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# A decade of car-cyclist collisions in Louisville: a spatio-temporal analysis.

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# A DECADE OF CAR-CYCLIST COLLISIONS IN LOUISVILLE: A SPATIO-TEMPORAL ANALYSIS

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ABSTRACT

A DECADE OF CAR-CYCLIST COLLISIONS IN LOUISVILLE:

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This thesis has considered factors of the built environment to discover if cay-cyclist collisions display any patterns that could be used to improve cycling safety. This thesis contains an introduction, a literature review, an overview of the study area and data, a description of the methods, results, and discussion and conclusion section. This thesis is significant because it has been the first study to consider cyclist volume as an explanatory variable of the spatiality of car-cyclist dependence for Louisville, Kentucky. Through descriptive and spatial statistics, trends in car-cyclists were identified. Collisions occur more frequently in the summer, during commute hours, at signalized intersections, and near bus stops. It also evaluated the use of third-party sources as exposure measure and explanatory variables. This thesis also put forward recommendations to better the information available to study cyclist collisions, and ways to improve the safety of cyclists in Louisville.

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# INTRODUCTION

*Problem and Research Question*

Traffic collisions are a common public safety problem in the U.S. and worldwide. In the last two decades traffic crashes have been increasing worldwide (Cantisani, Moretti, and Barbosa 2019). The World Health Organization estimates that more than half of traffic fatalities are vulnerable road users including pedestrians, bicyclists, and motorcyclists (WHO 2021). In 2019, there were an estimated 49,000 bicyclist injuries and 846 fatalities the United States (NCSA 2021). Cyclists are 12 times more likely to die in collisions than car drivers in the United States (Delmelle and Thill 2008). Worldwide, and in the United States, vulnerable road users are disproportionately at risk of being in killed in a traffic collision.

The geographical distribution of collision events is striking. Car-cyclist collisions are more likely to happen in intersections, areas with high traffic volume, and areas with high population density (Chaney and Kim 2014). Urban areas are comprised of a combination of these factors, resulting in a chaotic space where 78% of cyclist fatalities occur in the U.S. (NSCA 2021). Studying the geography of traffic collisions is necessary for reducing injuries.

Therefore, the overarching research question posed by this thesis was: Do car-cyclist collisions display any patterns that could be used to improve cycling safety? What are the hot spots of such collisions? The objective of this thesis was to investigate the spatial patterns and temporal trends in car-cyclist collisions from 2010-2019 in Louisville by using geographic information systems (GIS) and spatial statistic methods. The hypothesis was that car-cyclist collisions do not occur randomly; this type of collision is likely to occur in areas with both high cycling frequency and high car frequency.

*Significance*

Cycling, as a mode of transportation, has many known benefits. Cycling is associated with increased human health, leading to reduced obesity, reduced cardiovascular risk, and healthcare savings. Along with human health, cycling benefits the health of the environment. Trips taken by bike instead of car reduce greenhouse gas emissions and fossil fuel dependence (Vandenbulcke et al. 2009). Communities benefit from increased cycling by saving money on road paving, a reduction in traffic congestion, and a reduction in car collisions.

Cities that want to see an increase in cyclists and the benefits of a substantial cycling community should improve the safety of cycling. The presumption that a method of transportation is safe is the most important factor in using that transportation option (Ha and Thill 2011). The surest way to make cycling safer is to increase the number of cyclists. Both the benefits, and safety, of cycling increase congruently with the cycling population (Delmelle and Thill 2008). Additionally, safety of active transportation is linked to the infrastructure in the surrounding environment (Ando, Higuchi, and Mimura 2018). Therefore, the way residents perceive the safety of cycling in their community is through witnessing others cycle and the existence of infrastructure that is designed for cycling. Car-cyclist collisions is an important area of research for cities that want to make improvements to their infrastructure, encourage more citizens to cycle, and better the sustainability of the city.

Louisville's car-cyclist collisions have increased again since hitting a low in 2018. A total of 4 fatal cyclist collisions occurred in the state of Kentucky in 2020, and all of them occurred in Jefferson County (Green et. al, 2021). Year over year, Jefferson County had an increase in fatal collisions from 2010-2020, even though there was a decrease in collisions overall (Green et. al, 2021). Collisions with cyclists and fatalities continued to be a health and safety concern in Louisville.

In an effort to reinvest in the city after the COVID-19 pandemic, the city of Louisville created a Downtown Revitalization Team to make an action plan centered on public spaces, equity, and tourism in the city. The team set forth to improve the cities' sustainability, and explicitly stated a goal to improve the "safety" of the city (Daniels 2021). In particular, that bike safety is part of equitable and inclusive spaces is reflected in the Action Plan. In their report, it is recommended to make a significant investment in downtown mobility during fiscal years 2022-2024. The Action Plan puts forth goals to

invest $500,000 in bike lanes, $1.4 million in a multi-modal reconstruction of River Road, and $2.6 million to convert 7th, 8th, and E. Jefferson streets to two-way traffic (Brown and Buckner 2021, 5, 7, 12). The results of this thesis will be informative in guiding the development of infrastructure for the city of Louisville. It will provide insight to the current state of bike safety in the city and the results can help complete the goals outlined in the Action Plan.

This thesis is significant because car-cyclist collisions in Louisville have not been studied independently of pedestrian collisions since 2014. Bike Louisville (2014) last published a study on car-cyclist collisions from 2003-2012. Since then, the yearly average of car-cyclist collisions has decreased (Table 1) and deserve a reevaluation of their spatio-temporal trends. Bike Louisville's study (2014) did not include any measure of cyclist volume but does include car volume. Evaluating collision risk based on frequency of road travel is a novel area of research, with many studies beginning to create models to calculate local risk (Yao, Loo, & Yang 2016). This thesis will attempt to summarize risk for Louisville, which has not been done before, and it will utilize a third-party data source that has never been formally considered for the city of Louisville.

# LITERATURE REVIEW

Research on cycling sits within a large body of literature on traffic, micromobility, policies, and sports psychology. The literature review began with crafting a conceptual framework for the thesis. First, it discusses geographic approaches to traffic collisions. Then it explored more specific methods to spatially understanding cyclist collisions and cyclist exposure measures. The literature review ended with the creation of a theoretical framework for the thesis.

*Research on Collisions*

A large body of research has examined the characteristics of traffic collisions with applied implications. Collision analysis varies in data types and methods. Researchers can focus on a single mobility, selecting only pedestrians or cyclists, or study vulnerable road users as group. Some focus on injuries sustained while cycling. Existing micromobility literature has only lightly explored what has caused rider injuries beyond "the mere use of a micromobility device" (Fang, 2022, p. 2). Researchers also work within different spatial scales to study collisions. Micro-level studies may use specific intersections, while macro-level studies may use census block groups or traffic analysis zones (Chen and Zhou 2016). Traffic analysis zones are spaces divided by important roadways.

Geographic information systems (GIS) have been widely used to analyze collisions and contributory variables since the early 1990's (Yao, Loo, and Yang 2016).

Early studies joined collisions to road segments or collisions (Austin 1995, Levine, Kim, and Nitz 1995). Most research published uses GIS to conduct local spatial statistics to identify hot spots of collision activity. Often collision analysis is events-based and analyzed as points in space. Sometimes collisions are grouped into spatial units and analyzed with a link-attribute approach. Investigating risk factors or contributory variables to collisions is usually performed with collision event points grouped to road segments or area units such as block groups or census tracts (Yao, Loo, and Yang 2016).

*Research on Cyclist Collisions*

Hospital or police reported data are the most popular resources to study car-cyclist collisions. But these are both flawed, as collisions and near-miss events often go unreported. More concerning is the lack of spatial components in hospital reports that hinder a geographic analysis. For example, Poulos et. al (2012), assumed a collision or injury occurred near a child's place of residence to explore the existence of spatial autocorrelation of children cyclist injuries. While hospital data might be effective for children, who do not bike far from home (Poulos et. al 2012), this method is not transferrable to an adult population who are not limited to the vicinity of their residence when cycling. Therefore, police reported data is the more suitable resource for adult cyclists who commute or cycle recreationally and incur a traffic crash.

Studies based on a cohort of participants often rely on questionnaires and follow-ups. Poulos et. al (2015) had participants report on mileage biked, infrastructure used, near miss events and collisions. They found that both commuter and recreational cyclists spent the most time on road infrastructure with cars present (Poulos et al. 2015). They define their study as "exposure-based," calculating a crash rate per 1,000 cyclists, with bike lanes having a lower crash rate than shared lanes (Poulos et al. 2015). Cohort studies are flawed due to their small sample size (Poulos et al. 2015). In such smaller prospective studies, “severe accidents are unlikely to occur,” within the participant population and are left out of the exposure calculation (Vanparijs, Meeusen and de Geus 2015, 15).

Car-cyclist collisions exemplify Tobler’s first law of geography (Ji et al. 2021). Events have such spatial dependence that Ji et al. (2021) found that collisions often share independent variables at two meters distance, but not at two kilometers distance. Local tests best identify relationships between collision events, though some research compares the two (Chaney and Kim, 2014).

It is often assumed that frequencies of traffic accidents are proportional to the population of an area (Ando, Higuchi, and Mimura 2018). Studies have linked collisions to infrastructure have found that separate bike infrastructure is safer than neighborways, sharrows, or cyclists riding on sidewalks with pedestrians (Reynolds et. al 2009). An et. al (2022) linked collisions to cyclist trip volume, density of intersections, and distance from the central business district in Wuhan, China. Nearby Louisville in Cincinnati, neighborhood ethnicity, bus stops, and population density were found to be the most positive coefficients in modeling cyclist collisions (Chaney and Kim, 2014). Busses move in and out of a cyclists’ path on the far right side of the road. Even though it has not been found that busses collide with cyclists, bus stops are correlated with collision events as cyclists may attempt to pass a bus, or the bus narrows the roadway space (Chaney and Kim, 2014).

*Research on Cyclist Exposure*

Research on cycling exposure is varied methodologically. Researchers can define cyclist exposure as the risk of collision, or the time cyclists are exposed to cars. Though studies often cite the same benefits of cycling and safety concerns, they draw on different data sources and create different meanings of exposure. Some studies focus on demographics of cyclists, like their age, gender and socioeconomic status to create an exposure measure based on these groups.

Some studies focus on infrastructure to create an exposure measure based on place. Overlapping these personal and place-based approaches, some studies focus on behavior in space to create an exposure measure, utilizing data on helmet use, speed, and distractions in the environment. While exposure measures can be based on different data, they additionally can be communicated in different units. An exposure measure is often reflected in an incidence rate. Car-cyclist collisions can therefore be communicated in distance, time, trips, or traffic estimates (Vanparijs, Meeusen, and de Geus 2015; Chen and Zhou 2016). For the safety of one situation to another to be compared in a meaningful way, this incident rate must feature the same exposure measure units.

While collisions are discrete events, data on volume is often given in route segments, and is difficult to measure in an aerial unit. Only one paper (Delmelle and Thill 2008), bounded collisions into polygons in order to calculate a measure of risk. Delmelle and Thill (2008) used a neighborhood measure to define crash hazard as the number of crashes per census tract area. This implies collisions are the result of space available or space traversed by cyclists, though it did not consider road space.

*Theoretical Framework*

It should be accepted that collision events have contributory factors and are more like crime events than accidents. They are both issues of urban safety, and often the distribution of these events are similar and even share common characteristics (Ando, Higuchi, and Mimura 2018; Oluwajana 2018). Both events depend heavily on the physical space and urban investment (Ando, Higuchi, and Mimura 2018). And most importantly, both are discrete events that happen in space and can utilize the same methods of study. Therefore, the same theoretical frameworks used for crime analysis can be used to explain the spatiality of collisions.

Research on crime has found that criminal events concentrate at microgeographies. Wiesburd's (2015) law of crime concentration establishes that crime occurs in a "very tight bandwidth" of place and occurs there consistently (p. 143). The unit of spatial scale that crime is studied at should be as small as possible and is often studied at the street segment level. Collision events are recorded with geographic coordinates, making them easily geocoded and subsequently aggregated to different spatial scales. To get the best results, this thesis methodologically follows the way crime research has approached the modifiable areal unit problem, and aggregates collision events at two geographic levels including the census block group level and street segment level. These units align the collision events with the nearest features of urban design and contributory factors.

This thesis is informed by situational action theory, collective conscience theory, and social disorganization theory. Situational action theory would provide reasoning that collision events depend on a human-environment interaction; based on the individual, the environment they are in, and situational mechanisms. These are dependent on an individuals' perception and choice (Hart and Lersch, 2015). This theory would uphold that human induced factors resulted in the majority of collisions. A human factor could include a failure to yield, inattention, or a misjudgment of space.

