 concluded that using proper restraints could decrease the fatal crash risk of vehicle occupants by 54%. Occupants were four times more likely to be uninjured in serious crashes if using proper restraints. Demographic analysis found that young drivers (both male and female) aged 16 to 19 were overrepresented in unrestrained fatalities, although men more so than women. This trend persisted for the 20 to 24 age range but was less pronounced. The trend also continued for men in the 25 to 44 age range.

In a study of distracted driving, Ye et al. looked at socioeconomic factors associated with crash risk.[23] They found correlations between texting and age (younger drivers more likely), annual miles driven (more miles, more likely to text), and state. Holding a cell phone while driving correlated with age (younger drivers more likely), gender (women more likely), marital status (married more likely), and state.

Guo et al. studied the relationship between pedestrian crashes and demographic and land use factors to identify potential hot spots.[24] Factors correlated with crashes included low percentage of car ownership; higher AADT; higher bus stop density; middle-speed roads (45 mph to 60 mph); density of grocery stores and discount department stores; and higher density of barber shops, fast food restaurants, schools, and hotels. Older male pedestrians had higher rates of severe injury in pedestrian crashes.[25] In low-income areas pedestrians were more likely to engage in risk-taking behavior that led to crashes, while in high-income areas drivers were more likely to take risks. Analysis of pedestrian crashes in Australia found motorists to be at fault in 46 percent of crashes, pedestrians at fault in 36 percent of incidents, while the at-fault party for the remaining crashes was unknown or could not be identified (e.g., hit-and-run incidents).[26] Higher rates of severe and fatal crashes occurred on roads with higher speed limits. Alcohol consumption was a risk factor for pedestrians, but distraction was not.

Demographic and human factors have also been examined for motorcycle crashes.[27] Most motorcycle fatalities were men aged 21 to 25. Alcohol consumption was a major factor, with 35 percent of fatally injured motorcyclists having a blood-alcohol content (BAC) of over half the legal limit. Comparing the influence of different factors, motorcycle crashes

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[18] Kumfer, Wei, and Liu, "Effects of Demographic and Driver Factors on Single-Vehicle and Multivehicle Fatal Crashes."
[19] Stamatiadis et al., "Effect of Socioeconomic Factors on Kentucky Truck Driver Crashes."
[20] Sharmin et al., "Incorporating Demographic Proportions into Crash Count Models by Quasi-Induced Exposure Method."
[21] Rahman Shaon et al., "Incorporating Behavioral Variables into Crash Count Prediction by Severity."
[22] Lee and Schofer, "Restraint Use and Age and Sex Characteristics of Persons Involved in Fatal Motor Vehicle Crashes."
[23] Ye, Osman, and Ishak, "Accounting for Driver Distraction and Socioeconomic Characteristics in a Crash Risk Index."
[24] Guo et al., "Insights from Integrated Geo-Location Data for Pedestrian Crashes, Demographics, and Land Uses."
[25] Guo et al., "Mixed Effects Logistic Model to Address Demographics and Neighborhood Environment on Pedestrian Injury Severity."
[26] Oxley et al., "Understanding Pedestrian Crashes in Victoria."
[27] Turner and Georggi, "Analysis of Alcohol-Related Motorcycle Crashes in Florida and Recommended Countermeasures."

correlated more closely with behavioral and temporal factors than roadway or environmental features.[28] A separate study of motorcycle crashes confirmed the influence of behavioral factors, such as alcohol consumption and not using a helmet. [29] However, certain roadway and environmental factors were correlated with crashes as well, including road curvature, intersections, driveway access, and cloudy weather.

Chen et al. surveyed over 1,000 Americans to explore relationships between crash histories, risk-taking behaviors, demographic characteristics, and perceptions of traffic safety countermeasures.[30] Key findings included:

- Compared to both married men and all women, single men had higher driver's license revocation rates, received more traffic citations, were more likely to have a criminal record, and were less likely to wear a seat belt.
- Women were more likely to text and drive. Men were more likely to drink and drive.
- Married drivers were more likely to speed.
- Driver inattention or distraction were the most common crash factors. Habitually texting while driving increased the chances of injury and non-injury crashes.
- Controlling for VMT, drivers with CDLs were more likely to be involved in a crash.
- Respondents were most supportive of countermeasures that addressed impaired driving. Red light cameras had the support of 59% of respondents.

[28] Kim, Boski, and Yamashita, "Typology of Motorcycle Crashes."
[29] Lee et al., "Understanding Emerging Motorcyclist Segments in Crashes Using Florida Crash Data and Statewide Survey."
[30] Chen and Kockelman, "Americans' Crash Histories and Opinions on Safety Policy."

Chapter 3 Analytical Framework

As the literature review demonstrated, crashes do not occur in a vacuum, but are the result of interconnected and compounding factors of individual behaviors, societal norms, roadway design, and vehicle characteristics. Figure 3.1 provides a conceptual model for understanding how these factors combine and interact in the realm of highway safety. The schematic develops a multifaceted framework to understand the latent conditions impacting crash location, frequency, and severity. While factors located closely in space or time to a crash are likely to have stronger influence, latent factors play a vital but less understood role.

The schematic 1) demonstrates how crash factors are situated within and influenced by broader conditions related to individuals, groups, and society; and 2) reveals opportunities where engineering and public health interventions can be implemented to prevent crashes and improve safety outcomes.

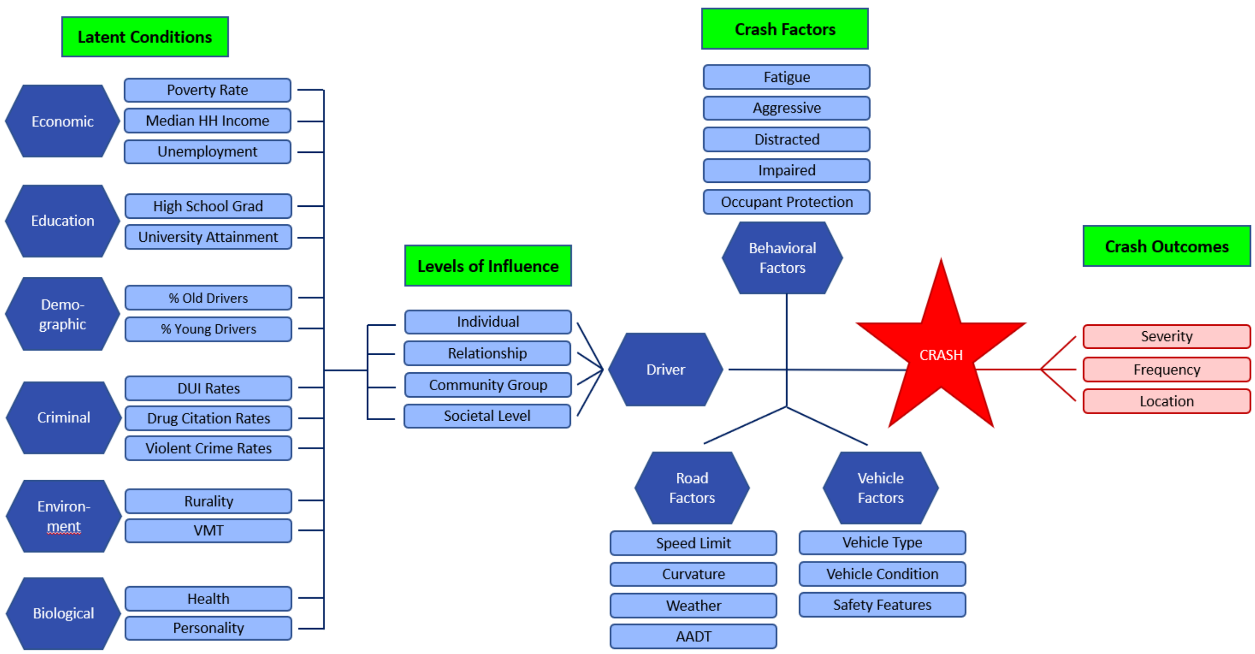

Figure 3.1 Crash Schematic

3.1 Latent Conditions

Latent conditions are unobservable and influence human behavior in multiple and compounding ways. As such, crash analysis must account for their impacts. They can be measured through observable proxies (e.g., poverty rate as an indicator of economic conditions). The schematic does not exhaustively catalogue latent conditions. Those included have been cited in the literature as correlating to some degree with crashes. Some are measured more easily than others, and data availability is better for some than others.

3.2 Levels of Influence

Public health literature identifies four levels through which latent conditions influence human behaviors:

- Individual level — Biological and personal history factors that may influence the likelihood of risk-taking behaviors (e.g., age, income, education, substance use)
- Relationship level — The nature of people's close relationships affects the likelihood of risk-taking behaviors (e.g., peers, partners, family members)
- Community level — Settings in which social relationships exist (e.g., schools, workplaces, neighborhoods, health systems)
- Societal level — Societal factors contribute to a climate that influences risk-taking behaviors (e.g., economic policies, educational policies, cultural norms, or societal conditions).

Understanding these levels of influence is critical for implementing interventions. For example, they can help traffic safety and public health practitioners decide what, where, and how cost-effective strategies should be implemented to mitigate risk-taking driving behaviors.

3.3 Crash Factors

Latent conditions filtered through levels of influence are pervasive and operate upon drivers. They affect the likelihood of engaging in risk-taking driving behaviors (e.g., not wearing a seatbelt, driving impaired, distracted, fatigued driving, aggression). These, in combination with the road and environmental factors, contribute to crash risk.

3.4 Crash Outcomes

Highway safety research focuses on crash statistics, including total crash counts, crash frequency, crash severities based on the presence of injuries and fatalities, and crash locations. Antecedent conditions, influences, and factors govern crash outcomes.

Chapter 4 Analysis of Behavioral Factors

Using the framework in Figure 3.1 as a guide, the research team performed exploratory statistical analysis of crash data that accounts for both the immediate circumstances of a crash as well as the social undercurrents that may influence risk-taking driving behaviors. Statistical analysis had three objectives:

- Explore how behavioral factors combine with non-behavioral factors to influence crash severity
- Explore behavioral factors individually to examine their interactions with other factors
- Expand the scope of variable types used beyond those typically employed in safety engineering research

4.1 Data and Analysis

The research team retrieved crash data for 2014 – 2018 from the Kentucky Crash Database. This database consists of data from crash reports filed by responding police officers. For the five-year period, the database includes 581,452 unique crashes. Using information on crash locations, crash data were joined with Highway Information System (HIS) data maintained by the Kentucky Transportation Cabinet (KYTC). The crash database and the HIS database are categorized into the following data classes:

- Behavioral: indicates if a particular behavior or human factor is implicated in the crash
- Crash: characteristics of the crash
- Driver: characteristics of the Unit 1 driver (typically the at-fault driver) in the crash
- Location: where the crash occurred
- Road: characteristics of the road where the crash occurred
- Time: when the crash occurred
- Vehicle: characteristics of the vehicles (or units) involved in the crash

Table 4.1 lists crash-related variables used in statistical analysis.

Table 4.1 Crash-Related Variables

Data Class	Data Field	Data Type	Data Source
Behavioral	Impaired	Y/N	Crash Database
Behavioral	Aggressive	Y/N	Crash Database
Behavioral	Unrestrained	Y/N	Crash Database
Behavioral	Distracted	Y/N	Crash Database
Driver	Age	Numeric	Crash Database
Driver	Gender	M/F	Crash Database
Location	Spatial	Numeric	Crash Database
Road	Intersection	Y/N	Crash Database
Road	Speed Limit	Numeric	Crash Database
Road	Road Condition	Dry/Not Dry	Crash Database
Road	Road Character	Straight & Flat/Not Straight & Flat	Crash Database
Road	Weather	Clear/Not Clear	Crash Database
Road	Rural Non-Interstate	Y/N	KYTC HIS
Road	Shoulder Width	Numeric	KYTC HIS
Road	Lanes	Numeric	KYTC HIS
Road	Last Count	Numeric	KYTC HIS
Road	Lane Width	Numeric	KYTC HIS
Road	Median Presence	Y/N	KYTC HIS

Data Class	Data Field	Data Type	Data Source
Time	Month	Numeric	Crash Database
Time	Collision Time	Numeric	Crash Database
Vehicle	Motorcycle Involved	Y/N	Crash Database
Vehicle	Pedestrian Involved	Y/N	Crash Database
Vehicle	Commercial Vehicle Involved	Y/N	Crash Database
Vehicle	Bicyclist Involved	Y/N	Crash Database

To examine how latent conditions may affect drivers the team included variables related to the social contexts in which crashes occurred. Analysis explored whether individual variables positively or negatively affected crash likelihood. To gauge the relevance of these factors, analysis focused on the Unit 1 driver and investigated the socioeconomic conditions of the Census block group where they resided. To produce these data, the team accessed Unit 1 home addresses for all crashes in the database and geocoded the addresses. Doing so allowed each crash to be linked to the relevant demographic and socioeconomic data. Two geocoding applications were used:

- U.S. Census Geocoder
- Esri ArcMap 10.8.1 Addresses Geocoding toolset

Of the 581,452 crashes in the database, 114,141 (19.6%) listed out-of-state home addresses or no address for Unit 1. Addresses for an additional 29,136 (0.5%) crashes could not be located through the geocoding processes. This left 438,175 for analysis.

The literature search identified socioeconomic variables to include in statistical models. Socioeconomic data at the Census block group level were accessed through ArcGIS Business Analyst[31], which houses demographic, business, consumer, and U.S. Census data. Also included in this analysis was the Area Deprivation Index.[32] The index assigns a numerical ranking to each block group to account for aggregated measures of socioeconomic disadvantage, including income, education, employment, and housing quality. Table 4.2 lists the demographic and socioeconomic variables included in the statistical models.

Table 4.2 List of Socioeconomic and Demographic Variables[33]

Data Class	Data Field	Data Type	Data Source
Demographic	% Black Pop	Numeric	Esri/US Census
Demographic	% Hispanic Pop	Numeric	Esri/US Census
Demographic	% White Pop	Numeric	Esri/US Census
Socioeconomic	Area Deprivation Index: State Rank	Numeric	The Neighborhood Atlas
Socioeconomic	Median Home Value	Numeric	Esri/US Census
Socioeconomic	Median Household Income	Numeric	Esri/US Census
Socioeconomic	% No Degree	Numeric	Esri/US Census
Socioeconomic	% No Diploma	Numeric	Esri/US Census
Socioeconomic	Per Capita Income	Numeric	Esri/US Census
Socioeconomic	% Population with Medicaid	Numeric	Esri/US Census
Socioeconomic	% Population with Medicare	Numeric	Esri/US Census
Socioeconomic	% Population with No Health Insurance	Numeric	Esri/US Census
Socioeconomic	Rural/Urban	Nominal	Esri/US Census

[31] Esri, "ArcGIS Business Analyst."
[32] Kind and Buckingham, "Making Neighborhood-Disadvantage Metrics Accessible — The Neighborhood Atlas."
[33] Percentages refer to proportion of individuals to the total within the block group.