Collective conscience theory provides explanation for collisions that occur in a contested space. A collective conscience is a shared idea of what is "right" and "wrong" to do (Hart and Lersch 2015). The collective conscience relates to common misunderstandings of bike legality. It is not well known that in Louisville Metro it is legal for a cyclist to be on a highway shoulder, and two bicycles can be operated side-by-side on a highway lane (Green et. al 2019). A lack of collective conscience in mobility norms would increase the risks of collisions in areas lacking existing bike infrastructure or directional signposts, where wayfinding and mobility decisions are not clearly guided for either party.

Looking to social disorganization theory, collisions are more likely to occur in neighborhoods of low investment, or transitional zones. These areas would have low infrastructure investment. Considering neighborhood factors as explanatory variables for collisions removes fault from individuals to a fault of geography. As Kubrin, Branic, and Hipp (2021) summarized, social disorganization theory applied to crimes and collision events moves the dialogue from "kinds of people" that commit such social errors to "kinds of places" where conditions spawn criminal activities (2). Recognizing that "disorder concentrates in small geographies" (Carter and Piza 2018, 1780) criminality and collisions are often analyzed and present the most statistically meaningful results at the block group level of spatial units (Oluwajana 2018). This theory can be used to explain the distribution of hotspots of collisions that are spatially associated with many built environmental factors.

The above theories provide support for the causes of collisions and justifies an interdisciplinary approach to the analysis of car-cyclist collisions. This thesis investigated the spatial, temporal, and contributory factors that cause collisions. To gain a deeper understanding of the causes of collisions, they have been likened to crime events. It was stated that both collisions and crime events are discrete events, impacted by common factors, and are dependent on space. It can also be said that collisions are like crime events due to the fear they instill in the public's perception of space. The fear of crime, or the fear of collisions, is the most limiting factor for peoples' choice of use of space. And like crime events, car-cyclist collisions may not align with the way space is perceived (Kamalipour, Faizi, and Mermarian, 2014). Space may be perceived as unsafe when that is not statistically supported. The reality of the reasons for collisions may not align with the collective conscience of the community: shared ideas about where is safe to cycle, where is not safe, beliefs about what causes collisions and who is at fault. Therefore, like crime prevention, reducing collisions must consider social conditions as well as environmental risk factors (Kamalipour, Faizi, and Mermarian, 2014). The theoretical framework outlined in this section allows for the humanization of discrete events.

# STUDY AREA AND DATA

Collisions happen in all areas of Louisville. The study area for this thesis is the extent for the Louisville-Jefferson County Metro. Louisville-Jefferson is a consolidated city-county with urban and suburban spaces. The study time ranges from 2010-2019. The last collision incorporated is on December 31, 2019. Ending the study period before 2020 was a conscious decision to avoid and drastic changes in transportation data from the global COVID-19 pandemic shutdowns which began in 2020.

This thesis utilized free data from the Louisville/Jefferson County, KY Information Consortium (LOJIC). LOJIC provides GIS files on many city projects and services. This thesis uses census data from LOJIC that contains 2010 population counts aggregated at the census block group level (LOJIC). It also used a number of point datasets from LOJIC to explore contributory factors to collisions, including street intersections, signalized intersections, bus stops, and LouVelo Bike Share stations. Lastly from LOJIC, it used a dataset containing all traffic signs in Louisville. All traffic signs were narrowed down to relevant ones by selecting from the sign description category ones with "Share the Road (plaque), Bicycle, Bike Lane, Bike Lane (Plaque), Bike Route Guide, Bike Xing, Bike Crossing (Text)," or "Bike Trail," as the description. This narrowed the records from 81,182 to 712.

The Kentucky State Police website contains a search tool to query all police recorded collision. Any collision with injury, fatality, or damage exceeding $500 is recorded by police or submitted by a part involved in an online form. The police record the type of collision as a directional analysis code. Using this tool, a query was conducted of collision events from between the dates of January 1, 2010, and December 31, 2019, in Jefferson County with a directional analysis code of “Collision with bicycle in intersection” and “Collision with bicyclist non-intersection.” The result of this query is a comma-separated values (CSV) file of 1,376 collisions between 6/9/2010 and 12/26/2019. Each collision has attribute features including date, time, coordinates, and is coded for the manner of collision (single vehicle, angle collision, sideswipe, etc.), traffic control features (stop sign, advisory speed sign, center line, etc.), and unit factors (human factor, vehicular factor, environmental factor).

The National Highway Traffic Safety Administration’s Fatality and Injury Reporting System Tool (FIRST) was used to query fatal collisions with cyclists in Louisville. The time frame selected was for the years 2010-2019; Kentucky was selected as the state, and Jefferson as the county. The only filter applied to the query was to select for the specific scenario of a crash involving a pedalcyclist. The query returned a table with links to reports and a downloadable excel file (CrashReport, 2021).

Some collisions occur on roadways where there is bike infrastructure. It is hard to determine the exact time roadway infrastructure is completed. The most up to date bike infrastructure map includes bikeways made in 2018 (LOJIC). Bike infrastructure was dated knowing this date, and information from the Louisville Metro’s Bike Master Plan Project Updates from the 2016-2020 update, the 2018-2020 update, and from the Streets for Peoples’ advocacy history (Glasser, 2013). Using these sources, a year to estimate completion was added as an attribute line by line for each of the 1,747 street segments of bike infrastructure in Louisville.

To make any statement about collision exposure risk, cyclist and car volume data is necessary (Roy et. al 2019). To create a measure of car volume, this thesis used the Kentucky Transportation Cabinet's traffic count data (Kentucky Transportation Cabinet 2021). The traffic count data contains an Average Annual Daily Traffic count for road segments in Louisville. This data is free and available to download through the Kentucky Transportation Cabinet's ArcGIS online map portal that was last updated on June 8, 2020. To create a measure of cyclist volume, this thesis utilized third party application data -Strava- provided to Louisville Metro and made available through an academic partnership. Strava is an application for smartphones that allows users to enable GPS tracking for fitness exercises. It is very popular with cyclists, runners, and hikers. Strava launched Strava Metro in 2014 to provide transportation planners and researchers with depersonalized user data. The rising popularity of Strava Metro for transportation planning and research represents a larger move away from traffic surveys to making user generated data have practical use (Lee and Sener 2021).

Even though Strava data comes from crowdsourcing and has inherent demographic biases, it is the best option for calculating cyclist exposure because there are no gaps in data collection (Ferster et. al 2017). Additionally, the spatial patterns of Strava users have been found to be representative for larger populations (Jestico, Nelson and Winters 2016). Strava data offers researchers detailed spatial and temporal trends of cyclists to study. The Strava data contains a count of number of cyclists on a road segment or intersection with varying temporal resolutions available. This thesis is the first study to analyze any Strava data for Louisville.

The Strava exposure data was a helpful tool in evaluating car-cyclist collisions. Throughout the time frame studied, from 2017-2019, Louisville had an average or 1,640 users recording rides on Strava. Louisville has a bike commuter rate comparable to other large cities in the south, with 0.4% of the population choosing to commute by bike (McKenzie 2012). With a population of 766,757, roughly 3,067 cycling commuters exist in Louisville. There is likely a large group of cyclists that do not use the app and are missing from this study.

For the purposes of this thesis, “roadway” and “motorway” are synonymous terms for the paved area of the road used for cars and bikes. “Roadway” and “Motorway” includes bike infrastructure that is part of the paved space from curb to curb, including the gutter or shoulder. A “motorist” or a “driver” is a person who operates a motor vehicle. A “cyclist,” “bicyclist,” or “pedalcyclist” are equivalent terms for a person who operates a manual bicycle. Terms vary across government and third parties, and their use may change throughout the thesis.

# METHODS

## *Initial Analysis*

All spatial analysis was conducted in Esri's ArcGIS Pro software. First, all collision events were geocoded and aggregated into census block groups and road segments. Aggregating collisions into road segments is a simple spatialization of events. Before aggregating collisions with bike lanes, multiple shapefiles were created from each to represent a temporal segment of the data. For example, all bike lanes that existed in 2010 were aggregated with all collisions that occurred after 2010, but, all bike lanes that were created in 2018 were only aggregated with collisions that happened after 2018. This has allowed the bike infrastructure to be evaluated by its impact on a road segment.

To investigate if car-cyclist collision events exhibit spatial clustering across the study area, a global high/low clustering (Getis-Ord General G) analysis was performed. To evaluate the spatial distribution of car-cyclist collisions, an Anselin Local Moran's I cluster and outlier analysis was performed with the data aggregated into the census block groups. Inverse distance was chosen as the conceptualization of spatial relationships measure so that neighboring census blocks are weighted more. This has identified statistically significant areas of hot spots and cold spots of car-cyclist collision events. Fatal collisions were tested for significant clustering using an Average Nearest Neighbor (ANN) analysis.

As car-cyclist collisions are discrete events that happen across space and time, the projected shapefile of collisions was time-enabled in ArcGIS so that a space-time cube could be created using ArcGIS. Space-time trends were analyzed with the emerging hotspot analysis tool. A space-time cube was created by aggregating collision points into $0.50mi^2$ bins. In the emerging hot spot analysis, the time step was 1 day, and the conceptualization of spatial relationships selected was contiguity-edges-corners, as the bins are all the same size.

*Integrating Strava Data*

To create an average of trips made per census block group or cyclists per census block group, January and July months of data from 2017-2020 were analyzed from Strava. Once requests were made, the data was de-identified, or removed of any application user information, and made available for download. January and July were selected as they represent the lowest and highest months of cyclist activity. Strava Metro downloads are available as an OpenStreetMap file of “edges” or paths on trips made by cyclists, and an Excel file of data about the edges. Each year file contained a “trip forward” and “trip backward” that was summarized into a “total trips” column. In ArcGIS, map files were projected and paired with their data files. Each month was then spatially joined with each other. It was then calculated in an attribute column the average monthly trips and average monthly cyclists per block group. Strava’s terms of use requires that raw counts are not represented but made into percentages or averages. Raw counts were only used to conduct a regression analysis in Microsoft Excel to assess the relationship between trip counts, cyclist counts, and car-cyclist collisions. Those numbers are not represented in this thesis, only the results of that regression.

*Regression and Risk*

Next, an Ordinary Least Squares (OLS) regression was performed at the block group level and at the road network level respectively. OLS was selected as the regression method as it is a common starting point for modeling spatial relationships. The variables for population, average Strava users, average Strava trips, and average road traffic were normalized (divided by 1,000) before doing the block group regression. The other covariates for the block group regression were the count of TARC bus stops, the count of bike signage, street intersections, and signalized intersections.

To perform a regression with the road network, ArcGIS was used to spatially join bus stops, bike signage, street intersections, and signalized intersections to street segments. The Open Street Map (OSM) line features containing the average Strava trips and users were summarized for these features if their center was in a street segment, with a search radius of 40 meters. This radius accounts for the fact that there are many more OSM segments that Kentucky DOT road segments. This way, OSM local roads count towards the average Strava trips of a larger collector roadway. Strava trips and AADT traffic measures were normalized (divided by 1,000). Interstates and state highways were removed from the traffic counts, as they feature high auto traffic and are illegal to cycle on. This leaves 989 roads in Louisville with traffic counts in the regression.

A Geographically Weighted Regression (GWR) was conducted at the block group level with the independent variables count of bus stops, the count of signalized intersections, and the average Strava trips. The model type selected was continuous (Gaussion) as the variables are aggregated into the block groups and the block groups are continuous across Louisville. The neighborhood type was number of neighbors and the selection method was golden search. The regression tried multiple number of neighbors and returned the model with the lowest Akaike Information Criterion (AICc). Each independent variable was mapped with its coefficients and t-values.

Lastly, a measure of risk will be calculated that creates a meaningful statement that summarizes the exposure risk of cyclists at a micro-level of analysis (e.g., 1 collision for every 100 trips). This statement allows the city to compare itself to other cities and to itself temporally as the exposure risk changes to evaluate itself and its improvements to cycling safety.

## RESULTS

*Temporality of Collision Events*

Between 2010 and 2020, Louisville had 1,376 car-cyclist collisions. Looking temporally, 2013 had the highest count of collisions and August was the month with the most collision events (Table 1). Friday was the day of the week with the most collisions (Table 2). Popular commute times had the highest commute times, with 5:00pm having the most collision events by hour (Table 3).