Data Class	Data Field	Data Type	Data Source
Socioeconomic	Unemployment Rate	Numeric	Esri/US Census

4.2 Research Design

The dependent variables in the study models were behavioral crashes. Driving behaviors reflect those included in Kentucky's *Strategic Highway Safety Plan (SHSP)*.[34] The Kentucky *SHSP* includes six emphasis areas, four of which involve driving behaviors: aggressive driving, distracted driving, impaired driving, and unrestrained driving (improper usage of seatbelt or child safety seat). Each behavior can be linked directly to fields on crash reports. Table 4.3 lists the crash fields that indicate each of the four driving behaviors.

Table 4.3 Crash Factor Codes Included for Each Driving Behavior Type

Aggressive	Distracted	Impaired	Unrestrained
Disregard Traffic Control	Cell Phone	Alcohol Involvement	Installed/Not in Use
Exceeded the Stated Speed Limit	Distraction	Drug Involvement	Not Installed
Failure to Yield Right of Way	Inattention		
Following Too Close			
Improper Passing			
Too Fast for Conditions			
Weaving in Traffic			

On crash reports these fields are not mutually exclusive — for a given crash, all, some, or none of the behavioral fields may be indicated. For some behavioral fields (e.g., unrestrained driving) the data should be accurate as it is straightforward to discern at a crash scene whether a vehicle occupant was wearing a seatbelt. Impaired driving data are more complicated. While alcohol impairment can be detected at a crash scene through breathalyzers and field sobriety tests, drug impairment may be less obvious and more difficult to detect. Additionally, driver blood tests can only be required for crashes resulting in a death or physical injury.

Identifying aggressive driving and distracted driving is more subjective. Compared to other states, Kentucky records higher distracted driving rates. This is likely a reflection of Kentucky placing greater emphasis on the indication of distracted driving as a factor (where appropriate). Both aggressive and distracted driving can be difficult to identify as a factor in single-vehicle crashes because their detection often requires a witness or self-reporting by the driver.

Despite these limitations, investigating behavioral data is critical as driving behaviors significantly influence highway safety. Table 4.4 lists driving behaviors and the frequency at which they were indicated as factors in Kentucky crashes from 2014 to 2018.

Table 4.4 Kentucky Crashes by Behavioral Types (2014 – 2018)

Behavioral Type	# Crashes	% Total
Distracted	263,930	45%
Aggressive	133,709	23%
Impaired	22,980	4%
Unrestrained	21,590	4%

4.3 Statistical Analyses

To analyze behavioral crashes, the team used binomial logistic regression, including in each model all the crash, roadway, environmental, socioeconomic, and demographic variables described above. Analysis was conducted in JMP Pro 15.2.0. Because analyses focused on the crash database, they did not consider the likelihood of a crash itself occurring. This would require an exposure measure that indicates, for each block group, the likelihood of residents being

[34] KYTC, "SAFEKY: Kentucky Strategic Highway Safety Plan 2020-2024."

on the road as a driver, passenger, pedestrian, bicyclist, or other user. Rather, analyses focused on the likelihood of a crash involving certain factors or resulting in certain outcomes.

4.4 Results

Results from the analyses are expressed in terms of odds ratios, which are a statistical measure of the strength of the relationship between independent and dependent variables. For instance, a variable with an odds ratio of two indicates the result is twice as likely to occur with the variable present compared to without the variable present. An odds ratio of one indicates the outcome has equal chance of occurrence with or without the variable present. An odds ratio of less than one indicates the outcome is less likely to occur with the variable present. Given an odds ratio of one indicates equal chance of occurrence, odds ratios are not considered statistically significant if the 95 percent confidence intervals cross one.

The first analysis investigated the relationship between crash severity and behavior type — aggressive driving, distracted driving, impaired driving, unrestrained (no seatbelt) driving. Crash severity was defined using crash codes on police reports, where **K** indicates a death and **A** indicates a suspected serious injury.

Figure 4.1 shows the odds ratios for severe crashes involving each behavior type. Crashes with an unrestrained occupant were 10.5 times more likely to result in a death or serious injury, followed by impaired driving crashes and aggressive driving crashes. Distracted driving crashes had a negative association with crash severity, with an odds ratio of 0.6. The implications of distracted driving having an odds ratio in the opposite direction than hypothesized are unclear. As data for distracted driving crashes are the least reliable of the four driving behaviors, this may contribute to the unanticipated finding.

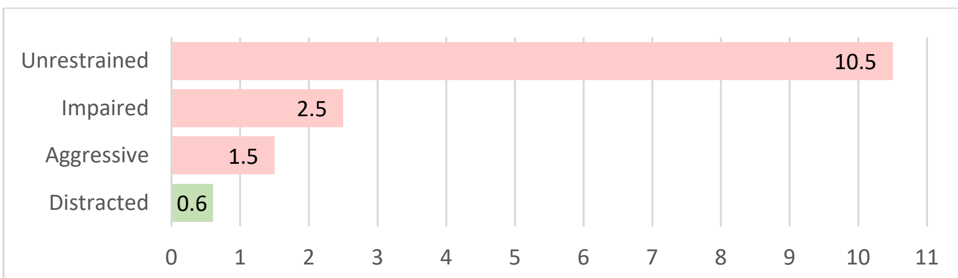

Figure 4.1 Severe Crash Odds Ratios for Behavioral Factors

The following sections individually review each behavior type. Odds ratios are presented and discussed for each as they relate to variables found in the models. Only variables with statistically significant odds ratios ($p \leq 0.0001$) are included in figures.

4.5 Aggressive Driving Crash Results

Figure 4.2 shows odds ratios for aggressive driving crashes. Variables shaded red had odds ratios > 1.0 (i.e., higher likelihoods), variables shaded gray (odds ratios = 1.0) had minimal impacts, and variables shaded green (odds ratios < 1.0) had the lowest impacts. For all continuous variables, results are shown for increasing values of the variable. For example, *% No Degree* is shown in green with an odds ratio of 0.54, indicating that drivers from Census block groups with higher percentages of residents without a college degree had a lower likelihood of being involved in aggressive driving crashes. Appendix I includes odds ratios and confidence intervals for all models.

Multiple roadway factors were significant to aggressive driving crashes. Crashes located at roadway intersections were more than twice as likely to involve aggressive driving as a factor. Other roadway factors predictive of aggressive driving crashes included greater lane width, higher number of lanes, and greater speed limit. Taken together, these factors describe roadways designed to handle higher vehicle volumes. One interpretation is the presence of other vehicles on the roadway increases the likelihood of aggressive driving crashes as several aggressive driving human factor codes relate to other vehicles (e.g., following too closely, failure to yield right of way, improper passing, weaving). More vehicles increased the likelihood of more traffic and congestion, more signalized intersections, and greater delays. These roads also tend to be engineered to a higher safety standard, which could suggest an influence from the road itself on driver behavior. Roads engineered to be the safest could have the unintended effect of promoting overconfidence in the driver, resulting in higher risk-taking behavior.

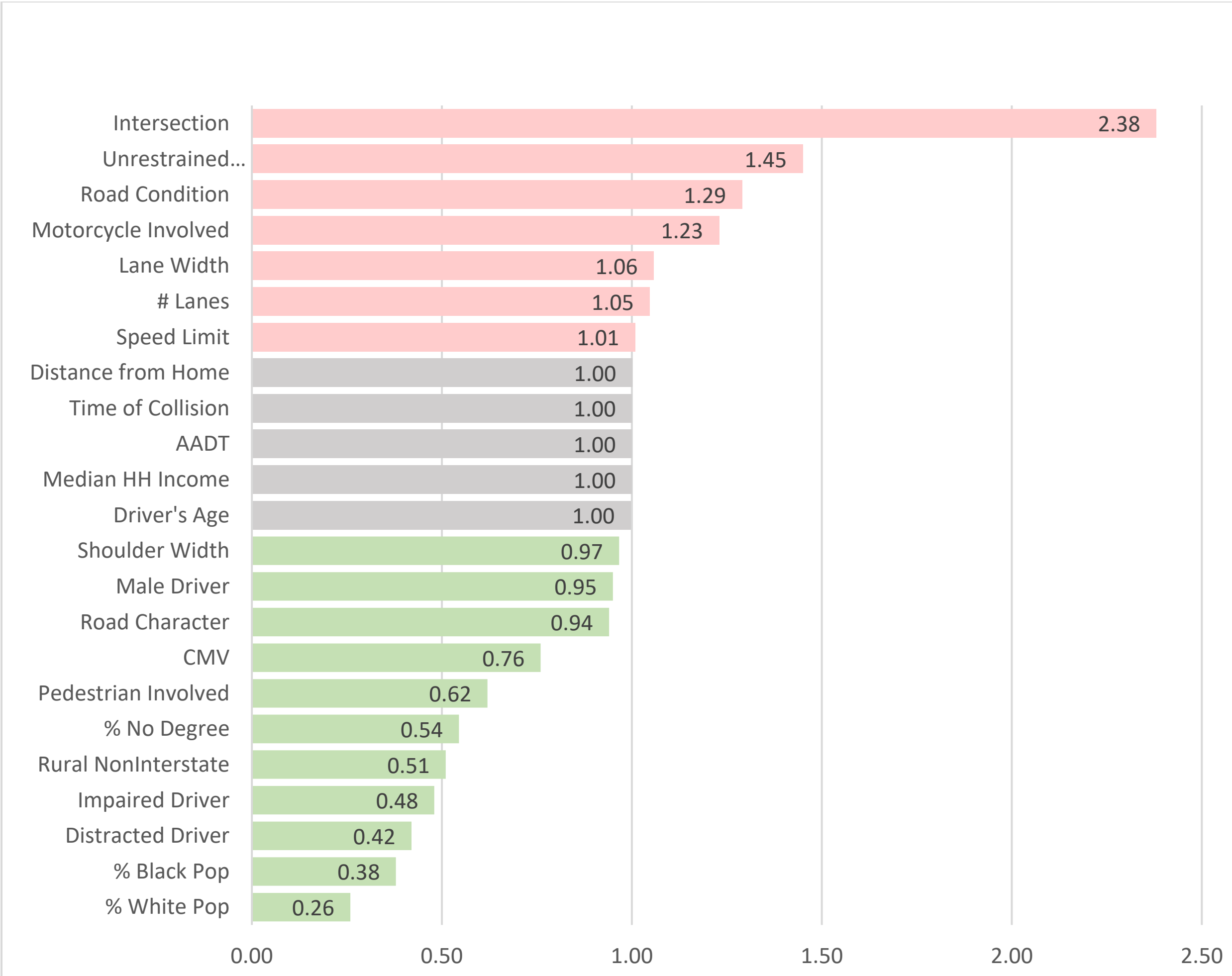

Figure 4.2 Aggressive Driving Crash Odds Ratios by Factor

Conversely, rural non-interstate roads were a protective factor with respect to aggressive driving crashes. Rural non-interstate roads tend to feature lower traffic volumes and have fewer safety engineering enhancements (e.g., wider lanes, shoulders, and medians). This type of environment may influence the driver to behave less aggressively because they perceive greater risk. Such roads also generally have less traffic and fewer opportunities for drivers to behave aggressively toward one another.

Relative to other behavioral factors, aggressive driving correlated positively with unrestrained driving, but correlated negatively with impaired driving and distracted driving. Among socioeconomic factors included in the model, those found to be statistically significant all had a negative likelihood of being associated with aggressive driving crashes. Female drivers were slightly more likely than male drivers to be involved in aggressive driving crashes, while driver age had a minimal impact on aggressive likelihood.

4.6 Distracted Driving Crash Results

Figure 4.3 shows odds ratios for distracted driving crashes. Intersections, greater lane width, higher number of lanes, and greater shoulder width had odds ratios greater than one. Like aggressive driving crashes, these elements indicate roads with higher traffic volumes and engineered to higher safety standards.

Several roadway elements had a negative association with distracted driving crashes — median presence, lower speed limit, horizontal and vertical curves, and rural non-interstate roads. Also, environmental factors such as poor weather and poor road condition had a negative association with distracted driving crashes. Taken together, these elements may be indicative of a more complex driving environment where drivers are more likely to attend to the act of driving, ultimately decreasing the likelihood of distraction-induced incidents.