*Table 1 Year and Month Summary for All Car-Cyclist Collisions in Louisville-Jefferson County.*

| Year/ Month | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | Total | % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| January | | 5 | 7 | 10 | 4 | 5 | 6 | 1 | 2 | 6 | 46 | 3.3% |
| February | | 5 | 6 | 10 | 3 | 4 | 4 | 9 | 1 | 3 | 45 | 3.2% |
| March | | 10 | 15 | 10 | 6 | 10 | 10 | 8 | 1 | 5 | 75 | 5.4% |
| April | | 19 | 11 | 17 | 14 | 11 | 7 | 12 | 2 | 11 | 104 | 7.5% |
| May | | 19 | 18 | 16 | 27 | 9 | 9 | 14 | 4 | 11 | 127 | 9.2% |
| June | 9 | 22 | 13 | 21 | 27 | 17 | 14 | 21 | 6 | 13 | 154 | 11.8% |
| July | 16 | 23 | 23 | 31 | 22 | 12 | 10 | 17 | 6 | 13 | 157 | 12.5% |
| August | 19 | 21 | 21 | 29 | 23 | 14 | 21 | 7 | 11 | 18 | 165 | 13.3% |
| September | 21 | 17 | 17 | 22 | 23 | 20 | 20 | 4 | 13 | 16 | 152 | 12.5% |
| October | 24 | 14 | 13 | 22 | 19 | 22 | 17 | 1 | 5 | 11 | 124 | 10.7% |
| November | 8 | 20 | 3 | 8 | 11 | 13 | 9 | 0 | 7 | 7 | 78 | 6.2% |
| December | 7 | 10 | 6 | 7 | 4 | 3 | 6 | 0 | 5 | 4 | 45 | 3.7% |
| Total | 104 | 185 | 153 | 203 | 183 | 140 | 133 | 94 | 63 | 118 | 1376 | 100% |

*Table 2 Day of Week Summary for All Car-Cyclist Collisions in Jefferson County.*

| Day of Week | Count | % |
|---|---|---|
| Sunday | 156 | 11.3% |
| Monday | 184 | 13.4% |
| Tuesday | 216 | 15.7% |
| Wednesday | 201 | 14.6% |
| Thursday | 215 | 15.6% |
| Friday | 226 | 16.7% |
| Saturday | 178 | 12.9% |
| Total for Week | 1376 | 100% |

*Table 3 Time of Day Summary for All Car-Cyclist Collisions in Louisville-Jefferson County.*

| Hour | Count | % | Hour | Count | % |
|---|---|---|---|---|---|
| 12:00 AM | 27 | 1.9% | 12:00 PM | 78 | 5.6% |
| 1:00 AM | 7 | 0.5% | 1:00 PM | 72 | 5.2% |
| 2:00 AM | 4 | 0.2% | 2:00 PM | 101 | 7.3% |
| 3:00 AM | 3 | 0.2% | 3:00 PM | 121 | 8.7% |
| 4:00 AM | 6 | 0.4% | 4:00 PM | 123 | 8.9% |
| 5:00 AM | 12 | 0.8% | 5:00 PM | 146 | 10.6% |
| 6:00 AM | 30 | 2.1% | 6:00 PM | 129 | 9.3% |
| 7:00 AM | 42 | 3.0% | 7:00 PM | 75 | 5.4% |
| 8:00 AM | 43 | 3.1% | 8:00 PM | 73 | 5.3% |
| 9:00 AM | 47 | 3.4% | 9:00 PM | 55 | 3.9% |
| 10:00 AM | 47 | 3.4% | 10:00 PM | 43 | 3.1% |
| 11:00 AM | 59 | 4.2% | 11:00 PM | 33 | 2.3% |

The quantity of cyclists also varies temporally. Due to changing weather and light over the course of the year, the number of recreational and commuter cyclists fluctuated throughout the year. Figure 1 shows Strava trips graphed with collision events. Strava trips and collisions reached maximum and minimums at similar times temporally. To assess if the quantity of cyclists is a good explanatory factor for collision events, trip volumes were temporally summarized, and a linear regression was performed with the collision counts. Trip volumes were summarized by month, weekday, and hour. Collisions were summarized by month (3 years x 12 months = 36 observations), by weekday (3 years x 12 months x 7 weekdays = 252 observations), and by hour (3 years x

12 months x 24 hours = 864 observations). At all temporal levels, the number of cyclists recording trips is a statistically significant explanatory variable of the number of collisions (Table 4). They show a weak positive relationship to the number of collisions. The narrower the time period, the more significant the correlation between the count of trips and count of collisions. The narrower the time period also offers the most observations to study. Recorded trips and collisions summarized at the hourly level offer the most significant predictor relationship. This is significant as here the exact number counts for temporal periods was used.

*Figure 1 Strava Trips and Collision Counts Summarized by Month.*

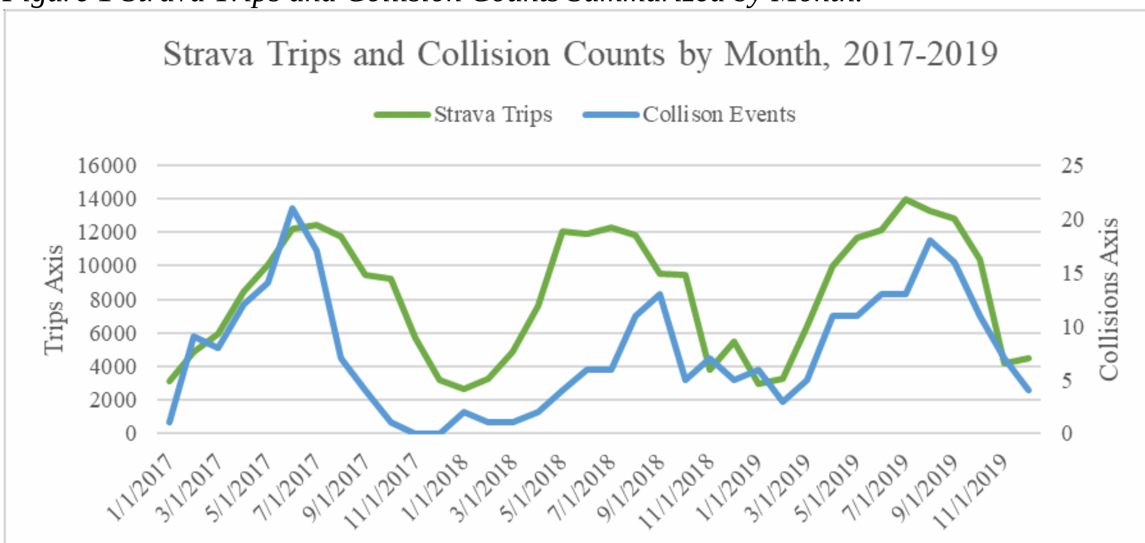


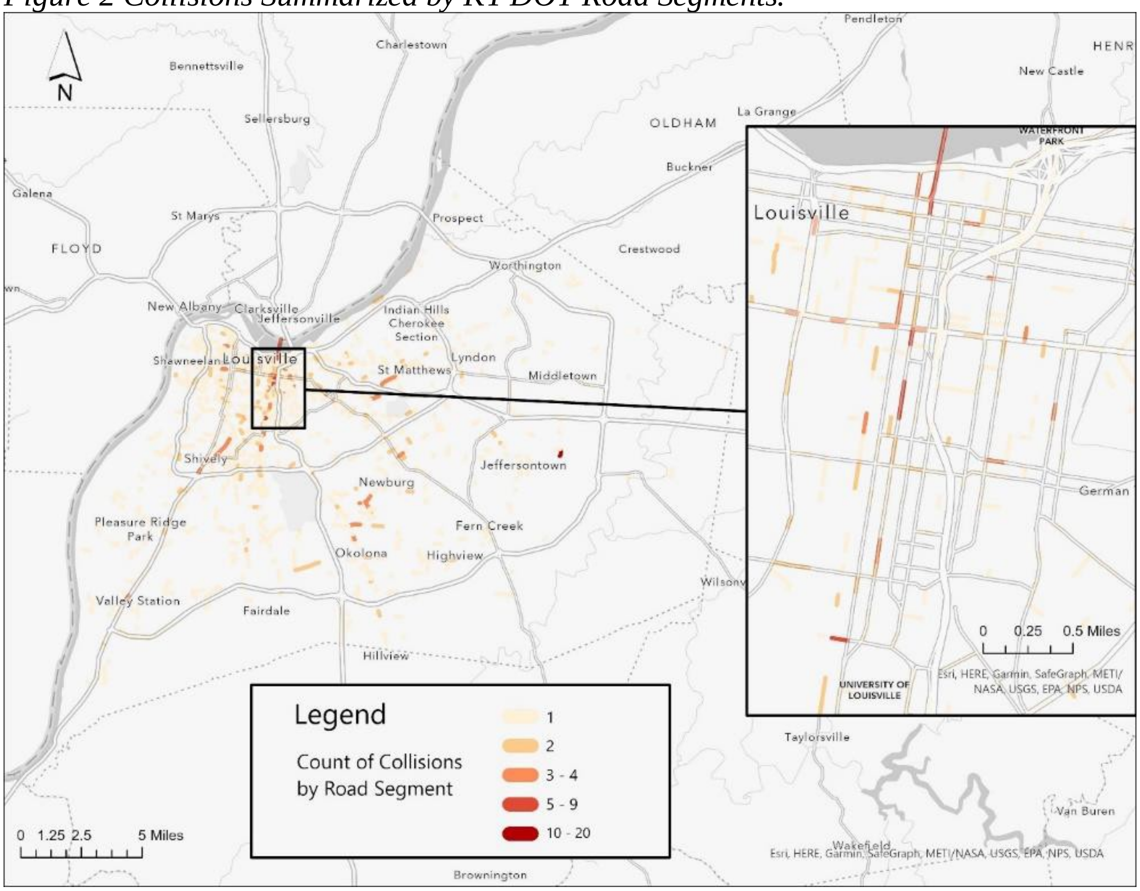

*Table 4 Regression Tesults of Strava Data and Collision Counts, 2017-2020.*

| | *Number of Observations* | *Coefficient* | *R Square* | *F* | *Significance F* | *P-value* |
|---|---|---|---|---|---|---|
| Total Volume Monthly | 36 | .001 | 0.455 | 28.42 | 6.36E-09 | 6.36E-06 |
| Trip Volume Weekday | 252 | .006 | 0.104 | 29.31 | 1.44E-10 | 1.44E-07 |
| Trip Volume Hourly | 864 | .005 | 0.433 | 55.68 | 1.78E-13 | 1.78E-10 |

### *Spatiality of Collision Events*

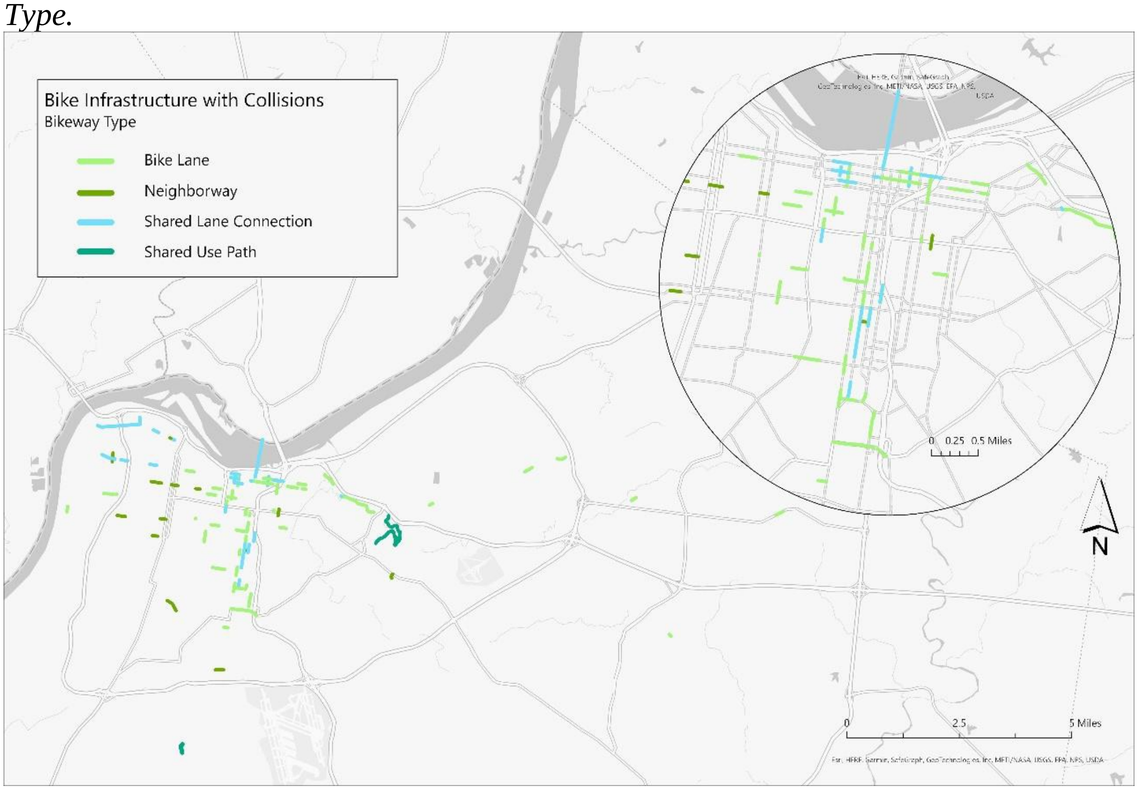
Collision events can be studied spatially by road segment. Figure 2 shows collisions spatially joined to road segments. Downtown Louisville consists of high counts of collisions along the George Rogers Clark Memorial Bridge that spans the Ohio River, and multiple segments along South 2nd Street. South 2nd Street is a two-way street with no bike infrastructure until it intersects with Broadway, then becoming an eastbound one-way street with a bike lane. Outside of the urban core, the outlier east of Jeffersontown is a segment of the Blankenbaker Parkway. Here, the Blankenbaker curves and has intersecting roads, entrances and exits from parking lots meet it. Collisions here are coded as “Collision with bicycle in intersection,” suggesting that these blind spots created by the roadways create a hazardous bike journey.

*Figure 2 Collisions Summarized by KY DOT Road Segments.*




Collisions on bike infrastructure are a function of the use of that road segment and the features there, such as intersections or entrances to the roadway. It cannot be stated that one type of infrastructure was less likely to have collisions. “Neighborways” and “Shared Lane Connection” style infrastructure features symbols painted on the roadway to identify that bikes utilize the same space as automobiles. Louisville-Jefferson County Metro has renamed these design features, as they are more commonly referred to as simply a shared lane or sharrow. A “Shared Use Path” is used by non-motorists and is usually separated from the roadway but can cross, merge or unmerge from a roadway (“Louisville Loop Design Guidelines,” 2009). Figure 3 shows the bike infrastructure that had collision events.

*Figure 3 Bike Infrastructure that Sustained Collisions After Completion, by Bikeway Type.*




All collision events have been analyzed using a high/low clustering (Getis-Ord General G). The results of the high/low clustering (Figure 4) showed the collisions grouped into census block groups with choropleth mapping. Given the statistically significant Getis-Ord General G statistic indicated by a large z-score and low p-value returned (Table 5), it is very unlikely that the spatial clustering of collision events was due to random chance.

Figure 4 shows the cluster and outlier analysis. The high-high clusters are contiguous block groups featuring high collision counts. Low-high outliers are low collision counts surrounded by high collision counts. Low-low clusters are contiguous block groups featuring low collision counts. High-low outliers are high collision counts surrounded by low collision counts. Downtown Louisville exhibits a collection of statistically significant clusters of high values of car-cyclist collisions, with low-high outliers surrounding downtown area. The downtown area north of the Shelby Park neighborhood (roughly W. Hill St.) features a weak boundary between block groups of high collisions and block groups of low collisions. The area in downtown to the east and west of the University of Louisville's campus features a sharper boundary of block groups of high collisions and block groups of low collisions. Busy roads (Dixie Highway, I65) create an east-west boundary for cyclists. The contiguous cluster of low-high outlier census blocks are bounded by roads with high use by cyclists (Algonquin Pkwy, S. 3rd St.). Southwest of these roads feature low cyclist activity. The southern and eastern areas of Louisville exhibited a collection of statistically significant clusters of low collisions, with high-low clusters emerging as outliers (Figure 4).

*Table 5 Getis-Ord General G Results.*

| | |
|---|---|
| Observed General G | 0.002746 |
| Expected General G | 0.001585 |
| Variance | 0.00 |
| z-score | 21.74 |
| p-value | 0.00 |

*Figure 4 Cluster and Outlier Analysis for Collision Counts in Block Groups.*

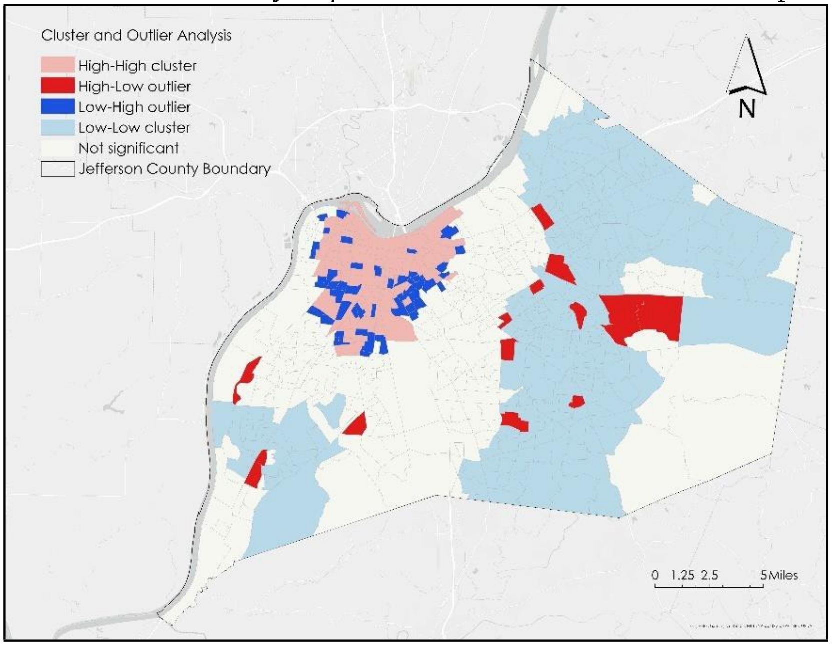



Table 6 summarizes accident factors for all car-cyclist collision events. Police recorded directional analysis codes and environmental factors represent spatial attributes. Even crash factors that are recorded as human factors are spatial; many reflect the way people interact with and move through space. Unfortunately, most of these factors go unreported or do not fit into a police code category. Table 6 shows that the most common human factor or environmental factor recorded for a car-cyclist collision is "Other or None Detected." Only a small percentage of collisions are recorded with helpful spatial factors, such as "View Obstructed/Limited," "Maintenance/Utility Work Zone," or "Misjudge Clearance." Alcohol involvement was a very small percentage of the human factors.

The directional analysis for a car-cyclist is either recorded as a "Collision with Bicycle in Intersection," or "Collision with Bicycle Non-Intersection," (Table 6). Collisions that occurred at an intersection make up a slight majority (56%) of collisions over non-intersection events (Table 6). An intersection can be defined as an area with two or more roadways coming together.

*Table 6 Accident Factors in Car-Cyclist Collision Events.*

| | | |
|---|---|---|
| Directional Analysis | | |
| *Collision with Bicycle in Intersection* | 771 | *56.0%* |
| *Collision with Bicycle Non-Intersection* | 605 | *43.9%* |
| Environmental Factors | | |
| *View Obstructed/Limited Due to Roadway* | 32 | *2.39%* |
| *Glare (Sun)* | 23 | *1.71%* |
| *Maintenance/Utility Work Zone* | 9 | *0.67%* |
| *Construction or Work Zone* | 4 | *0.29%* |
| *Other or None Detected* | 1270 | *94.9%* |
| Human Factors | | |
| *Inattention* | 298 | *20.7%* |
| *Failed to Yield Right of Way* | 156 | *10.8%* |
| *Distraction* | 26 | *1.80%* |
| *Misjudge Clearance* | 19 | *1.32%* |
| *Disregard Traffic Control* | 18 | *1.25%* |
| *Improper Passing* | 13 | *0.90%* |
| *Not Under Proper Control* | 12 | *0.83%* |
| *Following Too Close* | 9 | *0.62%* |
| *Alcohol Involvement* | 7 | *0.48%* |
| *Other or None Detected* | 880 | *61.1%* |

Recorded pre-collision actions had no spatial autocorrelation and occur randomly across Louisville. Table 7 summarizes vehicle information. The majority of vehicles remain at the crash scene (Table 7), allowing pre-collision maneuvers to be recorded. The top pre-collision actions for a car are “Going Straight Ahead,” “Making a Right Turn,” and “Making a Left Turn,” (Table 7). It should be considered that many turns occur outside of intersections. Parking lots and driveways are places of potential paths crossing. Environmental factors and human factors of collision events were not clustered and exhibited random distribution across Louisville. Pre-collision actions for cyclists are not included on the query from the Kentucky State Police.

*Table 7 Vehicle Information from Car-Cyclist Collision Events.*

| | | |
|---|---|---|
| Vehicle Identification | | |
| *Vehicle at Scene* | 1152 | *83.6%* |
| *Hit and Run* | 225 | *16.3%* |
| Pre-Collision Action | | |
| *Going Straight Ahead* | 649 | *46.0%* |
| *Making Right Turn* | 250 | *17.7%* |
| *Making Left Turn* | 211 | *14.9%* |
| *Slowing or Stopped* | 68 | *4.82%* |
| *Starting In Traffic* | 52 | *3.69%* |
| *Parked* | 37 | *2.62%* |
| *Other or Unknown* | 136 | *9.65%* |

It was found through an Average Nearest Neighbor (ANN) analysis that fatal collisions are randomly distributed throughout Jefferson County. They are not clustered or evenly dispersed. Figure 5 shows the spatiality of fatal collisions. The closest spatially were two fatal collisions occurred on Fern Valley Road. They occurred less than a quarter mile apart (680 ft.), and they both occurred in 2018. As a year, 2018 featured fewer cyclist trips recorded in Strava than 2017 and 2019. Fern Valley Rd. does have not have bike lanes, a median divides the motorways, and sidewalks exist in both directions.

Though fatal collisions are not clustered spatially or temporally, they do share trends in accident factors. All fatal collision events were recorded with a relation to trafficway as “On Roadway” (a vehicle did not exit the roadway, entering a sidewalk or trail). 94% occurred on dry road conditions, all occurred with clear or cloudy conditions (no rain, snow, or other precipitation), and 77% occurred in a non-intersection space. These are not intersections, but other locations where cyclists and cars potentially cross paths. Painted travel lanes, driveways entering the roadway, and bike lanes that exist between vehicle lanes or operate as a shared lane (such as neighborways) are coded as on roadway. A protected bike lane would be coded differently. Only one fatal collision occurred “on” a junction, which can be defined as an interchange. The roadway character of fatal collisions was normally straight and level, and the light conditions were dark, on a lighted or non-lighted highway.

*Figure 5 Fatal Car-Cyclist Collisions.*

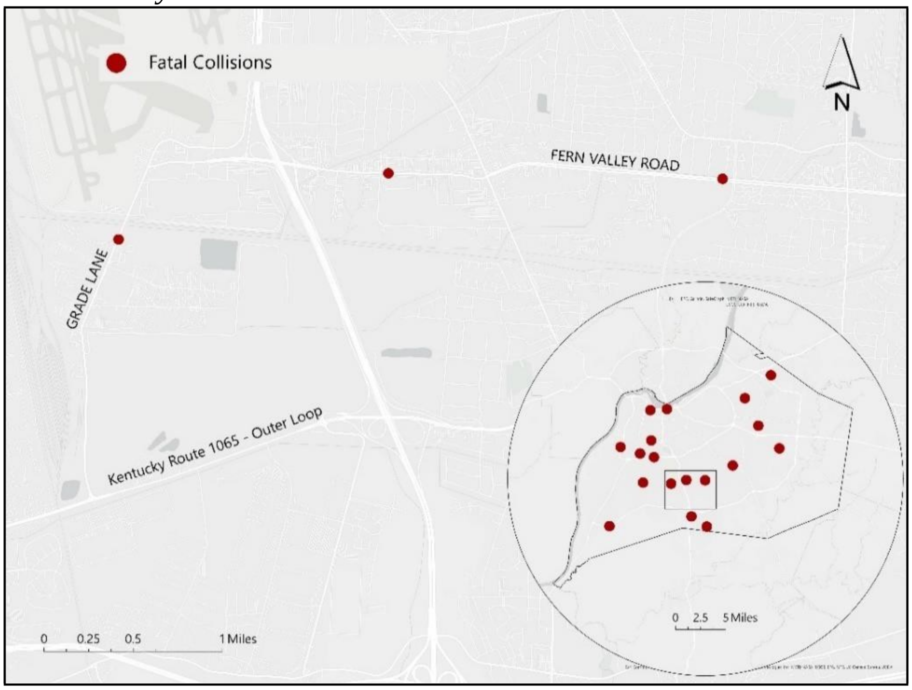



*Table 8 Spatial summary and accident factors of fatal car-cyclist collisions.*

| | |
|---|---|
| Route Signing | |
| *Local Street* | *17.4%* |
| *County Road* | *8.7%* |
| *State Highway* | *56.5%* |
| *U.S. Highway* | *8.7%* |
| Cyclist Direction | |
| *Facing Traffic* | *8.7%* |
| *With Traffic* | *43.5%* |
| *Unknown* | *43.5%* |
| Crash Type | |
| *Cyclist Ride Through – Sign Controlled Intersection* | *8.7%* |
| *Cyclist Lost Control* | *4.3%* |
| *Cyclist Left Turn – Same Direction* | *4.3%* |
| *Motorist Left Turn – Opposite Direction* | *4.3%* |
| *Motorist Overtaking – Undetected Cyclist* | *21.7%* |
| *Crossing Paths – Midblock* | *8.7%* |
| *Cyclist Ride Out - Midblock* | *4.3%* |
| *Unknown Approach Paths* | *39.1%* |