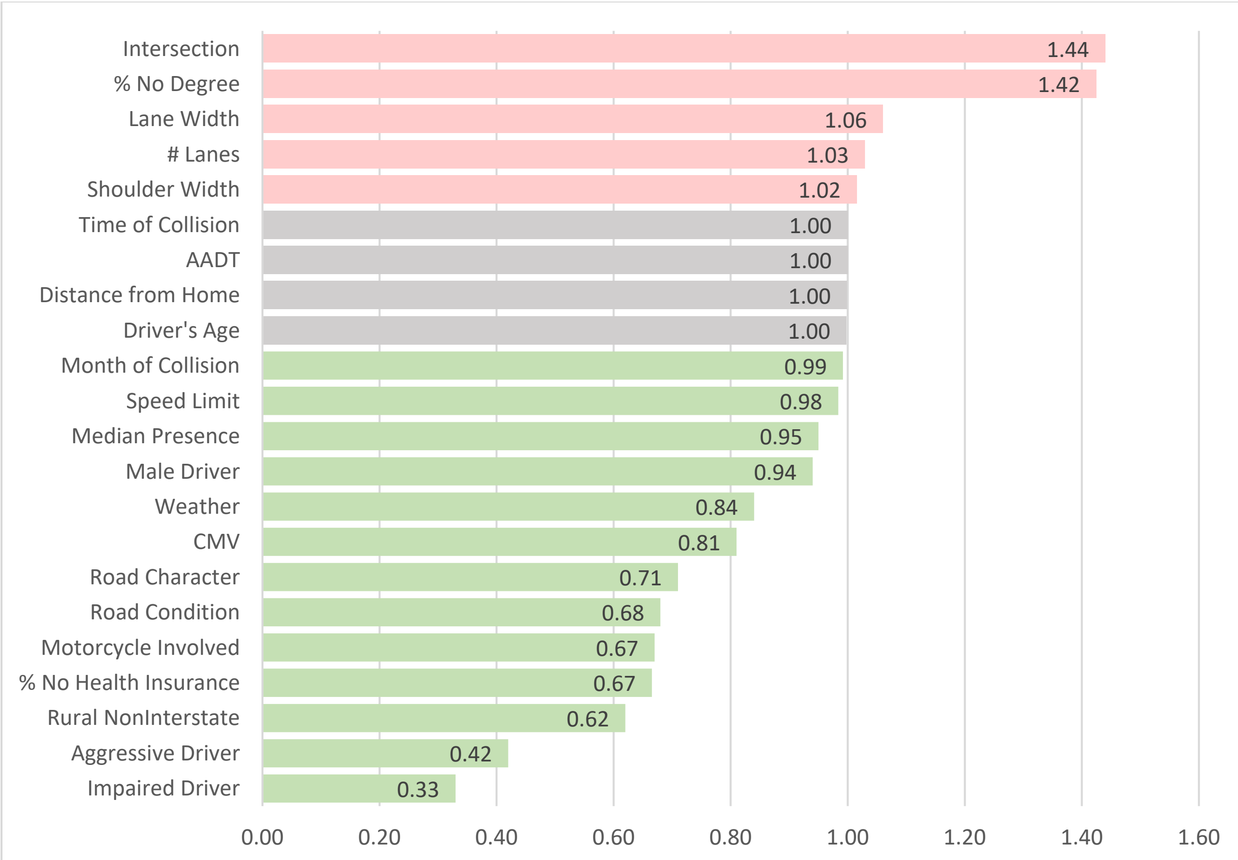

Figure 4.3 Distracted Driving Crash Odds Ratios by Factor

Unit 1 drivers from areas with a higher percentage of residents without a college degree were 1.5 times more likely to be involved in a distracted driving crash. However, Unit 1 drivers from areas with a higher percentage of residents without health insurance had a 33% lower likelihood of being involved in a distracted driving crash. Like aggressive driving, distracted driving crashes were slightly more likely to involve female drivers than male drivers.

4.7 Impaired Driving Crash Results

Figure 4.4 shows odds ratios for impaired driving crashes. Compared to aggressive and distracted driving, roadway factors for impaired driving crashes had a weaker relationship. Roads with more complex geometrics (e.g., curves and hills) and higher speed limits had a slightly positive association with impaired driving crashes. Roads with wider shoulders and lanes, as well as higher numbers of lanes, had a negative association with impaired driving crashes.

The strongest positive association with impaired driving crashes was lack of seatbelt usage. This suggests that impaired drivers were also more likely to not wear seatbelts. Impairment, itself, may lead to this association, or some drivers could be more predisposed to risk-taking behaviors. Impaired driving crashes, however, showed a negative association with aggressive driving and distracted driving crashes.

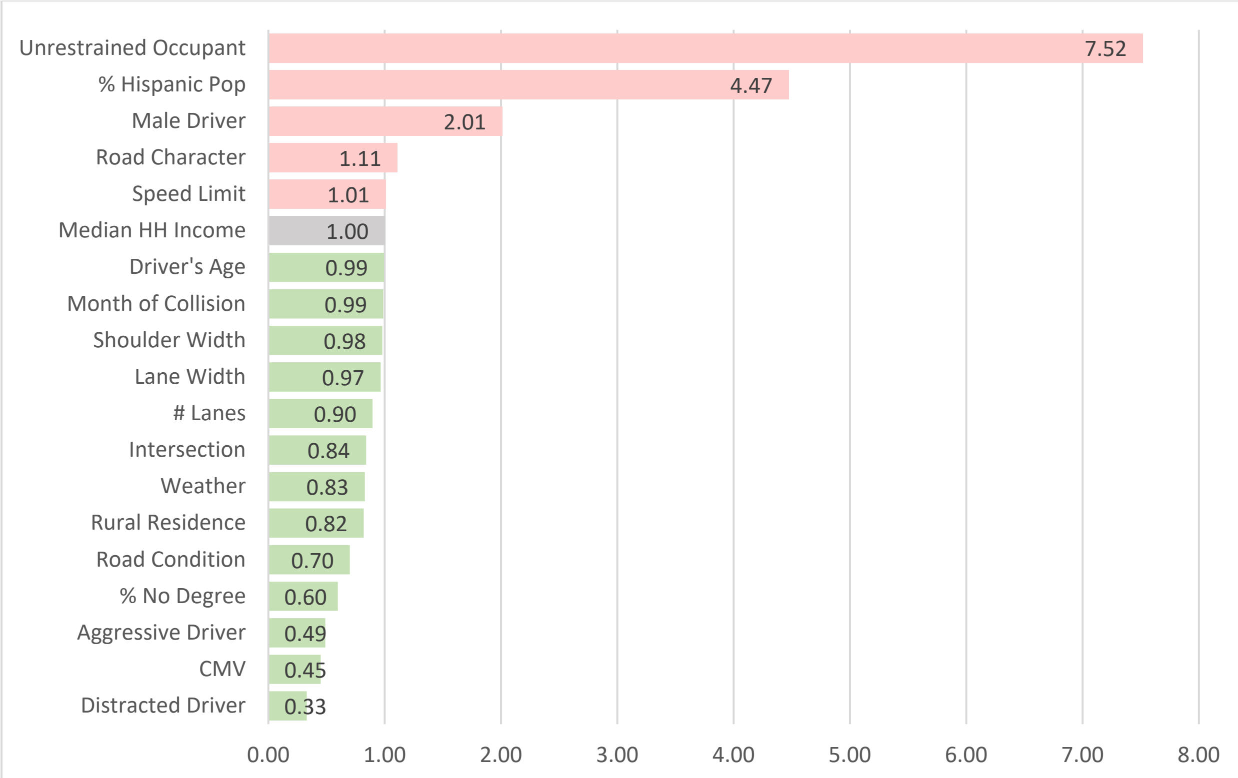

Figure 4.4 Impaired Driving Crash Odds Ratios by Factor

Impaired driving crashes were twice as likely to involve male drivers than female drivers, and more than four times as likely to involve a driver from areas with higher percentage of Hispanic populations. Impaired driving crashes were less likely to involve a driver from rural areas or in areas with a higher percentage of the population having a college degree.

4.8 Unrestrained Driving Crash Results

Unrestrained driving is a little different from the others examined in that this behavior does not necessarily have any causal factor in the crash, itself. For example, driving aggressively in certain road conditions or characteristics has a compounding effect on crash likelihood. However, in the case of unrestrained driving, the driver not wearing a seatbelt does not change the likelihood of a crash. The impact of unrestrained driving is more likely to be found in the crash outcome, where the likelihood of severe injury or death is much higher when not wearing a seatbelt.

Nevertheless, several roadway factors were associated with unrestrained driving (Figure 4.5). Unrestrained crashes were 1.54 times more likely on rural non-interstate roads and 1.23 times more likely on roads with more complex geometrics (e.g., curves and hills). These crashes were less likely on roads with wider lanes and higher numbers of lanes. These factors may simply reflect how roads differ in rural and urban areas. In Kentucky, seatbelt usage rates are higher in urban areas, so it is expected that roads in rural areas would be more associated with unrestrained crashes.

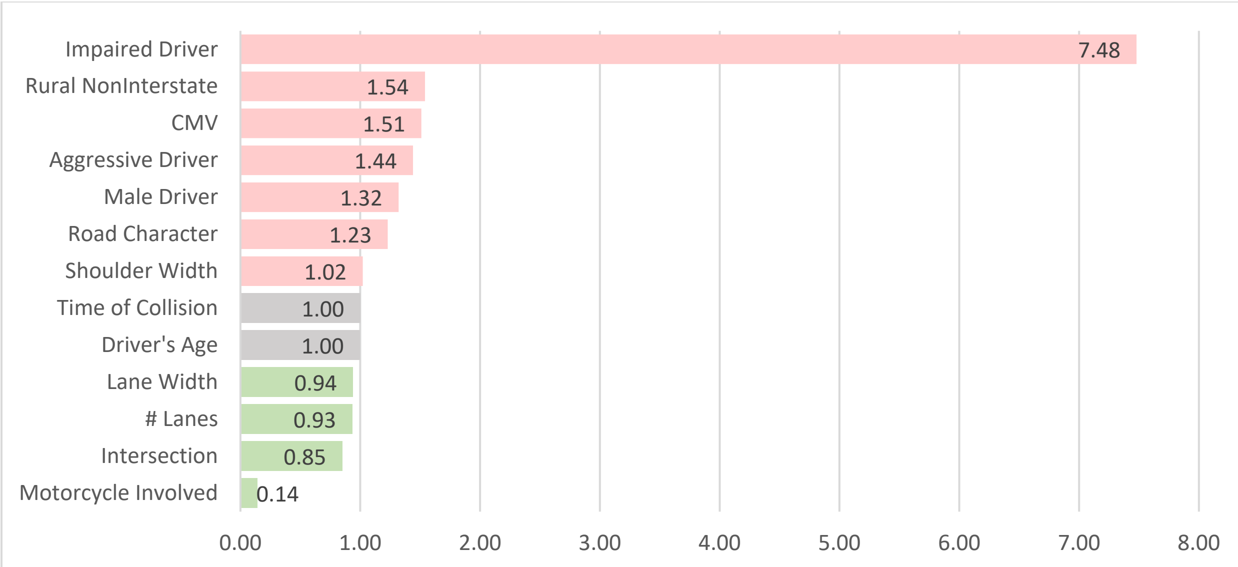

Figure 4.5 Unrestrained Driving Crash Odds Ratios by Factor

Unrestrained crashes were over seven times more likely to occur in conjunction with impaired driving. They were 1.32 times more likely to involve a male driver than a female driver, and 1.51 times more likely to involve a commercial motor vehicle (CMV). It is surprising to see CMVs implicated given the professionalization of CMV driving, but this indicates an intervention opportunity for highway safety practitioners.

Chapter 5 Segmentation Analysis

The next analyses used a different, nontraditional dataset to model behavioral crashes. Geodemographic segmentation data are a form of combined demographic, socioeconomic, and geographic data originally developed in marketing to help businesses better understand their customer base and develop strategies to advertise their products. To create the data, a multivariate statistical classification technique divides the population into groups under the assumption that differences within groups are less than differences between groups. Factors that inform segmentation include demographic and socioeconomic conditions, the emergence of new markets as the result of population growth, cultural shifts, and geographic differences. Each population segment identifies a unique consumer market group in the U.S. Population segments are spatially explicit and identified with individual areal units. Often the data are produced in Census spatial units (i.e., block, block group, tract).

Geodemographic segmentation data offer an alternative approach to understanding how demographic, socioeconomic, cultural, and geographic differences among the population may impact the likelihood of crashes involving risk-taking behaviors. Rather than trying to determine which, if any, specific socioeconomic variable is most predictive of crashes, this approach leverages combined measures previously developed and implemented for other research purposes. Because segmentation data are derived for marketing purposes, they provide an opportunity for highway safety practitioners to better understand the context in which populations associated with different risk-taking behaviors live. And it provides an opportunity to craft countermeasures focused on these population groups for maximum effectiveness. Finally, because the data are spatial, they help highway safety practitioners identify how and where to implement countermeasures.

5.1 Esri Market Segmentation Data

The research team used Esri Tapestry® segmentation data in the analysis.[35] The Esri data consist of 69 distinct population segments, which are split into LifeMode groups and Urbanization groups. LifeMode groups are population segments with similar demographics (e.g., the same generational cohort), and socioeconomic characteristics (e.g., a particular household income level). For example, LifeMode 1 is *Affluent Estates* and includes population segments featuring middle-aged to retirement aged and well-educated residents with high household incomes. The *Affluent Estates* LifeMode group contains five population segments broken down further based on various factors. Figure 5.1 indicates the percentage of Kentucky households assigned to each LifeMode group, and Figure 5.2 maps the distribution of LifeMode groups throughout Kentucky.