A more specific explanation of the collision event for fatal events is found in the crash type category. Not all of the FIRST reports from this time period featured a selection for the crash type, and the ones that did feature this do not display any statistical significance or spatial clustering. Table 8 includes a list of the crash types. “Bicyclist Ride Through – Sign Controlled Intersection” indicated the motorist had right-of-way and a cyclist did not stop at a stoplight-controlled intersection (NCSA, 2022). “Crossing Paths - Midblock” and “Cyclist Ride Out – Midblock” indicate a collision occurred between a motorist and a cyclist at a non-intersection midblock location (NCSA, 2022). “Motorist Left Turn” and “Cyclist Left Turn” inform that a collision happened at a place where decisions about directions and timing are made by the motorist and cyclist, but they do not indicate which party had the right of way (NCSA, 2022). “Motorist Overtaking – Undetected Bicyclist” indicates that a motorist was passing a cyclist that was traveling with traffic and did not see the cyclist (NCSA, 2022). “Cyclist Lost Control” is a collision event that occurred because the cyclist was riding too fast for conditions, oversteered, or lost control of the bike (NCSA, 2022). Losing control of the bike is often due to surface conditions of the road, including potholes and debris in the motorway.

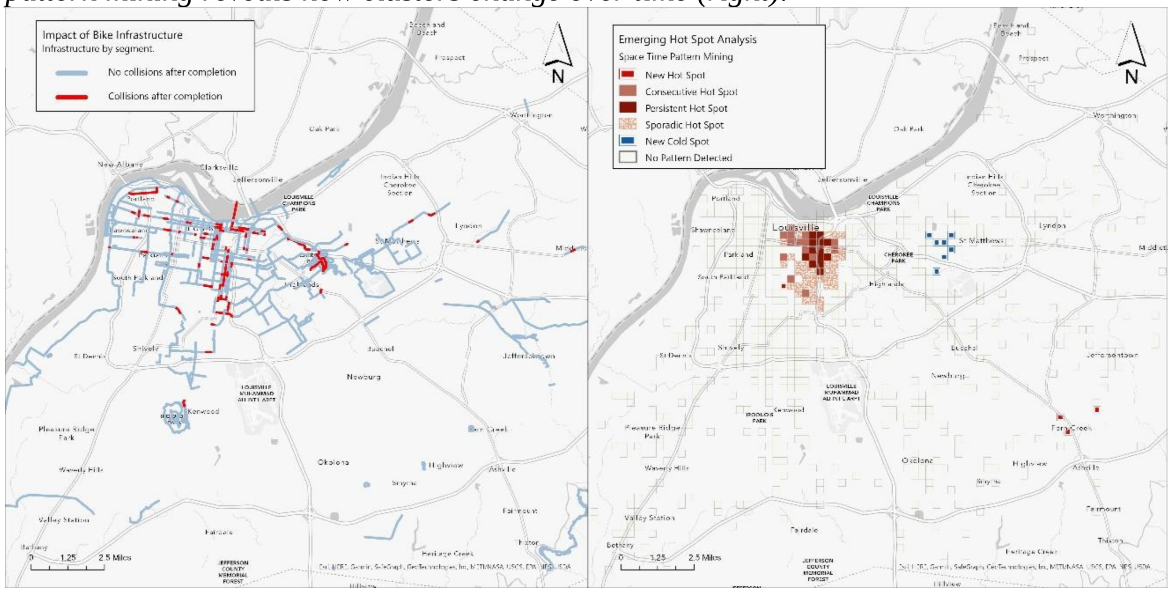
Space and time can be combined in an analysis of bike infrastructure and clustering trends. Figure 6 shows where collisions occurred on bike infrastructure after they were installed and where they did not. Only some bike infrastructure featured collisions after their creation (Figure 6). Infrastructure that did not sustain any collisions after their creations potentially made the space safer, or possibly lie within a low traffic, low cyclist area. Figure 6 also contains a map of emerging hot spots and cold spots of

Louisville. The area around W. Broadway and the I65 junctions surrounding on Chestnut St. and S. 1st St. represent persistent hot spots of collisions. This means this area has been statistically significant for 90% of the time-step intervals. Surrounding to the south and east are consecutive hot spots, and to the south and east are sporadic hot spots. Consecutive hot spots are significant at the end of the time-steps, and sporadic spots are These occur in areas with bike infrastructure installed after 2014.

New hot spots occurred at S. 11th and W. Hill St. where bike infrastructure was installed in 2014 and 2016, respectively. Hotspots where Bardstown Rd. meets Fern Creek Rd. and Fairground Rd., and at Mary Dell Ln. and Billtown Rd. do not have any nearby bike infrastructure. These roads feature 35 or 45 mph speed limits.

New cold spots occurred in the Cherokee Gardens and Rockcreek Lexington Road neighborhoods. Only Seneca Park Rd., Pee Wee Reese Rd. and Rock Creek Drive feature bike infrastructure – both old (2010) and new (2018). Where Lexington Rd. meets Cherry Ln. and Dover Rd., and where Frankfort Ave. and Fairlawn intersect are additionally cold spots. These roads have slower speed limits at 25 or 35 mph.

*Figure 6 The Impact of Bike Infrastructure.*
*Bike infrastructure that sustained collisions after their completion (left). Space-time pattern mining reveals how clusters change over time (right).*



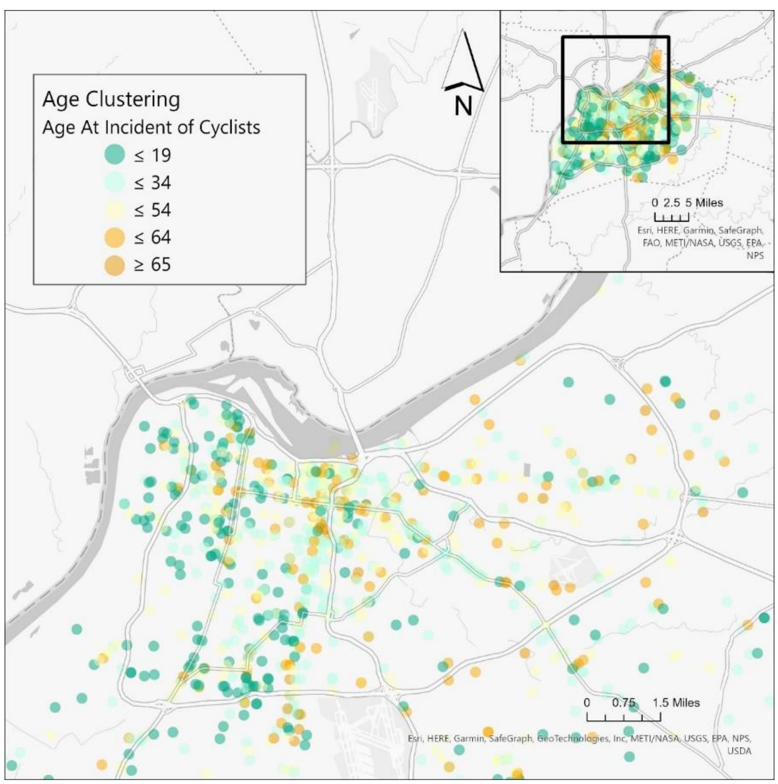

*Demographics and Injury Severity*

The demographics of drivers and cyclists involved in car-cyclist collisions present differences in age and gender. Gender and age summaries for both populations can be found in Table 4. Drivers involved are evenly split between genders, whereas cyclists are 82.6% male and 17.3% female (Table 9). The gender demographics of Strava users also reflect that Louisville has more male cyclists than female. Table 9 shows 87.96% of trips were recorded by male app users, and only 12.03% were recorded by female users. The cyclists involved in collisions have a median age of 30, and drivers involved have an older median age of 43 (Table 9). Exact ages are not available from the Strava data to calculate a median age. Gender was found to be spatially random. The age of cyclists was found to be significantly clustered (z-score of 4.61). Younger cyclists were involved in more collisions in west and south Louisville (Figure 7).

*Table 9 Gender and Age Summary for Drivers and Cyclists Involved in Collision Events, and Strava App Users.*

| Group | Drivers | | Cyclists | | Strava Users |
|---|---|---|---|---|---|
| Gender | | | | | |
| *Male* | 663 | *55.2%* | 1115 | *82.6%* | *87.96%* |
| *Female* | 538 | *44.7%* | 234 | *17.3%* | *12.03%* |
| Age Range | | | | | |
| *Under 13* | 3 | *0.25%* | 144 | *10.94%* | *0%* |
| *13-19* | 50 | *4.17%* | 199 | *15.12%* | *5.28%* |
| *20-34* | 376 | *31.35%* | 399 | *30.31%* | *29.38%* |
| *35-54* | 418 | *34.86%* | 386 | *29.33%* | *41.61%* |
| *55 – 64* | 203 | *16.93%* | 148 | *11.24%* | *18.10%* |
| *65 - Plus* | 149 | *12.42%* | 40 | *3.03%* | *5.60%* |
| Median Age | 43 | | 30 | | N/A |

*Figure 7 Age of Cyclists at Collision Events.*

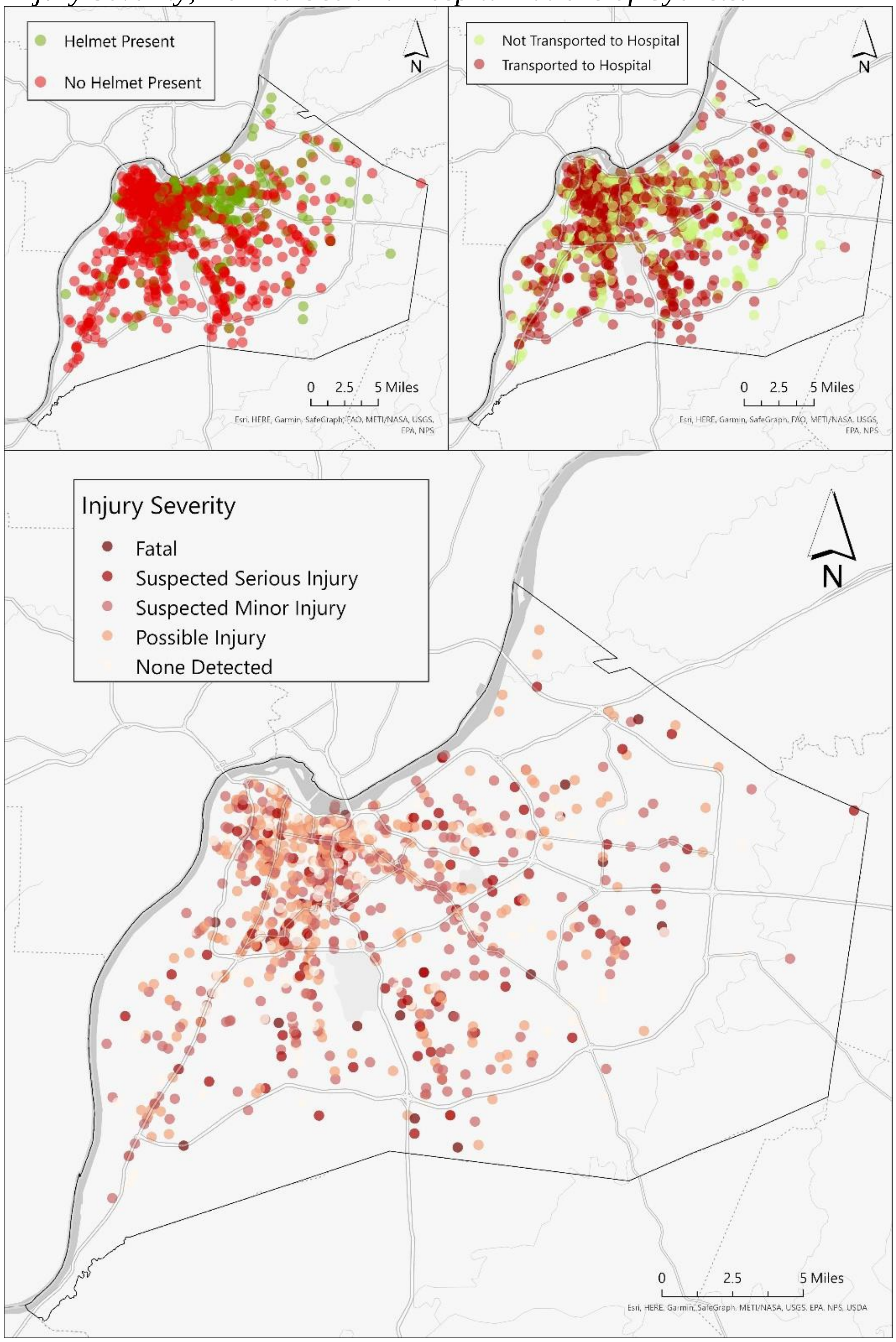


Police reports also contain a record of injury severity. Table 10 summarizes the differences between drivers and cyclists in collision events. The majority of drivers have no injury detected and do not require any transportation to a hospital (Table 10). Cyclists often sustain injuries ranging in severity, and 67% of those involved require transportation to a hospital (Table 10). For fatal collisions, 5 cyclists died at the scene of the collision, 8 died at another location, and 8 did not have a death location recorded (CrashReport). Injury severity was found to be clustered spatially (z-score of 3.27), as well as helmet use (z-score of 14.86), and the occurrence of cyclists transported to a hospital (z-score of 3.19). Only 20% of cyclists were wearing a helmet. Figure 15 displays the shared trends of these factors, where eastern Louisville exhibits a higher count of helmet use, a lower count of transportation to hospitals, and lower in jury severities.

*Table 10 Summary of Injury Severity for Drivers and Cyclists Involved in Collisions.*

| Group | Drivers | | Cyclists | |
|---|---|---|---|---|
| Injury Severity | | | | |
| *None Detected* | 1176 | *98.7%* | 373 | *27.8%* |
| *Possible Injury* | 4 | *0.33%* | 432 | *32.2%* |
| *Suspected Minor Injury* | 8 | *0.67%* | 396 | *29.5%* |
| *Suspected Serious Injury* | 2 | *0.16%* | 120 | *8.96%* |
| *Fatal* | 0 | - | 21 | *1.56%* |
| Transported to Hospital | | | | |
| *Transported* | 16 | *0.01%* | 858 | *67.0%* |
| *Not Transported* | 1174 | *98.6%* | 481 | *35.9%* |

*Figure 8 Injury Severity, Helmet Use and Hospitalizations of Cyclists.*




Louisville had 21 fatal car-cyclist collisions during the study period. The racial demographics of these reflect the general population of Louisville, with 73.9% of fatalities being reported as white (Table 11). Disproportionately, 91.3% of fatalities are male. Most fatalities of cyclists occur within the age groups 19-40 and 41-60 (Table 11). Those cyclists involved in fatalities reflect the greater population of cyclists in Louisville.

*Table 11 Demographics of Fatal Car-Cyclist Collisions.*

| | |
|---|---|
| Race | |
| *White* | *73.9%* |
| *Other* | *21.7%* |
| Gender | |
| *Male* | *91.3%* |
| *Female* | *8.6%* |
| Age Range | |
| *18 and Under* | *17.3%* |
| *19-40* | *34.8%* |
| *41-60* | *34.8%* |
| *61-79* | *13.0%* |
| *80 and Up* | *0.0%* |

*Regression and Exposure Risk*

The block group OLS results are summarized in Table 12. The adjusted r-squared value shows that the independent variables selected explained 68% of collisions spatiality. None of the variables in this regression are redundant indicated by variance inflation factor (VIF) values less than 7.5. The magnitude of average trips showed a statistically significant and positive association with collisions as expected. The variable of average road traffic had a significant and negative coefficient, meaning that collisions were less likely to occur in areas of high road traffic (Table 12). The same is true for street intersections.

The road network OLS results are summarized in Table 13. The adjusted r-squared value shows that the variables selected explain 59% of the collisions spatially. None of the variables in this regression had a VIF greater than 7.5, indicating multicollinearity was not a concern among the independent variables. The variables for street intersections, bike signs, and mileage bike infrastructure all had negative coefficients (Table 13).

The possible values of the adjusted r-squared ranges from 0 to 1, and thus the higher the number the better the fit the variables are to explain collision spatiality. The block group OLS has a higher r-squared than the road network OLS, as they feature different variables. The road network OLS featured a higher Akaike's Info Criterion (AICc) (Table 13). Even though it has a smaller r-squared, the AICc indicates it is the better model. Both models feature significant Joint F-statistics, Joint Wald statistics, Koenker (BP) statistics, and Jarque-Bera statistics. Both regressions exhibit nonstationarity.

*Table 12 Summary of Block Group Ordinary Least Squares.*

| | | | | |
|---|---|---|---|---|
| *Output* | | | | |
| Number of Observations | 575 | | | |
| R-Squared | 0.69 | | | |
| Adjusted R-Squared | 0.68 | | | |
| Akaike's Info Criterion | 2637.30 | | | |
| Joint F-statistic | 180.27 (Prob 0.000*) | | | |
| Joint Wald Statistic | 190.12 (Prob 0.000*) | | | |
| Koenker (BP) Statistic | 82.76 (Prob 0.000*) | | | |
| Jarque-Bera Statistic | 2130.73 (Prob 0.000*) | | | |
| *Variables* | | | | |
| | Coefficient | Std. Error | t-Stat | Probability |
| Population | 0.598 | 0.236 | 2.529 | 0.011 |
| Avg. Trips | 0.107 | 0.014 | 7.569 | 0.000 |
| Avg. Road Traffic | -0.014 | -1.064 | 0.287 | 0.013 |
| TARC Count | 0.111 | 0.017 | 6.490 | 0.000 |
| Bike Signs | 0.023 | 0.702 | 0.482 | 0.033 |
| Signalized Intersections | 0.713 | 0.036 | 19.637 | 0.000 |
| Street Intersections | -0.030 | 0.006 | -4.771 | 0.000 |

*Table 13 Summary of Road Network Ordinary Least Squares.*

| | | | | |
|---|---|---|---|---|
| *Output* | | | | |
| Number of Observations | 989 | | | |
| R-Squared | 0.57 | | | |
| Adjusted R-Squared | 0.57 | | | |
| Akaike's Info Criterion | 4103.68 | | | |
| Joint F-statistic | 190.27 (Prob 0.000*) | | | |
| Joint Wald Statistic | 323.88 (Prob 0.000*) | | | |
| Koenker (BP) Statistic | 141.68 (Prob 0.000*) | | | |
| Jarque-Bera Statistic | 22141.35 (Prob 0.000*) | | | |
| *Variables* | | | | |
| | Coefficient | Std. Error | t-Stat | Probability |
| Avg. Trips | 0.203 | 0.020 | 9.883 | 0.000 |
| Avg. Road Traffic | -0.009 | 0.207 | 0.008 | -1.262 |
| TARC Count | 0.119 | 0.012 | 9.295 | 0.000 |
| Bike Signs | -0.014 | -0.360 | 0.718 | 0.041 |
| Signalized Intersections | 0.580 | 0.035 | 16.314 | 0.000 |
| Street Intersections | -0.007 | 0.480 | 0.016 | -0.705 |
| Mileage Bike Infrastructure | -0.121 | 0.059 | -2.039 | -2.384 |

*Table 14 Spatial Autocorrelation Report for OLS Residuals Across Block Groups.*

| | |
|---|---|
| Moran's Index | 0.063 |
| Expected Index | -0.001 |
| Variance | 0.000 |
| z-score | 5.225 |
| p-value | 0.000 |

Table 14 shows the results of a Moran's I spatial autocorrelation of the standard residuals of the block group OLS. Given the z-score, in Table 14, there is less than 1% likelihood that this clustered pattern could be the result of random chance. The residuals were highly clustered, as noted in the significant Jarque-Bera statistic as well (Table 12).

*Table 15 Spatial Autocorrelation Report for OLS Residuals Across the Road Network.*

| | |
|---|---|
| Moran's Index | 0.068 |
| Expected Index | -0.001 |
| Variance | 0.000 |
| z-score | 5.171 |
| p-value | 0.000 |

Table 15 shows the results of a Moran's I spatial autocorrelation of the standard residuals of the road network OLS. Given the z-score of 5.171 in Table 15, there is a less than 1% likelihood that this clustered pattern could be the result of random chance. The residuals are highly clustered, again evident in a significant Jarque-Bera statistic (Table 13).

Both the models for the block groups and the road network have high clustering of residuals, and it can be seen in Figure 9 and Figure 10 where high and low residuals occur. The model is overpredicting in areas with low collisions. In both Figure 9 and Figure 10, low values for the standard residuals cluster where Louisville Champions Park, Cave Hill Cemetery, Cherokee Park, and the Louisville Internal Airport are located.

The model is also underpredicting in areas with high collisions. In both Figure 9 and Figure 10, high values for the standard residuals cluster around downtown, and west of the University of Louisville's campus, near S 7th St. and Dixie Highway.

*Figure 9 Results from OLS at the Block Group Level.*

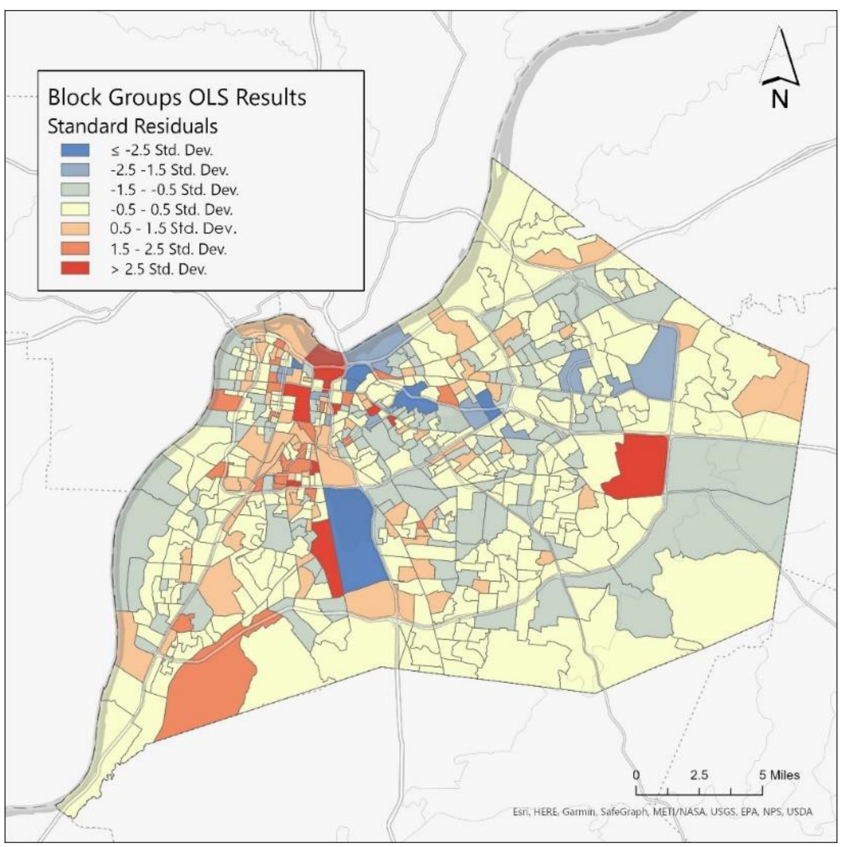
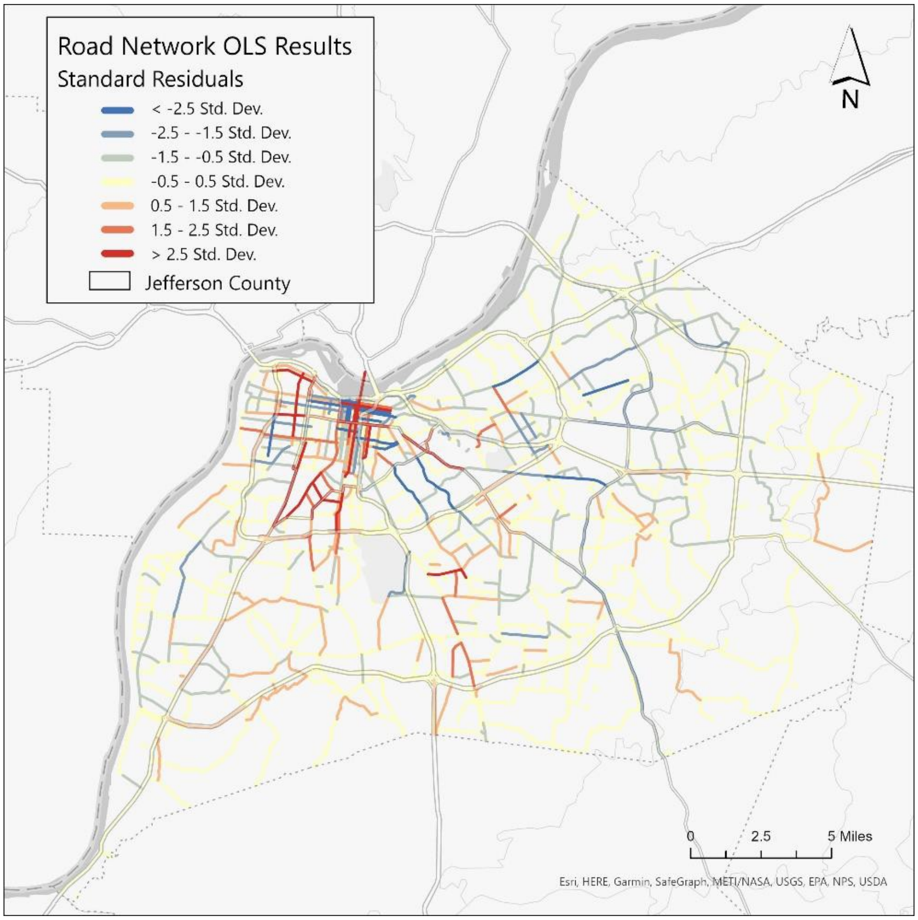