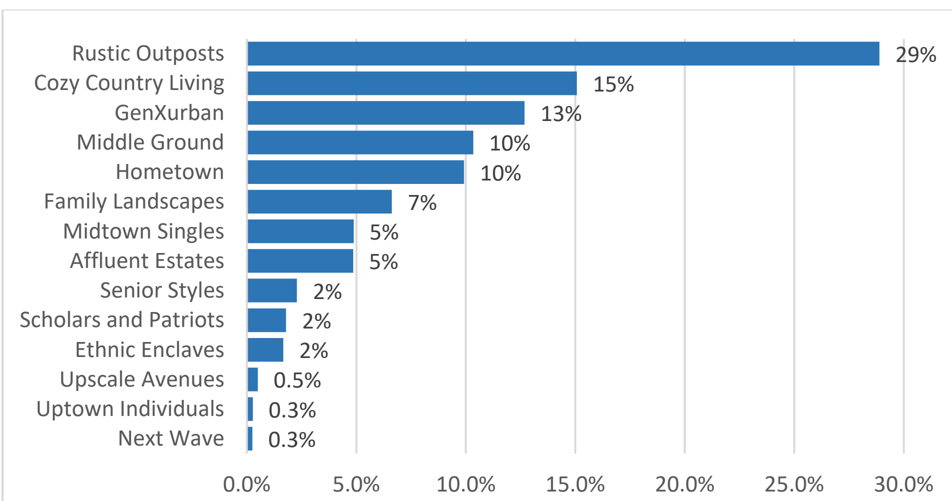

Figure 5.1 Percent of Total Kentucky households by LifeMode Tapestry® Segments

35 Esri, "Methodology Statement: 2020 Esri Tapestry® Segmentation."

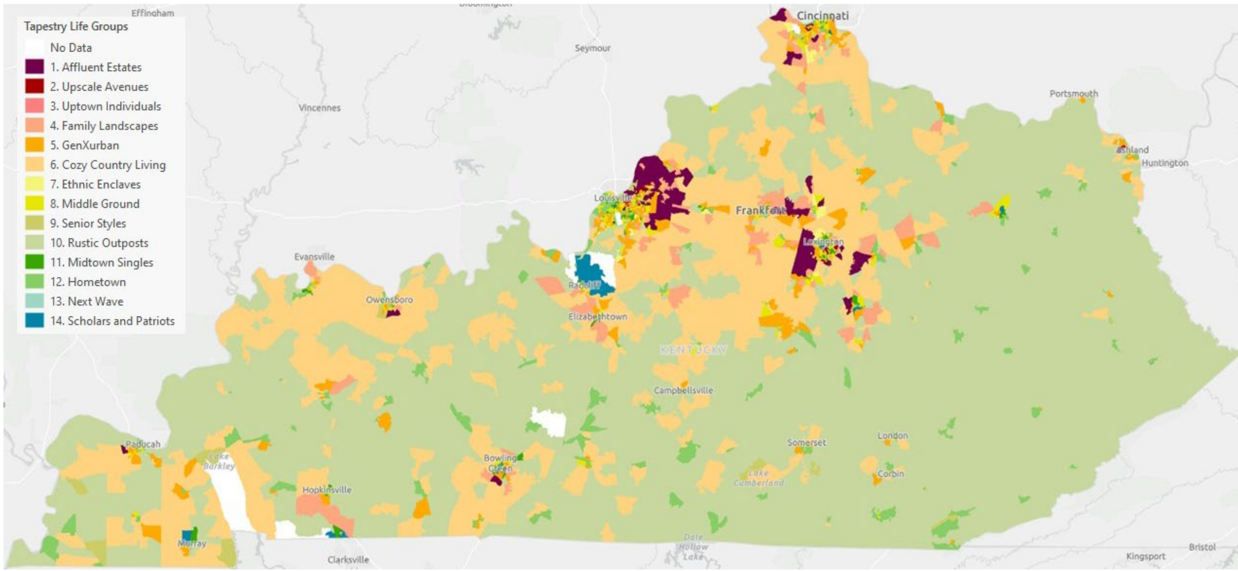

Figure 5.2 Distribution of LifeMode Tapestry® segments in Kentucky

LifeMode 10 (*Rustic Outposts*) is the largest LifeMode group in Kentucky by both population and land area. *Rustic Outposts* denotes "country life with older families in older homes." This makes sense in the context of Kentucky, which has a higher-than-average share of residents living in rural areas. LifeMode 10 is most associated with southern and Appalachian locales in the U.S. The second largest group in Kentucky is LifeMode 6 *Cozy Country Living*, which is also rural but is in closer proximity to urbanized areas and features households with higher incomes than those in LifeMode 10. By population, this is the largest LifeMode group in the U.S and tends to be associated with the Midwest.

Urbanized areas in Kentucky are more diverse culturally and socioeconomically, so numerous LifeMode groups are found in these areas. By population, the largest in Kentucky are *GenXurban* (middle-aged residents living in single-family homes), *Middle Ground* (Millennials early in their careers), and *Hometown* (lower income residents in small towns and older urban neighborhoods). Full descriptions for all Tapestry® segments and the methodology used for defining them are available from Esri.[36]

5.2 Segmentation Analysis Design

To conduct analyses, the research team accessed Esri Tapestry® segmentation data at the Census block group level. For these models, population segmentation data were the only dependent variables included. Binomial logistic regression was used for each of the four behavior types and all crashes. Additional models for each of the behaviors were developed for *severe* crashes, or crashes that resulted in a serious injury or death. As before, these models do not predict the likelihood of a crash occurring, but rather the likelihood of a behavioral involved crash that occurred being associated with the population segments.

To test the methodology, the team developed a model for the population segmentation data and their association with all severe crashes, regardless of whether risk-taking behavior was involved. Figure 5.3 maps the results of the segmentation analysis for crash severity. Darker shades of red indicate higher likelihood of residents in those areas being involved in a severe crash compared to a crash that results in no injury or only minor injuries. Residents in rural areas, particularly in southeastern Kentucky and parts of western Kentucky, had the highest likelihood for severe crashes.

36 Esri.

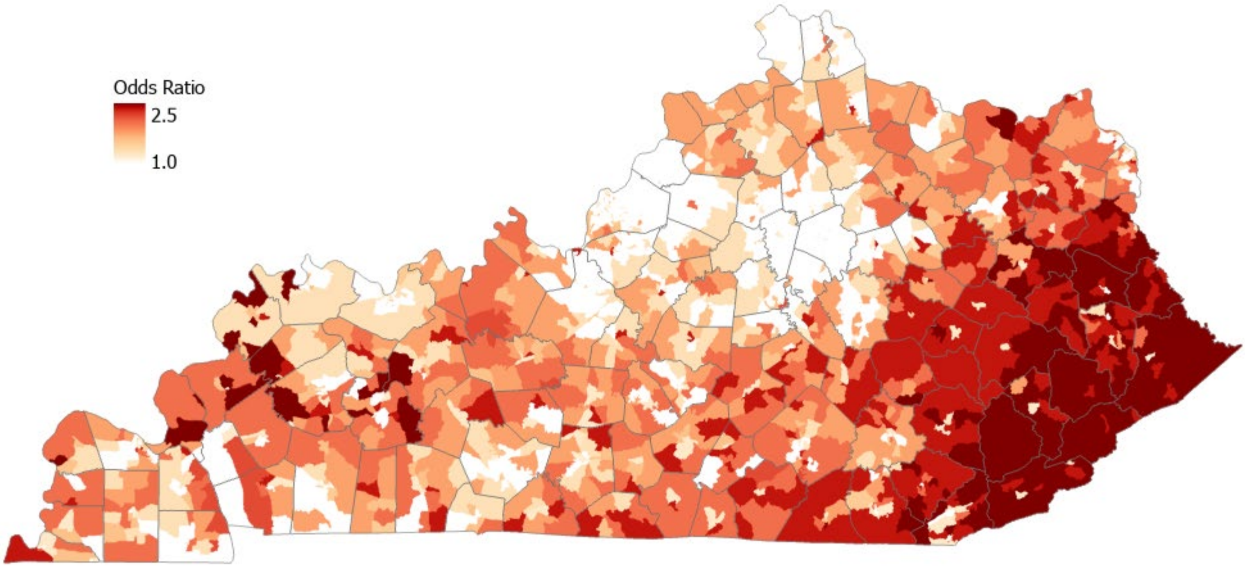

Figure 5.3 Odds Ratios by Block Group for Severe (Fatal and Serious Injury) Crashes

Of the 69 population segment types included in the U.S. dataset, 57 are found in Kentucky. The Esri data assigns entire Census block groups to a single population segment, so block groups were the spatial unit of analysis. Table 5.1 lists the Kentucky population segments, the percentage of Kentucky households associated with each population segment, and model results for each of the four behavioral types.

Table 5.1 Odds Ratios for Population Segments and the Four Risky Behavior Involved Crash Types

LifeMode	Segment	Description	% KY HHs	All Crashes Odds Ratios				Severe Crashes Odds Ratios			
				Aggressive	Distracted	Impaired	Unrestrained	Aggressive	Distracted	Impaired	Unrestrained
Affluent Estates	1A	Top Tier	0.6%	1.33							
	1B	Professional Pride	1.0%	1.30		0.65					
	1C	Boomburbs	0.6%	1.35		0.57					
	1D	Savvy Suburbanites	1.4%	1.16							
	1E	Exurbanites	1.3%	1.23		0.67					
Upscale Avenues	2A	Urban Chic	0.3%	1.48							
	2D	Enterprising Professionals	0.2%	1.56	0.69						
Uptown Individuals	3A	Laptops and Lattes	< .1%	2.24							
	3B	Metro Renters	0.2%	1.65							
Family Landscapes	4A	Workday Drive	2.2%			0.77					
	4B	Home Improvement	0.7%								
	4C	Middleburg	3.7%								
GenXurban	5A	Empty Nesters	2.3%								
	5B	In Style	3.0%	1.11							
	5C	Parks and Rec	0.7%								
	5D	Rustbelt Traditions	3.1%								
	5E	Midlife Constants	3.6%	0.85							
Cozy Country Living	6A	Green Acres	3.9%	0.82	0.93						
	6B	Salt of the Earth	5.7%	0.70	0.94		1.38		1.33		1.53
	6C	The Great Outdoors	0.4%	0.76	0.80						
	6D	Prairie Living	0.6%	0.75	0.81		1.73				
	6E	Rural Resort Dwellers	0.6%	0.64	0.77		2.03				2.31
	6F	Heartland Communities	4.0%	0.69			1.63		1.58		1.84
Sprouting Explorers	7A	Up and Coming Families	1.4%		0.84						
	7C	Urban Edge Families	0.2%								
	7D	Forging Opportunity	< .1%					9.72			
Middle Ground	8B	Emerald City	1.5%	1.27							
	8C	Young Professionals	2.1%	1.27	0.89						
	8E	Front Porches	1.7%								
	8F	Old and Newcomers	2.9%								
	8G	Hometown Heritage	2.1%				1.71				
Senior Styles	9A	Silver & Gold	< .1%								
	9B	Golden Years	0.5%	1.24	1.22						
	9C	The Elders	< .1%								

LifeMode	Segment	Description	% KY HHs	All Crashes Odds Ratios				Severe Crashes Odds Ratios			
				Aggressive	Distracted	Impaired	Unrestrained	Aggressive	Distracted	Impaired	Unrestrained
	9D	Senior Escapes	0.2%	0.63							
	9E	Retirement Communities	0.7%								
	9F	Social Security Set	0.8%				1.70				
Rustic Outposts	10A	Southern Satellites	8.5%	0.62	0.85		1.82	1.31	1.75	1.69	2.30
	10B	Rooted Rural	6.4%	0.55	0.83		2.08	1.33	1.76	1.76	2.68
	10C	Economic BedRock	6.3%	0.43	0.72	1.48	2.55	1.45	1.79	2.95	3.75
	10D	Down the Road	1.1%				1.54				
	10E	Rural Bypasses	6.6%	0.52	0.81		2.42	1.35	1.93	2.20	3.34
Midtown Singles	11B	Young and Restless	1.4%	1.54	0.70						
	11C	Metro Fusion	0.9%	1.29	0.85						
	11D	Set to Impress	1.8%	1.20	0.91						
	11E	City Commons	0.9%	1.17			2.10				
Hometown	12A	Family Foundations	0.4%				1.72				
	12B	Traditional Living	2.6%				1.33				
	12C	Small Town Sincerity	5.9%	0.66			1.79				1.80
	12D	Modest Income Homes	1.0%	1.17			1.90				
Next Wave	13C	NeWest Residents	0.1%	1.89	0.59	1.84					
	13D	Fresh Ambitions	0.1%	1.54	0.55						
Scholars and Patriots	14A	Military Proximity	0.3%								
	14B	College Towns	1.2%	1.28							
	14C	Dorms to Diplomas	0.3%	1.96	0.73						

5.3 Segmentation Analysis and Aggressive Driving

Aggressive driving crashes were the only type positively associated with high income population segments, including all five segments in LifeMode 1 (*Affluent Estates*), in addition to segments in LifeMode 2 (*Upscale Avenues*) and LifeMode 3 (*Uptown Individuals*). The population segment with the highest likelihood was *Laptops and Lattes* at 2.25, which encompasses single, white, well-educated professionals living in urban neighborhoods.

Some low income and/or young and urban population segments also had increased likelihood for aggressive driving crashes. These include neighborhoods with urban renters, recent immigrants, or college-aged students. Of these, the highest likelihood was for *Dorms to Diplomas* at 1.96. These neighborhoods are located near college campuses and are home to a significant number of students.

Figure 5.4 maps population segments with odds ratios above 1.0 for aggressive driving crashes. They are most common in urban areas (e.g., Louisville, Lexington, northern Kentucky) and smaller college towns (e.g., Richmond, Bowling Green, Morehead, Georgetown, Murray).

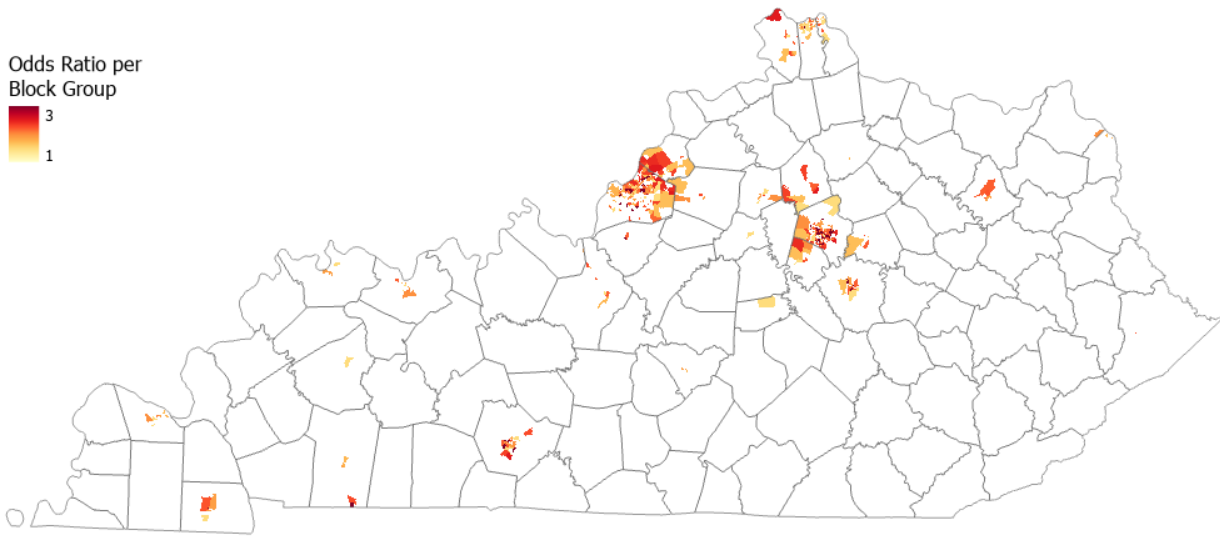

Figure 5.4 Odds Ratios by Block Group for Aggressive Driving Crashes

Figure 5.5 maps population segment block groups with increased likelihood for severe crashes that involved aggressive driving. Increased likelihood was most common in rural areas. Combined with the prior map, this demonstrates that while drivers from rural areas were less likely to get involved in a crash involving aggressive driving, crash outcomes tended to be more severe.

One population segment type, 7D (*Forging Opportunity*), stood out with a high odds ratio of 9.72. This population segment describes urban periphery neighborhoods characterized by multigenerational households, elevated poverty rates, and higher than average percentages of race/ethnicities other than White or Black. The only block group in Kentucky identified as this segment is in southwestern Jefferson County.

Other population segments most associated with severe crashes that involved aggressive driving are all included in the *Rustic Outposts* LifeMode group. None of these population segments were positively associated with aggressive driving crashes in general — only those resulting in serious injury or death.

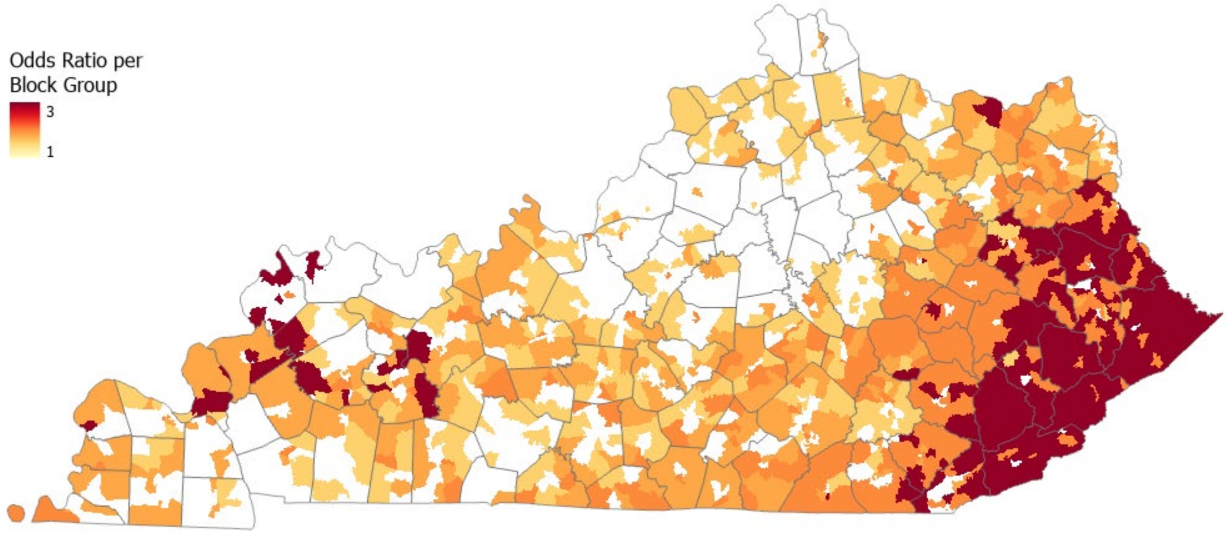

Figure 5.5 Odds Ratios by Block Group for Aggressive Driving Crashes Resulting in Death or Serious Injury

5.4 Segmentation Analysis and Distracted Driving

Segmentation analysis had limited value for analyzing distracted driving crashes. Only one population segment had a p-value ≤ 0.0001 and an odds ratio above 1.0. That segment, 9B (*Golden Years*), had an odds ratio of 1.24. It includes communities with people at or nearing retirement from professional careers who are financially secure and active in leisure pursuits, including travel, dining out, museums, concerts, and sports. Interestingly, this population segment is also described as being well-connected technologically and having high internet usage, features which may lead to cell phone usage and distraction. Figure 5.6 shows the block groups associated with Segment 9B. Most are in Jefferson County (Louisville), in addition to Boone County, Madison County, Daviess County, and McCracken County.

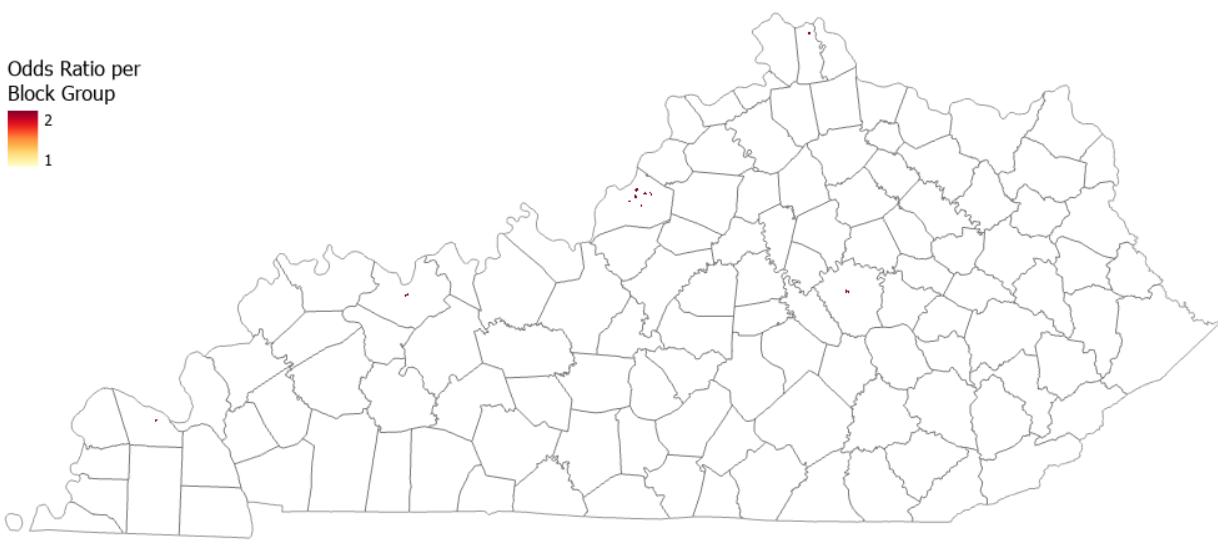

Figure 5.6 Odds Ratios by Block Group for Distracted Driving Crashes

Figure 5.7 maps block groups with odds ratios above one for distracted driving severe crashes. Virtually all these population segments are in rural or urban peripheral areas. This indicates that while distracted driving was not necessarily more common in these areas, crash outcomes were more severe.

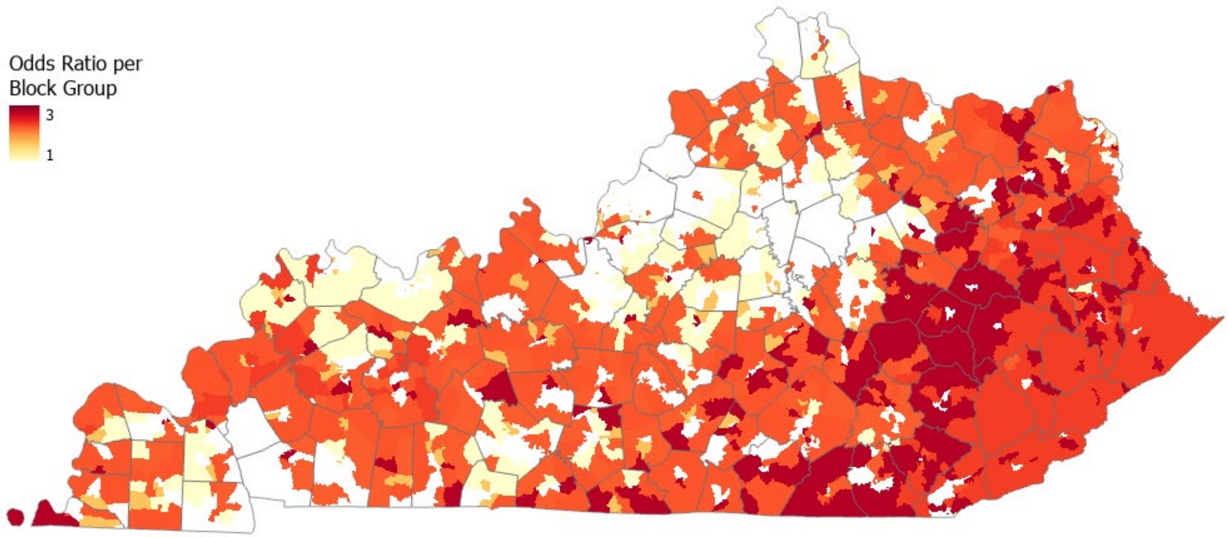

Figure 5.7 Odds Ratios by Block Group for Distracted Driving Crashes Resulting in Death or Serious Injury.

5.5 Segmentation Analysis and Impaired Driving

Two population segment types had odds ratios above one for impaired driving crashes: 10C (*Economic BedRock*) and 13C (*NeWest Residents*). Segment 10C (odds ratio = 1.48) encompasses rural areas where mining and other resource extraction industries are common. In Kentucky, coal mining has historically been a major source of employment in southeastern and western Kentucky. However, coal mining jobs decreased drastically by 78 percent from 2010 to 2020, leading to further economic distress in already resource limited areas. These areas are also where the opioid crisis has struck particularly hard.

Segment 13C (odds ratio = 1.84) includes neighborhoods, most often in urban areas, with higher numbers of recent immigrants. Households are characterized by young families with children, employment in blue collar or service industries, rental housing, and below average income. There are five such block groups in Kentucky (two in Louisville, three in Lexington). Figure 5.8 maps the population segment block groups with odds ratios above one for impaired driving crashes.

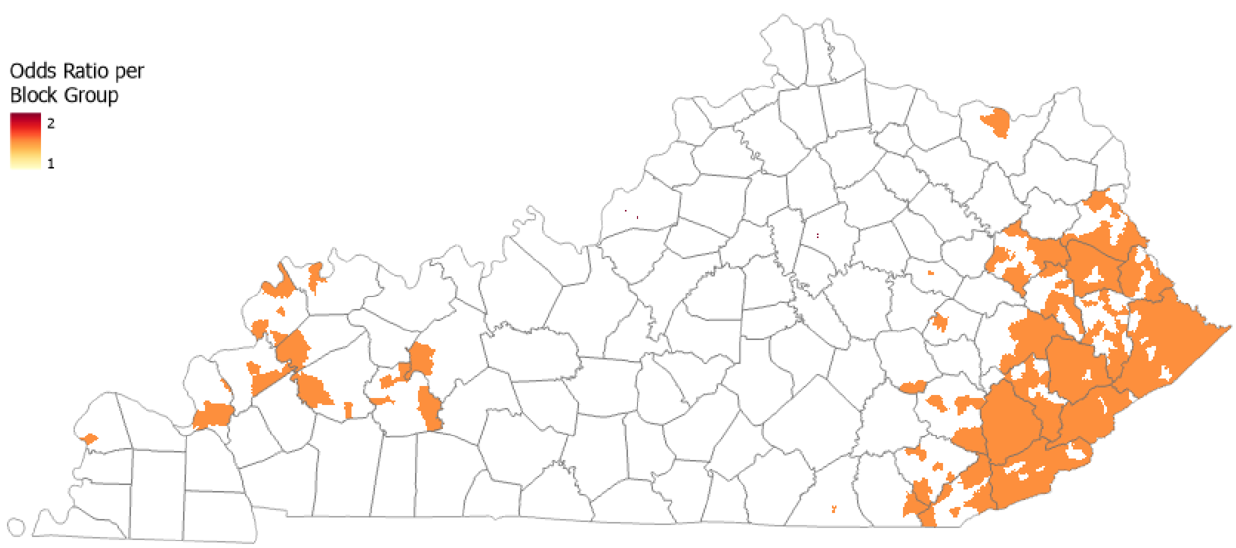

Figure 5.8 Odds Ratios by Block Group for Impaired Driving Crashes

Figure 5.9 maps population segment block groups with odds ratios above one for impaired driving severe crashes. It reveals the location of rural block groups in the *Economic BedRock* segment along with smaller block groups in Jefferson and Fayette counties associated with the *NeWest Residents* segment.

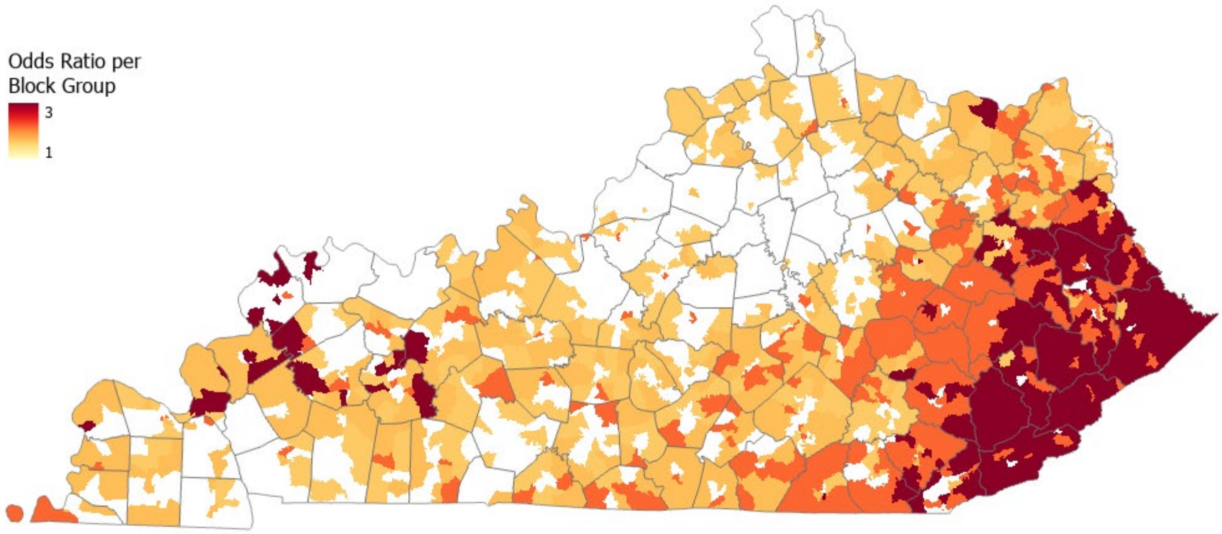

Figure 5.9 Odds Ratios by Block Group for Impaired Driving Crashes Resulting in Death or Serious Injury

5.6 Segmentation Analysis and Unrestrained Driving

Crashes in which a vehicle occupant was not restrained had odds ratios above one for 16 population segment types, with the highest odds found in rural segments. Segment 10C (*Economic BedRock*) had an odds ratio of 2.55, and Segment 10E (*Rural Bypasses*) had an odds ratio of 2.42. All five segments in the *Rustic Outposts* LifeMode group had odds ratios above 1. Another rural group, LifeMode 6 (*Cozy Country Living*), had four segments with odds ratios above 1, with Segment 6E (*Rural Resort Dwellers*) being the highest at 2.03. Urban segments in LifeMode group 12 (*Hometown*) had a strong association with unrestrained driving crashes. Three segments in this group encompass inner city lower income neighborhoods in large cities, while the fourth includes older and lower income neighborhoods in small towns. All population segments in this group had odds ratios above 1, with Segment 12D (*Modest Income Homes*) having the highest at 1.9. Figure 5.10 maps population segment block groups with odds ratios above one for unrestrained driving crashes. The highest odds ratios are in southeastern Kentucky and parts of western Kentucky. This map has close affinities with Kentucky's annual seatbelt survey, which consistently shows lower seatbelt usage in rural areas.