*Figure 10 Results from OLS at the Road Segment Level.*




Variables were evaluated for non-linear relationships. Signalized intersections, average Strava trips, and TARC bus stop locations had the most positive relationship with collision events for both the block group OLS and the street segments OLS. Figure 11 shows the scatterplots from the block group analysis, where TARC bus stops are “TARCCOUNT.” Average Strava trips are “AVGTRIPSNORM” (Figure 11). Signalized intersections are “SIGNALS” (Figure 11). Figure 12 shows the scatterplots from the street segment OLS. Signalized intersections are “SIGNALINT” (Figure 12). TARC bus stop counts are “BUSSTOPS” (Figure 12). Average Strava trips are

“AVGTRIPSNORM” (Figure 12). Removing variables one by one from the OLS analyses only slightly improved the models and did not produce random residuals.

*Figure 11 Scatterplots of OLS Variables from Block Group Analysis.*

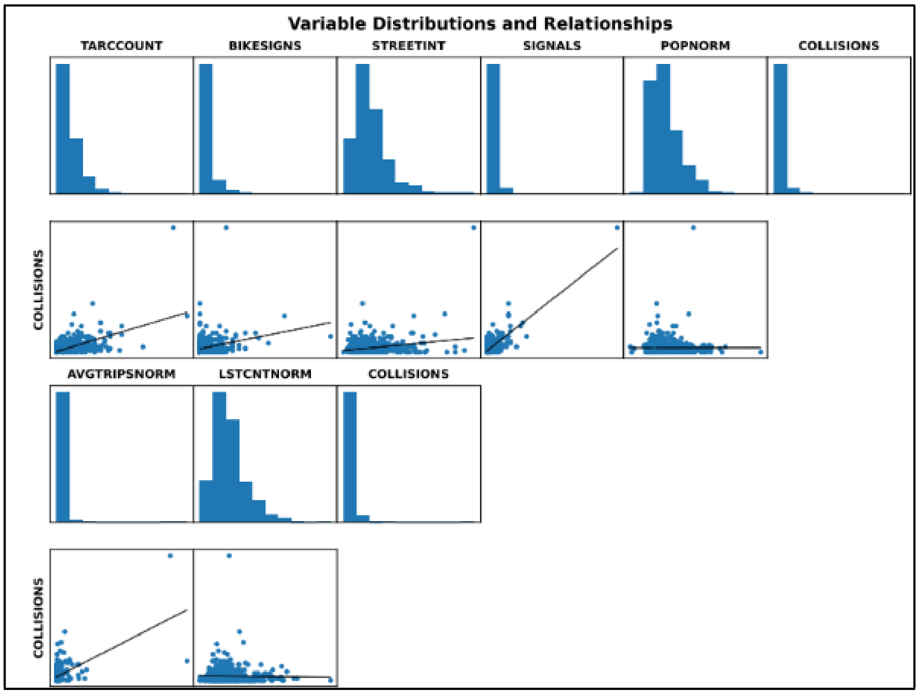
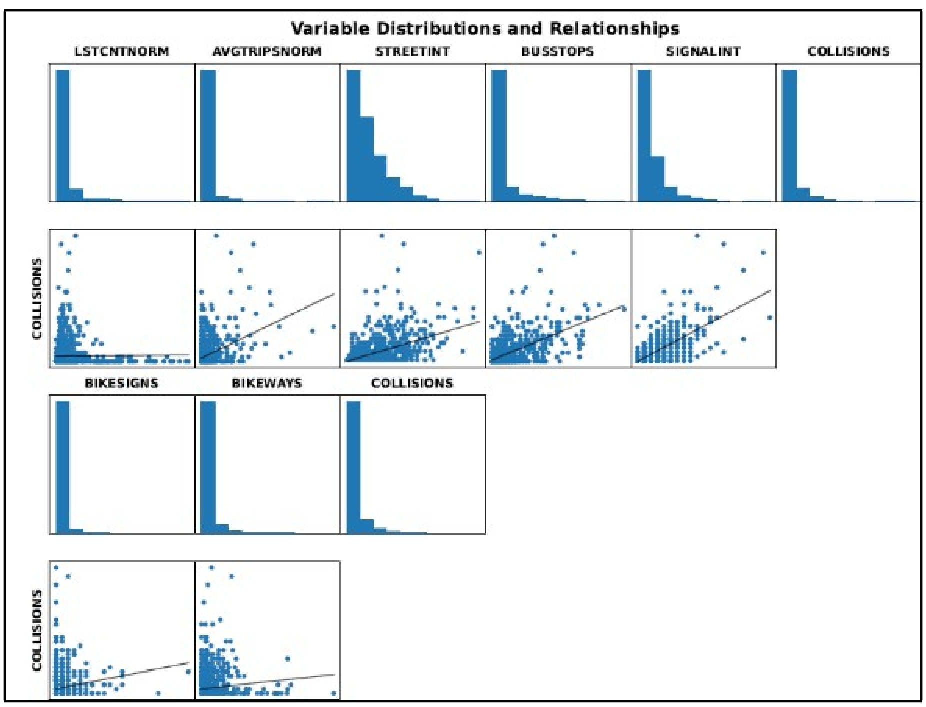



*Figure 12 Scatterplots of OLS Variables from Street Segment Analysis.*



Both models show misspecification and nonstationarity. It is best to evaluate them with a local model instead of a global model. The Geographically Weight Regression (GWR) can better understand the variables' nonstationarity. Due to the block groups having the lower Jarque-Bera and the higher r-squared, it was determined to be the best candidate for the GWR. The variables tested were the TARC count of bus stops in each block group, the count of signalized intersections in each block group, and the average Strava trips. These variables were the combination that produced random residuals (Table 14). These variables also had the strongest linear relationship to collisions in the OLS.

*Figure 13 Results from Block Group Geographically Weighted Regression.*

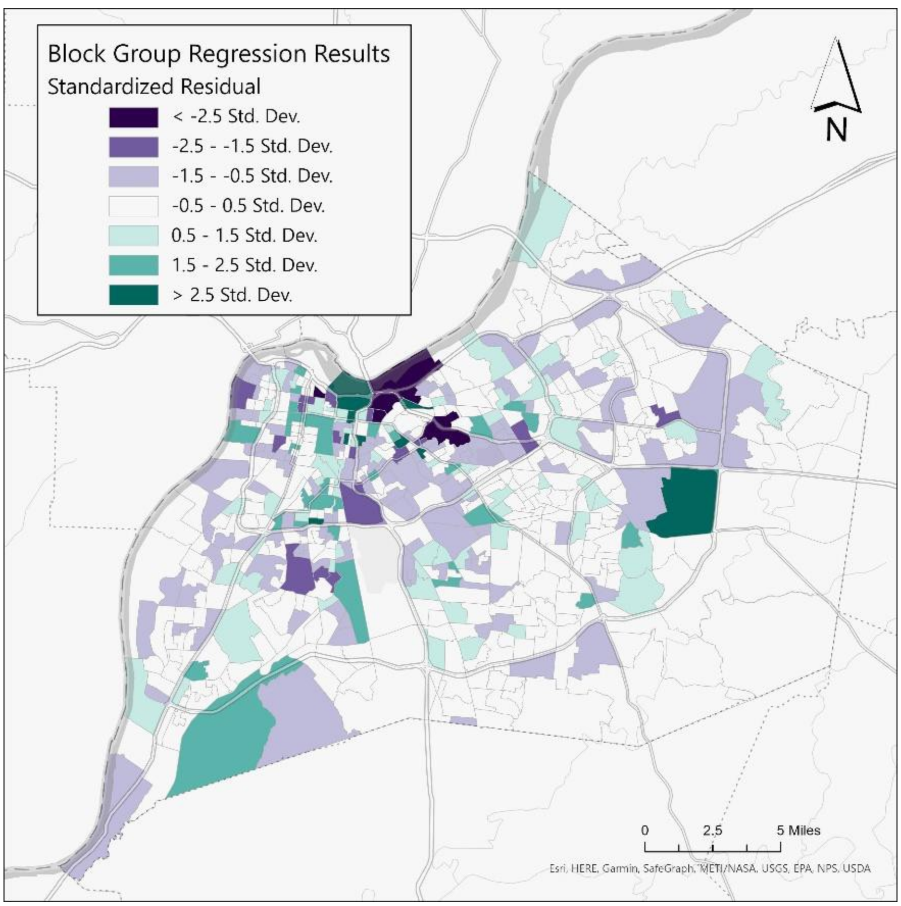


*Table 13 Output Report for Block Group GWR.*

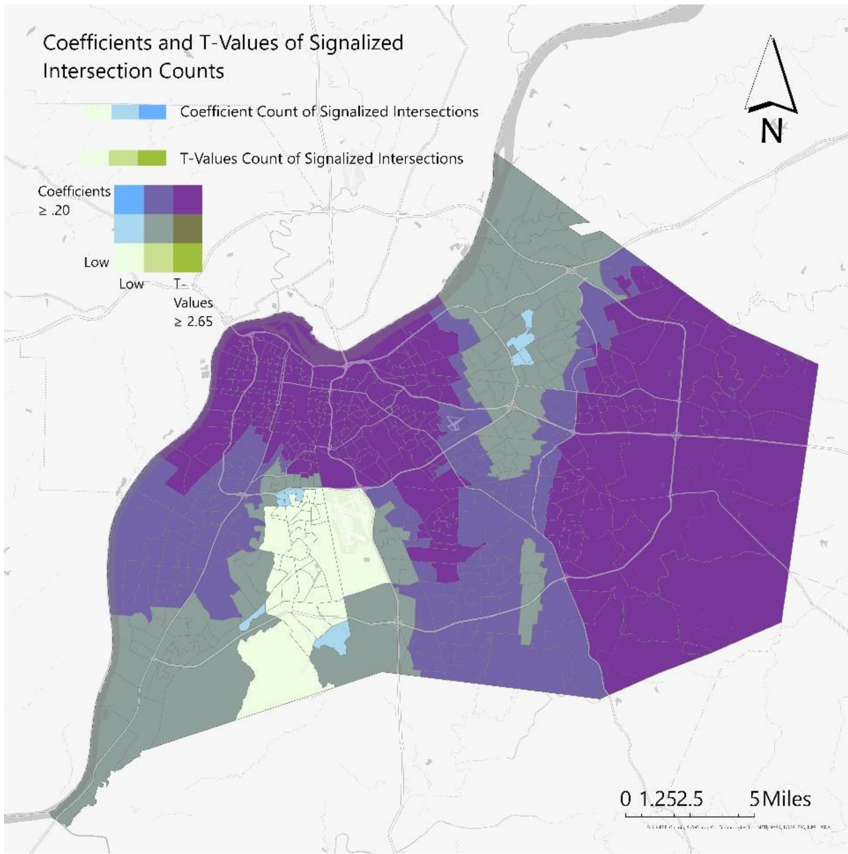
| | |
|---|---|
| R-Squared | 0.675 |
| Adjusted R-Squared | 0.673 |
| AICc | 2655.62 |
| Sigma-Squared | 5.870 |
| Sigma-Squared MLE | 5.830 |
| Effective Degrees of Freedom | 571.00 |