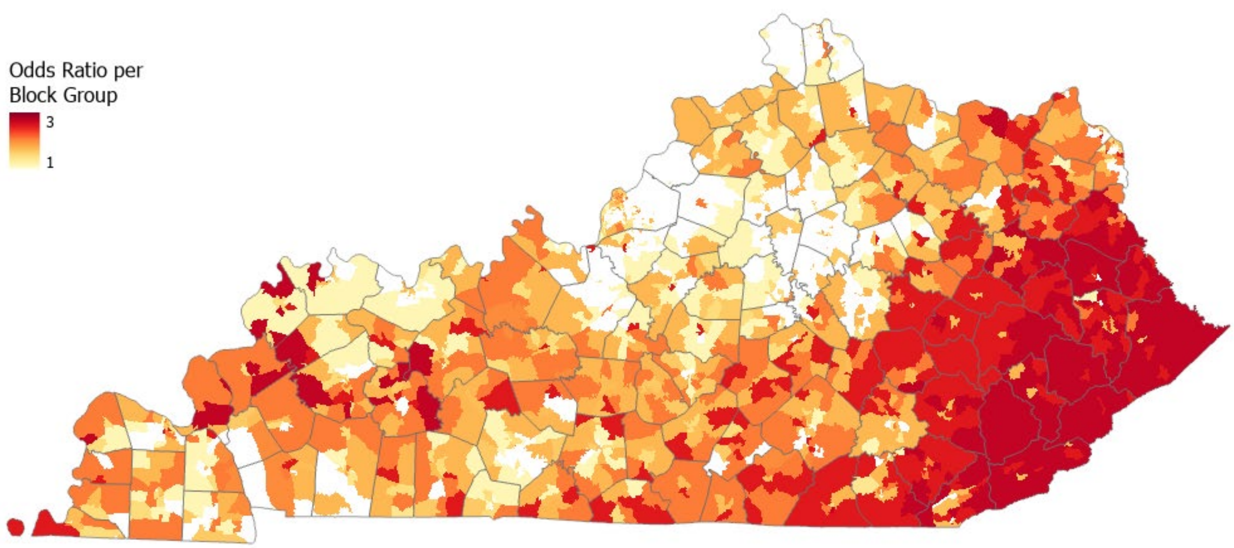

Figure 5.10 Odds Ratios by Block Group for Crashes Where a Vehicle Occupant Was Not Restrained

Figure 5.11 maps population segment block groups with odds ratios above one for crashes in which a vehicle occupant was not restrained and a death or serious injury resulted. Unlike maps for other behaviors covered in this chapter, this map is nearly identical to the map of odds ratios for all unrestrained crashes (Figure 5.10), demonstrating how influential seatbelt usage is on crash severity.

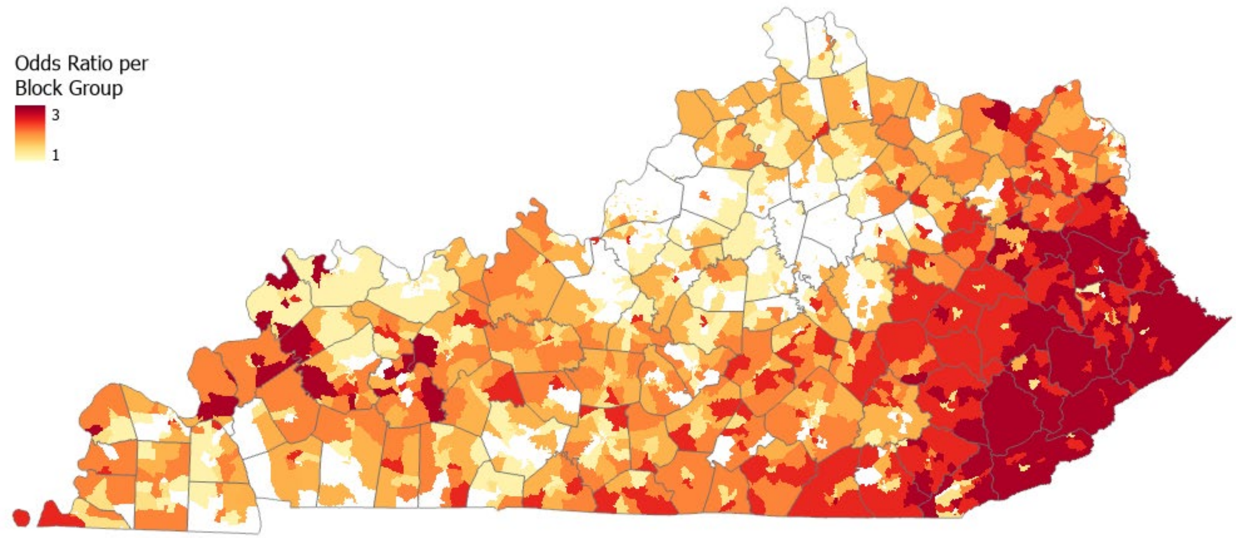

Figure 5.11 Odds Ratios by Block Group for Crashes Where a Vehicle Occupant Was Not Restrained and the Crash Resulted in Death or Serious Injury

5.7 Discussion

Geodemographic segmentation data offers an alternative and innovative approach to understanding how sociodemographic characteristics may help identify at-risk driver populations. Designed for marketing purposes, Esri segmentation data defines unique groups of consumers based on their demographic, socioeconomic, and cultural needs. These factors have been shown to influence decision-making processes and behaviors. Segmentation data provides an opportunity for traffic safety researchers and practitioners to capitalize on information that already helps promote effective advertisement and maximizes on consumer needs and behavior. Through the lens of behavioral economics, a behavioral science field that combines economics and psychology to understand and predict human behavior, segmentation data can provide essential information to understand and change the traffic safety culture in Kentucky. For example, future efforts can focus on developing and implementing tailored messaging for driver subgroups at risk for impaired driving crashes using lifestyle and behavior factors unique to their tapestry segment. Incorporating interdisciplinary approaches such as segmentation data and behavioral economics can help us understand driver behavior and develop strategies and interventions that may be more palatable and useful to at-risk drivers.

Chapter 6 Network Screening

While previous analyses investigated causal associations for behavioral-related crashes, this chapter applies that knowledge to identify roadway corridors where behavioral-related crashes are overrepresented. It develops a method safety practitioners can use to (1) identify where behavior-involved crashes occur and (2) facilitate countermeasure deployment.

6.1 SPF, EEC, and Network Screening

The *Highway Safety Manual* (HSM)[37] promotes the use of sophisticated statistical models for identifying problem areas and prioritizing safety investments. These methods include three techniques: safety performance functions (SPF), excess expected crashes (EEC), and network screening.

SPFs model crash frequency based on traffic volume and roadway segment homogeneity.[38] Statistical techniques, such as negative binomial regression, are used to predict the number of crashes on a roadway segment with a given traffic volume. Roadway segmentation is a critical step in developing SPFs. Segments must be created and grouped based on roadway characteristics meaningful for analysis (e.g., number of lanes, lane widths, and setting (urban vs. rural)). For each roadway class, SPFs are generated and tested using cumulative residual (CURE) plots and other goodness of fit measures. The better the CURE plot, the more reliable the model is expected to be.[39]

Along with using SPF models to calculate predicted crashes for each segment in the roadway classes, an Empirical Bayes (EB) method can be used to calculate the expected number of crashes on the roadway segments using historical crash data and the model's crash predictions. The model prediction has greater influence on the EB expected crashes when there is less overdispersion (i.e., better models have less overdispersion). The difference between SPF-predicted crashes and EB-expected crashes is excess expected crashes (EEC).[40] The EEC value reflects the number of excess crashes a segment has experienced relative to other segments of the same type.

The EEC values can be used by practitioners to screen the roadway network to identify roadway segments with higher-than-expected crashes. Network screening is a technique for prioritizing locations for consideration of safety investments based on crash history, roadway factors, and anticipated future crashes. KYTC uses network screening to assist with allocating Highway Safety Improvement Program (HSIP) funds to enhance safety on Kentucky roadways.[41]

The research team used SPFs, EECs, and network screening techniques to investigate behavioral crashes at the roadway segment level. Rather than developing models for all crashes, these techniques were deployed to develop separate models for each behavioral crash type (aggressive, distracted, impaired, and unrestrained).

6.2 Setup

To establish homogenous roadway segments, state-maintained roads were divided into classes and segmented in ArcGIS. Interstates and parkways were placed into a single class based upon their unique and shared characteristics that differentiate them from other roadways. All other roads were split into classes based on the following criteria:

- Urban/rural location of the road segment
- Number of lanes — two-lane roads in one class and roads with three or more lanes in another class
- Shoulder width — segments with shoulder widths less than four feet in one class and those with shoulder widths greater than four feet in another class
- Divided/undivided design of the roadway

These factors were selected based on expert judgment and experience in successfully developing SPFs for Kentucky highways, combined with the results of the statistical models presented in Chapter 4.

The team used five years of crash data (2015 – 2019) to build and test SPF models. Crashes were linked to roadways in ArcGIS based on the RT_UNIQUE (route identifier) and crash mile point. Table 6.1 lists the 13 roadway segment classes and the number of crashes assigned to each segment for each behavioral type.

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[37] AASHTO, *The Highway Safety Manual*.
[38] Souleyrette et al., "Safety Analysis for SHIFT Implementation."
[39] Blackden et al., "Automating Safety Performance Function Development to Improve Regression Models."
[40] Souleyrette et al., "Safety Analysis for SHIFT Implementation."
[41] Hamilton and Coley, "Kentucky's Network Screening Process."

Table 6.1 Roadway Classifications for SPF Development

Class ID	Segment Description	# Segments	Total Crashes	Aggressive Crashes	Distracted Crashes	Impaired Crashes	Unrestrained Crashes
1	Interstate + Parkway	2,171	44,504	10,029	15,622	1,150	1,266
2	Rural 2 Lane; Shoulder < 4’	12,525	92,087	11,917	27,166	5,326	7,155
3	Rural 2 Lane; Shoulder > 4’	3,700	29,822	4,317	11,067	1,229	1,896
4	Rural 3+ Lanes; Shoulder < 4’; Divided	19	250	33	100	4	5
5	Rural 3+ Lanes; Shoulder > 4’; Divided	356	4,168	755	1,343	146	192
6	Rural 3+ Lanes; Shoulder < 4’; Undivided	98	1,799	308	937	39	82
7	Rural 3+ Lanes; Shoulder > 4’; Undivided	451	4,253	750	1,738	160	246
8	Urban 2 Lanes; Shoulder < 4’	7,223	127,107	33,499	57,007	5,134	5,146
9	Urban 2 Lanes; Shoulder > 4’	1,900	22,921	5,232	11,309	703	979
10	Urban 3+ Lanes; Shoulder < 4’; Divided	599	21,510	7,776	9,915	476	487
11	Urban 3+ Lanes; Shoulder > 4’; Divided	855	22,121	7,158	10,447	608	682
12	Urban 3+ Lanes; Shoulder < 4’; Undivided	1,687	90,067	28,751	44,092	2,335	2,678
13	Urban 3+ Lanes; Shoulder > 4’; Undivided	973	28,347	7,799	15,052	663	880

SPFs were developed for each combination of road segment and behavioral type using the SPF-R package in RStudio.[42] CURE plots were generated for each model and analyzed for goodness of fit. Figure 6.1 shows CURE plots for Road Segment Class 2. The plots demonstrated good model fit for aggressive, impaired, and unrestrained driving, while the distracted driving plot indicated the most omitted variable bias.

[42] Souleyrette et al., “Safety Analysis for SHIFT Implementation.”

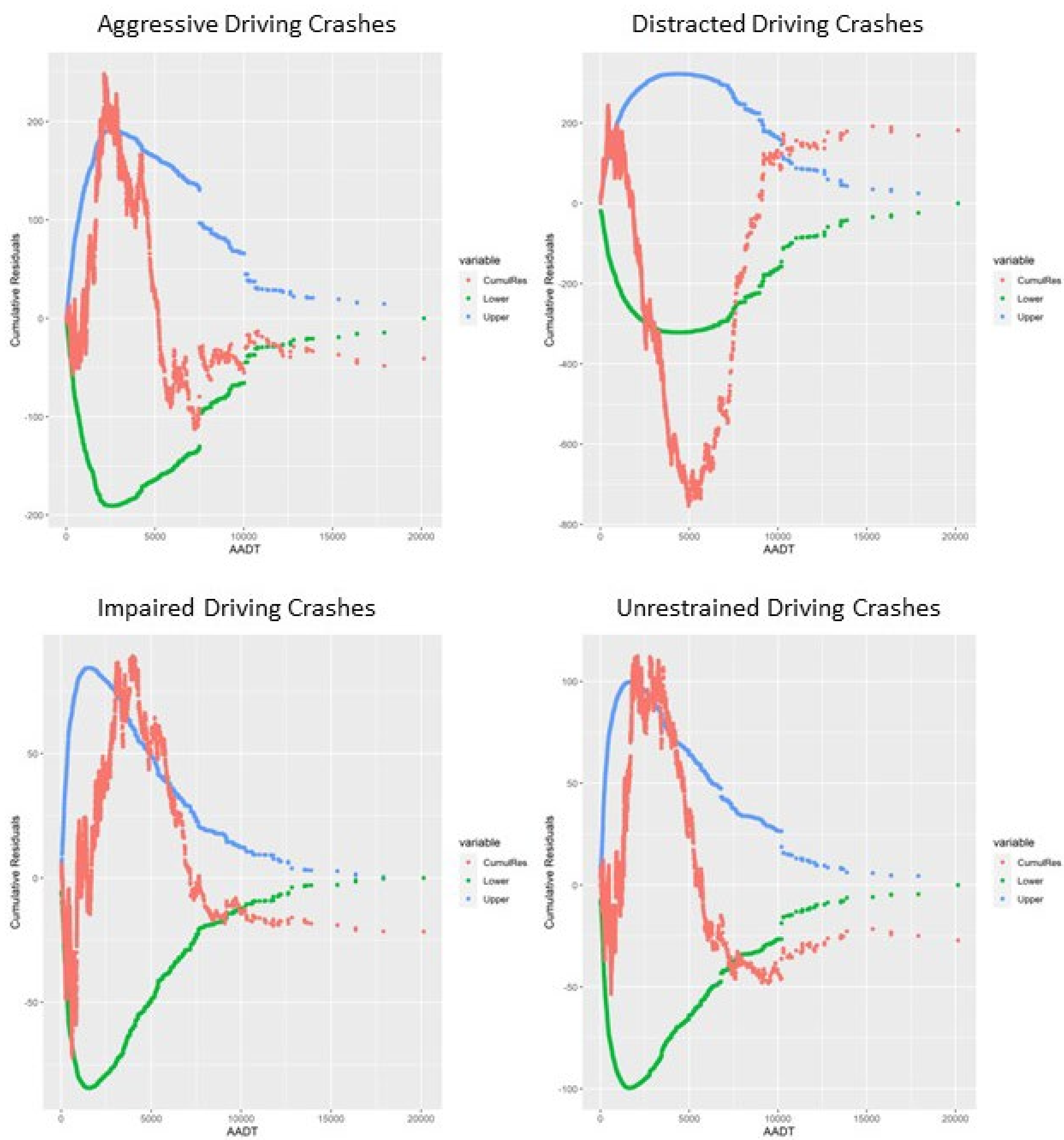

Figure 6.1 Sample CURE Plots for Rural 2-Lane + Shoulder < 4 Feet Wide Roads

6.3 Results

EECs were calculated on all segments for each roadway class and behavioral type. Table 6.2 lists the number and percentage of roadway segments with EECs greater than zero for each behavioral type.

Table 6.2 Number and Percentage of EEC Segments Greater Than Zero for Each Behavioral Type

Behavior	# Segments with EEC > 0	% All Segments with EEC > 0
Aggressive	8,282	28%

Distracted	9,298	31%
Impaired	7,233	24%
No Restraint	7,744	26%

To conduct network screening, model results for all roadway segments, regardless of roadway class, were combined for each behavioral type. The top one percent of EEC segments were mapped in ArcGIS (Figure 6.2). Roadway segments are clustered around the highest population areas of Louisville, Lexington, and northern Kentucky. The aggressive driving map exhibits the strongest clustering, while the unrestrained map has the least.

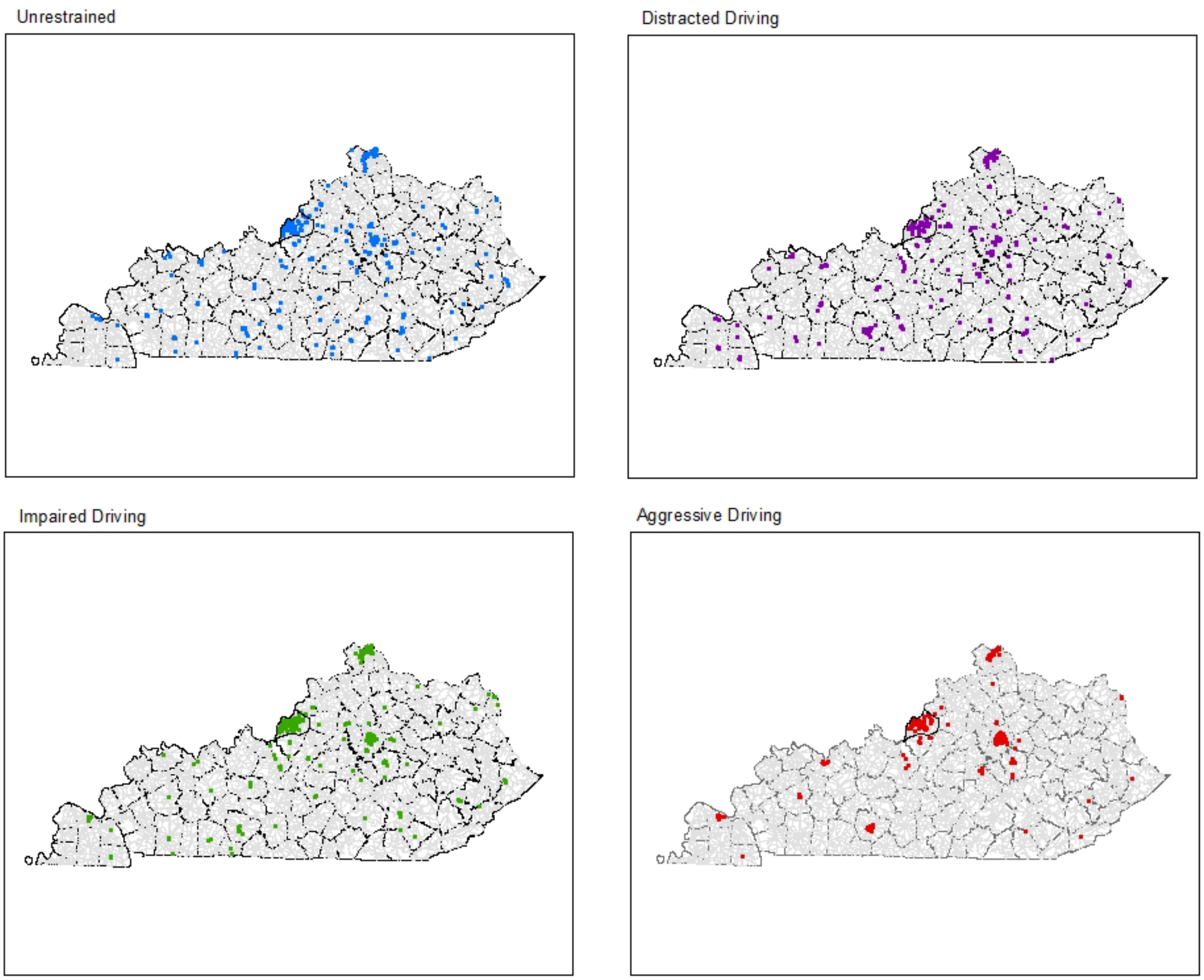

Figure 6.2 Top One Percent of EEC Segments Statewide for Each of the Four Behavioral Types

Figure 6.3 maps the top one percent of EEC roadway segments located in Jefferson County (the state's most populous county). At this scale, patterns are more evident, with multiple roadway segments combining to form corridors of high behavioral-related crashes. A review reveals problematic corridors for each behavioral type:

- Unrestrained: West Broadway, Dixie Highway, 7th Street Road, and Taylor Blvd.
- Distracted: Shelbyville Rd.
- Impaired: Baxter Ave., 7th Street Rd., Taylor Blvd.
- Aggressive: Baxter Ave. / Bardstown Rd., surface street approaches to interchanges with I-265 and I-264.

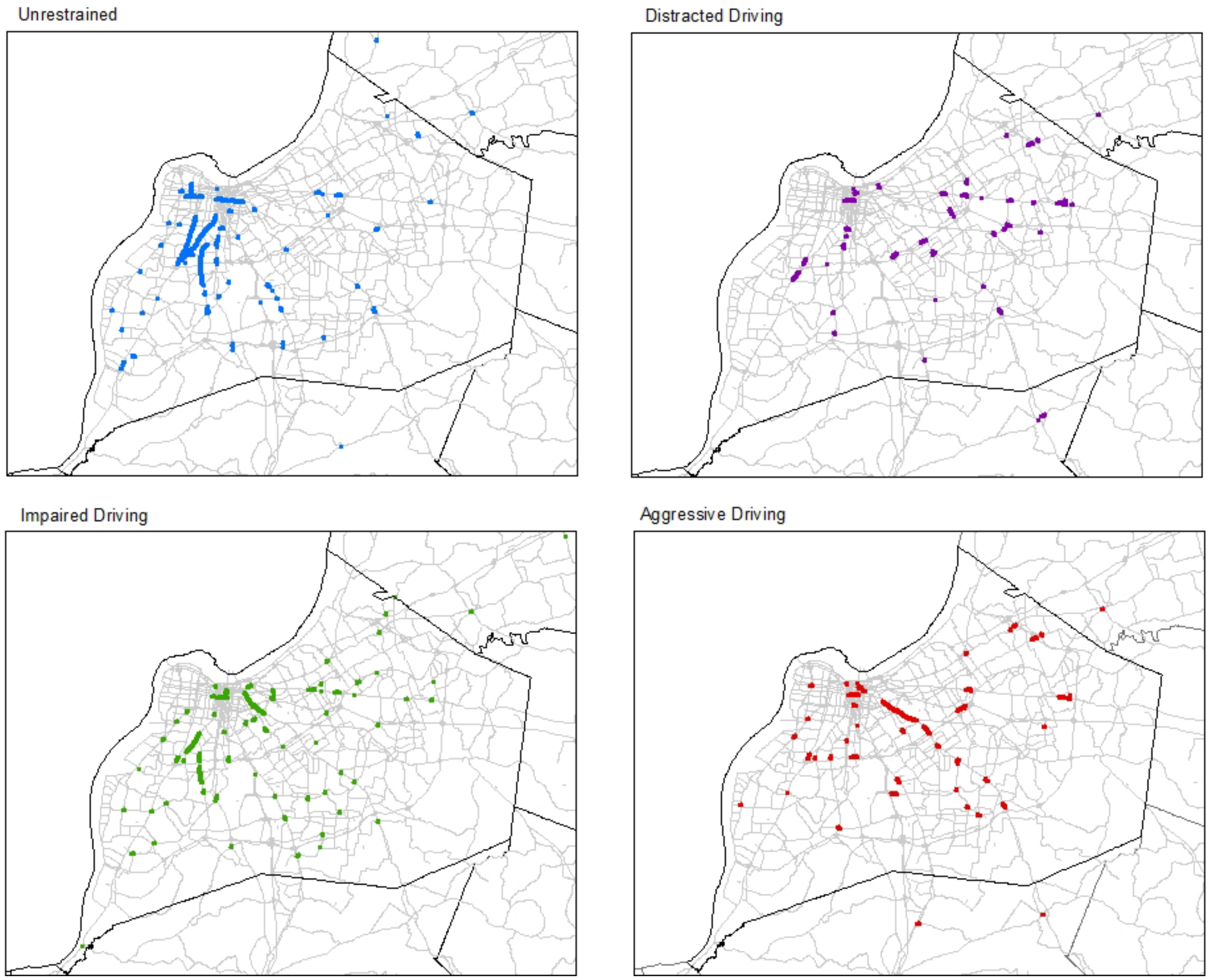

Figure 6.3 Top One Percent of EEC Segments in Jefferson County for Each of the Four Behavioral Types.

6.3 Alternative Approach

An alternative approach is to consider roadway segments that have already gone through the process of SPF modeling, EEC calculations, and network screening but without incorporating behavioral data. High EEC segments identified here have highest potential for safety improvements. Once these EECs have been calculated, network screening can integrate behavioral data by identifying high EEC segments where behavioral-related crashes are overrepresented. This knowledge can then be used to implement behavioral-oriented countermeasures where appropriate.

The team tried this approach using the same segmentation and crash data from prior analyses. SPFs were modeled, EECs calculated, and network screening conducted to find the high-crash roadway segments for all crashes, regardless of behavioral involvement. Once this was completed, behavioral data were brought in using the following steps.

For each roadway class, an average percentage of all crashes for each behavioral type was generated. For example, in Roadway Class 1 (interstates and parkways), 23 percent of crashes involved aggressive driving, 3 percent involved impaired driving, 35 percent involved distracted driving, and 3 percent involved unrestrained driving.

These percentages were then used to calculate for each roadway segment in each roadway class an EEC value for each type of behavior, where:

- EEAC indicates excess expected aggressive driving crashes
- EEDC indicates excess expected distracted driving crashes
- EEIC indicates excess expected impaired driving crashes
- EEUC indicates excess expected unrestrained driving crashes

These values were calculated for each roadway segment using the following equation (modified here for aggressive driving):

$\mathbf{EEAC_1} = AC_1 - (AvgAC * (Tot_1 - EEC_1))$

Where,

AC_1 = historic aggressive crashes for segment 1

AvgAC = average percentage of observed aggressive crashes for the roadway class

Tot_1 = total observed crashes for segment 1

EEC_1 = excess expected crashes for segment 1

The resulting values denote how many more (or fewer) behavioral-related crashes than expected occurred on each road segment. The behavioral EEC value can then be divided by the segment's total EEC to determine what percentage of EEC is related to behavior. Table 6.3 lists the top 30 EEC road segments and the behavioral EEC percentages for each. Values highlighted in red indicate those where a behavioral factor was involved in 50 percent or more of the total EEC for the segment.

Having access to behavioral EECs can help practitioners select effective countermeasures. This example focused on the highest overall EEC roadway segments and the percentage of EEC related to behavioral factors. However, the analytical lens could just as well be placed directly on behavioral crashes. Both approaches have value and can be applied when appropriate by practitioners.

Table 6.3 Network Screening Results Demonstrate Segments Where Behavioral Crashes are Overrepresented

RID	BMP	EMP	EEC	EEAC	EEIC	EEDC	EEUC	%EEAC	%EEIC	%EEDC	%EEUC
059-I -0075 -000	188.6	190.2	765	266	6	372	8	35%	1%	49%	1%
056-US-0031E -000	13.1	14.6	648	213	20	252	23	33%	3%	39%	4%
030-KY-2831 -000	0.5	2.5	615	85	-1	382	9	14%	0%	62%	1%
056-US-0031E -000	14.6	15.6	547	140	35	151	17	26%	6%	28%	3%
034-US-0027 -000	2.7	3.5	546	386	9	98	8	71%	2%	18%	1%
056-US-0031W -000	8.6	10.7	519	152	13	251	35	29%	3%	48%	7%
034-US-0027 -000	3.5	4.6	444	299	1	63	-5	67%	0%	14%	-1%
059-US-0025 -000	6.2	7.2	416	121	1	279	17	29%	0%	67%	4%
056-US-0150 -000	2.1	2.6	403	95	11	153	11	23%	3%	38%	3%
056-CS-1011F -000	0.0	0.9	399	108	8	152	20	27%	2%	38%	5%
042-KY-0121X -000	0.0	1.3	393	24	1	299	5	6%	0%	76%	1%
056-US-0031W -000	15.6	17.5	391	88	9	234	36	23%	2%	60%	9%
034-US-0027 -000	1.5	2.0	381	190	5	95	7	50%	1%	25%	2%
056-I -0065 -000	132.8	135.2	378	154	0	113	13	41%	0%	30%	4%
018-US-0641 -000	7.7	8.3	377	70	-4	306	2	19%	-1%	81%	0%
030-US-0431 -000	10.9	11.3	363	72	2	220	0	20%	0%	61%	0%
114-US-0231 -000	9.5	10.0	352	122	5	248	3	35%	1%	71%	1%
058-KY-0321 -000	7.7	8.6	350	3	5	229	9	1%	1%	66%	3%
114-US-0231 -000	10.4	11.3	348	160	-2	219	2	46%	0%	63%	1%
056-KY-1020 -000	10.1	12.1	346	108	5	147	24	31%	2%	43%	7%
034-US-0027 -000	4.7	5.1	346	160	4	77	5	46%	1%	22%	2%
034-KY-0004 -000	13.6	14.8	331	215	6	96	0	65%	2%	29%	0%
056-KY-1865 -000	4.4	5.3	331	93	17	127	32	28%	5%	38%	10%
056-US-0150 -000	2.7	3.6	315	107	11	105	18	34%	3%	33%	6%
018-US-0641 -000	8.6	9.2	307	50	0	232	5	16%	0%	75%	2%
059-I -0075 -000	186.8	187.6	304	59	0	196	1	19%	0%	64%	0%
030-KY-0054 -000	2.6	3.3	303	19	0	239	-3	6%	0%	79%	-1%

RID	BMP	EMP	EEC	EEAC	EEIC	EEDC	EEUC	%EEAC	%EEIC	%EEDC	%EEUC
034-US-0025 -000	13.4	14.1	297	151	9	41	9	51%	3%	14%	3%
030-US-0431 -000	10.6	10.9	283	35	0	162	6	12%	0%	57%	2%
073-US-0060 -000	10.1	10.6	283	84	4	164	1	30%	1%	58%	0%

Chapter 7 Implementation Potential

This report proposed a methodology for quantifying expected safety improvements associated with behavioral modification strategies. First, criteria must be developed to identify when and where behavioral modification strategies could complement and/or substitute for engineering strategies. Next, expected costs and benefits need to be estimated for these strategies. The methodology is sketched out below:

1. Identify if there are statistically significant issues with behavioral-related crashes and if so, the specific problem. This is done by:
   - Identifying crash or other linked safety database items (fields) that indicate behavioral-related issues
   - Identifying which keywords in crash or other linked database narratives indicate behavioral-related issues
   - Defining corridors, areas, or road classes (recognizing that segmentation will affect results and that the countermeasures available may require different segmentation)
   - Ranking corridors, areas, or road classes by the extent of behavioral issues based on:
     - Crash data items
       - All behavioral problem types combined (some countermeasures may apply to all behavioral issues)
       - Individual behavioral problem types (some countermeasures may be specific to certain behavioral issues)
     - Narrative text processing
       - All behavioral problem types combined (some countermeasures may apply to all behavioral issues)
       - Individual behavioral problem types (some countermeasures may be specific to certain behavioral issues)
     - Compare lists. If they are similar, it is quicker to use only crash data items as they are more readily available to analysts.

2. Identify countermeasures
   - Develop or obtain a list of behavioral modification strategies
     - A search of the CMF Clearinghouse using the keywords *behavior*, *aggressive*, *eating*, *impaired*, *reckless*, *drinking*, *drunk* or, *drugs* returns no results; 149 CMFs are identified using *speeding*, 25 using *rage*, 10 using *distracted*, and 8 using *fatigue*.
       - Aggressive driving (speeding, road rage, reckless driving, …)
       - Distracted driving (cell phone, eating, passenger distraction, …)
       - Impaired driving (drugs, alcohol, fatigued…)
       - Other?
     - See also the NHTSA list, especially those rated 5 stars
     - See also the statistical analysis of Tapestry® data for outreach and communications ideas
   - Map corridors, areas, or road classes for each problem type
   - For corridors ranked highly across all behavioral issues, consider broad behavioral modification strategies
   - For corridors ranked highly for one behavioral problem type, consider targeted behavioral modification strategies

3. In some cases, it may be more cost-effective to address behavior issues than to improve roadways
   - For each corridor ranked highly, examine crashes more closely and in context to see if a behavioral-related modification is likely to help (education, enforcement, public health). If not, consider engineering or enhanced emergency response.

4. Test bed projects
   - Compare corridors ranked highly for behavioral issues and proposed/ongoing KYTC projects, including:
     - Sample of 200 random projects used SHIFT for methodological improvement
     - All SHIFT projects
     - Funded SHIFT projects
     - HSIP projects identified using EEC (locations or corridors)

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Appendix A Odds Ratios and Confidence Intervals

Aggressive Driving

For Aggressive odds of 1 versus 0

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
White Pop	0.161109	0.135403	0.191695	6.2069805
Black Pop	0.226076	0.185853	0.275004	4.4232938
%NoDegree	0.530287	0.502208	0.559936	1.8857712
ShldWidFixed	0.967288	0.964552	0.970033	1.0338178
Age	0.996766	0.996275	0.997258	1.003244
LASTCNT	1.000002	1.000002	1.000003	0.9999977
CollisionTime	1.000003	1.000002	1.000003	0.9999973
Distance	1.000868	1.000422	1.001315	0.9991326
SpeedLimitFixed	1.008766	1.007864	1.009669	0.9913098
LANES	1.053066	1.042403	1.063838	0.949608
LaneWidthFixed	1.058776	1.051855	1.065742	0.9444869

Odds Ratios for Distracted

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	2.3661753	<.0001*	2.3218106	2.4113877
1	0	0.422623	<.0001*	0.414699	0.4306983

Odds Ratios for Impaired

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	2.0674565	<.0001*	1.9571061	2.1840288
1	0	0.4836861	<.0001*	0.4578694	0.5109585

Odds Ratios for Rural_NonInterstate

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.9504751	<.0001*	1.8950969	2.0074716
1	0	0.5126956	<.0001*	0.4981391	0.5276775

Odds Ratios for Pedestrian

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.5847113	<.0001*	1.3837696	1.8148323
1	0	0.6310298	<.0001*	0.5510151	0.7226637

Odds Ratios for CommercialVehicle

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.3264477	<.0001*	1.2496546	1.4079598
1	0	0.7538933	<.0001*	0.7102476	0.8002211

Odds Ratios for RdCharFixed

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.0618392	<.0001*	1.040996	1.0830998
1	0	0.9417622	<.0001*	0.923276	0.9606185

Odds Ratios for GenderM

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.0523196	<.0001*	1.0336244	1.0713529
1	0	0.9502817	<.0001*	0.9333993	0.9674694

Odds Ratios for Motorcycle

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.8130276	<.0001*	0.7513965	0.8797137
1	0	1.2299706	<.0001*	1.1367335	1.3308552

Odds Ratios for RdCondFixed

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.7556727	<.0001*	0.7404934	0.7711632
1	0	1.3233242	<.0001*	1.2967423	1.3504509

Odds Ratios for Unrestrained

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.6857657	<.0001*	0.6538493	0.7192401
1	0	1.4582239	<.0001*	1.3903563	1.5294043

Odds Ratios for IntersectionWith_Indicator_

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
N	Y	0.4190001	<.0001*	0.410853	0.4273088
Y	N	2.3866342	<.0001*	2.3402277	2.4339608

Distracted Driving

For Distracted odds of 1 versus 0

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
%NOHI	0.487823	0.424651	0.560394	2.0499221
SpeedLimitFixed	0.984205	0.983488	0.984922	1.0160487
Month	0.991739	0.989516	0.993967	1.00833
Age	0.997904	0.997482	0.998325	1.0021006
Distance	0.998802	0.998402	0.999201	1.0011998
LASTCNT	1.000002	1.000001	1.000002	0.9999984
CollisionTime	1.000004	1.000003	1.000004	0.9999963
ShldWidFixed	1.018436	1.015861	1.021017	0.9818976
LANES	1.025086	1.015099	1.035172	0.9755278
LaneWidthFixed	1.061016	1.054752	1.067317	0.9424929
%NoDegree	1.302586	1.238021	1.370518	0.7677034

Odds Ratios for Impaired

Odds Ratios for Aggressive

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	2.3971548	<.0001*	2.3521459	2.4430249
1	0	0.4171612	<.0001*	0.4093286	0.4251437

Odds Ratios for Rural_NonInterstate

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.5555232	<.0001*	1.520394	1.591464
1	0	0.6428705	<.0001*	0.6283523	0.6577242

Odds Ratios for Motorcycle

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.4948329	<.0001*	1.3902892	1.6072377
1	0	0.6689711	<.0001*	0.6221855	0.7192748

Odds Ratios for RdCondFixed

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.4719277	<.0001*	1.4323677	1.5125804
1	0	0.6793812	<.0001*	0.6611219	0.6981448

Odds Ratios for RdCharFixed

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.3901149	<.0001*	1.3666387	1.4139944
1	0	0.719365	<.0001*	0.7072164	0.7317223

Odds Ratios for CommercialVehicle

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.2451963	<.0001*	1.1852375	1.3081884
1	0	0.8030862	<.0001*	0.7644159	0.8437128

Odds Ratios for WeatherFixed

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.1956358	<.0001*	1.1580607	1.23443
1	0	0.8363751	<.0001*	0.8100905	0.8635126

Odds Ratios for GenderM

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.0663049	<.0001*	1.0497854	1.0830844
1	0	0.937818	<.0001*	0.9232891	0.9525756

Odds Ratios for MedTypeMedianPresence

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.059406	<.0001*	1.0351775	1.0842017
1	0	0.9439251	<.0001*	0.9223376	0.9660179

Odds Ratios for IntersectionWith_Indicator_

Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
N	Y	0.7017388	<.0001*	0.6888922	0.714825
Y	N	1.4250316	<.0001*	1.3989438	1.4516059

Impaired Driving

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
%NoDegree	0.61487	0.514575	0.734713	1.6263606
LANES	0.871451	0.854676	0.888555	1.147512
LaneWidthFixed	0.962536	0.948283	0.977003	1.0389226
ShldWidFixed	0.976044	0.969421	0.982711	1.0245444
Month	0.986879	0.981287	0.992504	1.013295
Age	0.994414	0.993282	0.995547	1.0056174
2019 Median Household Income	0.999996	0.999995	0.999997	1.0000042
SpeedLimitFixed	1.007764	1.005947	1.009585	0.9922958
Hispanic Pop	2.754987	1.910973	3.971775	0.3629781

Odds Ratios for Distracted					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	3.0552502	<.0001*	2.9134581	3.2039429
1	0	0.3273054	<.0001*	0.3121154	0.3432347

Odds Ratios for CommercialVehicle					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	2.2875799	<.0001*	1.9570559	2.6739255
1	0	0.4371432	<.0001*	0.373982	0.5109716

Odds Ratios for Aggressive					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	2.044201	<.0001*	1.9347283	2.1598679
1	0	0.4891887	<.0001*	0.4629913	0.5168684

Odds Ratios for RdCondFixed					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.4365403	<.0001*	1.3419135	1.5378399
1	0	0.6961169	<.0001*	0.6502627	0.7452045

Odds Ratios for RurNumeric					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.2184471	<.0001*	1.1625872	1.2769908
1	0	0.8207168	<.0001*	0.783091	0.8601505

Odds Ratios for WeatherFixed					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	1.2077435	<.0001*	1.1124188	1.3112367
1	0	0.8279904	<.0001*	0.7626388	0.898942

Odds Ratios for IntersectionWith_Indicator_					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
N	Y	1.1744332	<.0001*	1.1140564	1.2380821
Y	N	0.8514746	<.0001*	0.8077009	0.8976206

Odds Ratios for RdCharFixed					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.8917674	<.0001*	0.8551236	0.9299816
1	0	1.1213686	<.0001*	1.0752901	1.1694216

Odds Ratios for GenderM					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.49563	<.0001*	0.474547	0.5176496
1	0	2.0176341	<.0001*	1.9318086	2.1072727

Odds Ratios for Unrestrained					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.1338697	<.0001*	0.1269687	0.1411459
1	0	7.4699481	<.0001*	7.0848668	7.8759596

Unrestrained Driving

For Unrestrained odds of 1 versus 0

Unit Odds Ratios

Per unit change in regressor

Term	Odds Ratio	Lower 95%	Upper 95%	Reciprocal
LANES	0.889711	0.874505	0.905182	1.12396
LaneWidthFixed	0.94314	0.930542	0.955908	1.060288
Age	0.997665	0.996717	0.998614	1.0023403
CollisionTime	0.999998	0.999997	0.999999	1.0000019
ShldWidFixed	1.015361	1.010085	1.020665	0.9848715

Odds Ratios for Motorcycle					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	6.9410939	<.0001*	5.0500771	9.5402076
1	0	0.1440695	<.0001*	0.1048195	0.1980168

Odds Ratios for IntersectionWith_Indicator_					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
N	Y	1.1817533	<.0001*	1.1298985	1.2359879
Y	N	0.8462003	<.0001*	0.8090694	0.8850353

Odds Ratios for RdCharFixed					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.853914	<.0001*	0.8242884	0.8846044
1	0	1.1710781	<.0001*	1.1304488	1.2131676

Odds Ratios for GenderM					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.7613409	<.0001*	0.7350383	0.7885848
1	0	1.313472	<.0001*	1.2680944	1.3604734

Odds Ratios for Aggressive					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.7640965	<.0001*	0.7339212	0.7955125
1	0	1.3087351	<.0001*	1.2570513	1.362544

Odds Ratios for CommercialVehicle					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.6972774	<.0001*	0.637764	0.7623444
1	0	1.4341494	<.0001*	1.3117431	1.5679781

Odds Ratios for Rural_NonInterstate					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.5853519	<.0001*	0.561328	0.6104041
1	0	1.7083739	<.0001*	1.6382589	1.7814898

Odds Ratios for Impaired					
Level1	/Level2	Odds Ratio	Prob>Chisq	Lower 95%	Upper 95%
0	1	0.1373502	<.0001*	0.1313829	0.1435886
1	0	7.2806567	<.0001*	6.9643414	7.6113388