*Table 14 Spatial Autocorrelation Report for GWR Residuals Across the Block Groups.*

| | |
|---|---|
| Moran's Index | -0.003 |
| Expected Index | -0.017 |
| Variance | 0.000 |
| z-score | -0.167 |
| p-value | 0.866 |

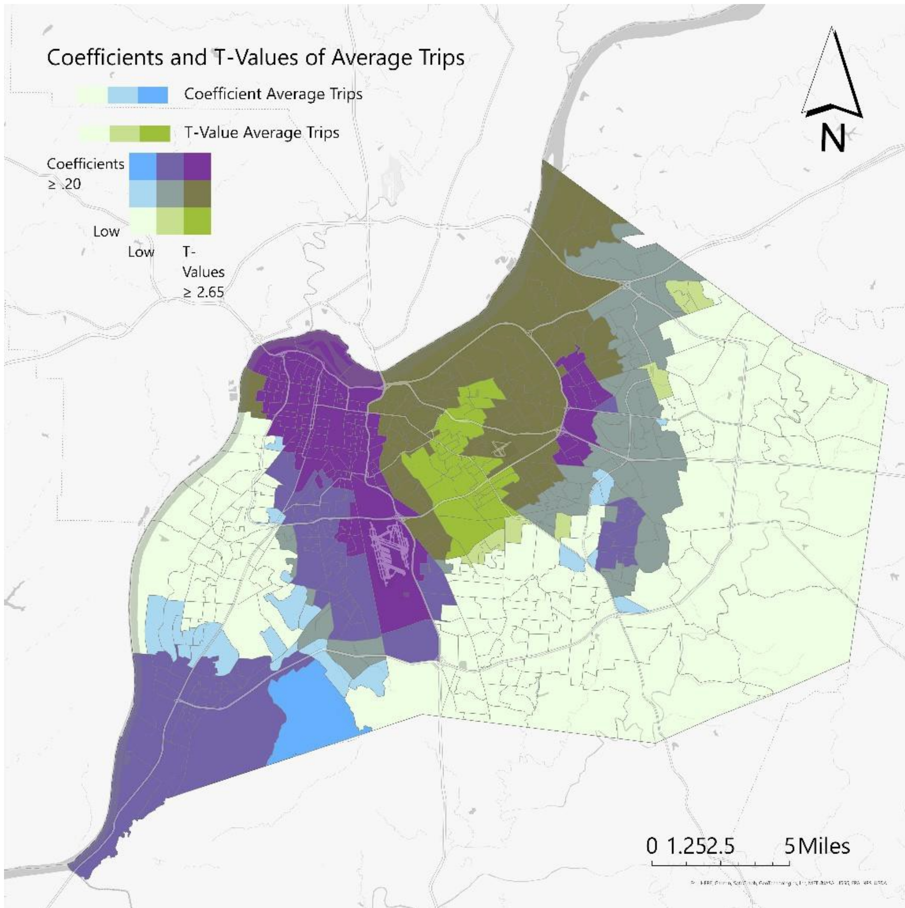
The residuals of the block group GWR are random (Table 14). There is strong variation across Louisville in how the variables effect collisions. The more positive standard deviations (dark green in color) show a strong positive relationship with the explanatory variables (Figure 13). The negative standard deviations (dark purple in color) show a strong negative relationship with the explanatory variables (Figure 13). Collisions are found in areas where the variables are high in count and low in count. The relationship between the variables is spatially random across Louisville, and therefore the coefficients *and t-values* for each variable were explored. The GWR is successful in showing the spatial variation of these variables. The condition numbers did not indicate local collinearity was a problem. None of the coefficients or t-values were negative. The coefficients and t-values are mapped with a bivariate color scheme. Illustrating them together in one map for each variable offered a better interpretation of the significance and strength of each variable. The deepest purple color in the maps represent areas where the coefficient is greater than or equal to .20 and the t-value is greater than or equal to 2.65. Coefficients and standard errors were very small, resulting in a high t-value.

*Figure 14 Signalized Intersections Variable Significance*



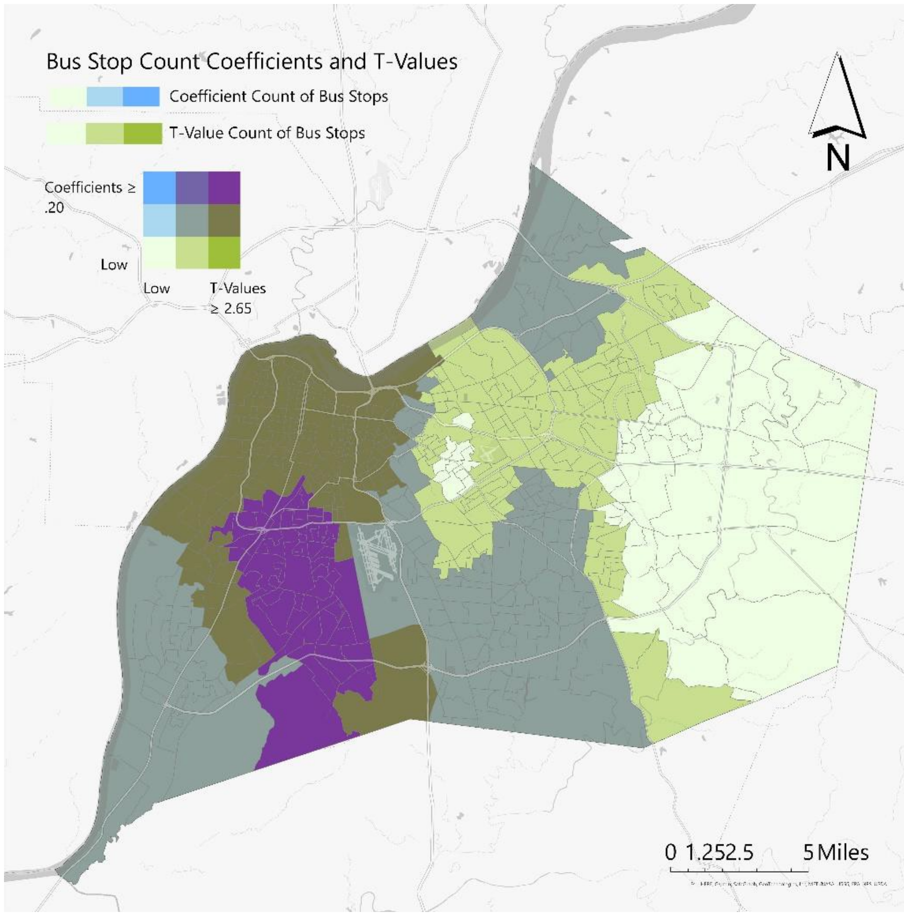

The coefficients show where the variable is explaining more of the count of collision events. T-values show where these coefficients are significant. Signalized intersections were found to be significant in the downtown area within the Watterson Expressway (264) and east of the Hurstbourne Parkway (Figure 14). They had a weaker coefficient but were still significant west of Dixie Highway and between I65 and Bardstown Road (Figure 14). These areas correspond with the areas of low-low and high-clow clusters in Figure 4.

*Figure 15 Average Trips Variable Significance*



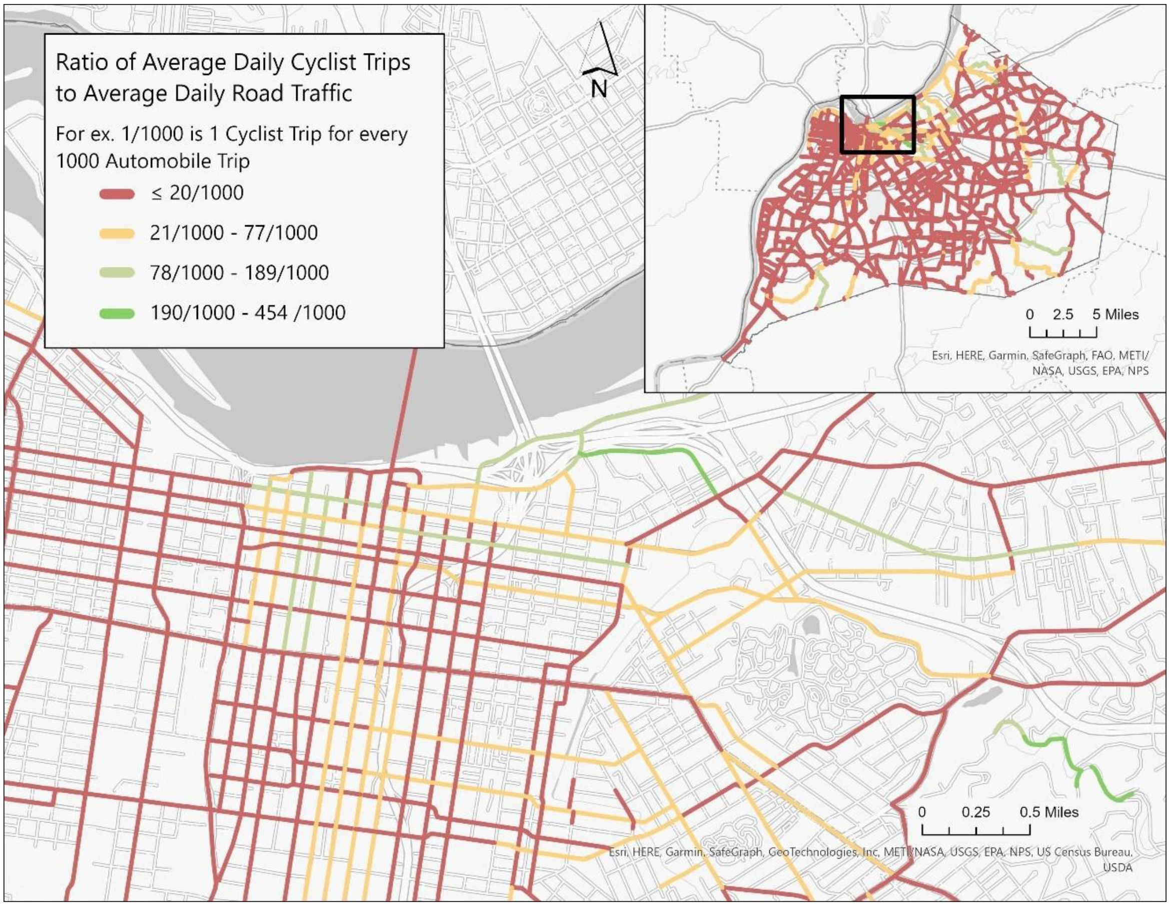

Average cyclist trips were found to be significant in the downtown area within the Watterson Expressway (264) and north of Algonquin Parkway. They had a weaker coefficient but were still significant in census block groups north of I64 and I71 (Figure 15).

*Figure 16 Bus Stop Counts Variable Significance*




The count of bus stops was found to be significant west of I65 in downtown Louisville, and west of Southside Drive but east of Dixie Highway (Figure 16). This area contained a high-low outlier and low-low outliers in the cluster and outlier analysis (Figure 4).

*Figure 17 Looking at Risk: Cycling Traffic Compared to Road Traffic.*




Comparing a ratio between cycling traffic and road automobile traffic can visually illustrate the risk cyclists face on roadways in Louisville. Figure 17 shows the average daily trips as a percentage of the daily road traffic. Only Adams St., the Scenic Loop of Cherokee Park, KY-6326 (at Ramsey Middle School), and Simcoe Ln. at the Summit Mall (Malone's entrance) feature road segments where cyclist traffic is 19% or more of the road traffic. Despite there being a large amount of recorded cyclist trips, on most road segments they make up a small percentage of the road traffic. Cyclists' exposure risk is high in much of Louisville's road network. The Strava trip counts from 2019 suggest that 1 in every 1,000 cycling trips results in a collision, or that .001% of trips have a collision event. A cyclist may cycle every day, or sparingly. Each ride has the same risk, but some cyclists are exposed to this risk more frequently.

# DISCUSSION AND CONCLUSIONS

Car-cyclist collisions in Louisville have not been studied independently since 2012. They represent an important area of urban safety that has now been reevaluated with new data. This thesis found that collision events are temporally tied to the cyclist volume in Louisville. Collisions, and cyclist activity, peaks in the summer months. Collisions exhibit spatial clustering and feature high counts in the urban core, with outliers in the surrounding suburbs. West Louisville featured younger persons involved as cyclists in collisions, while east Louisville had an older average age involved as cyclists in collisions. It is commonly found that there are less women cyclists in demographic research of cyclists (Sanders, 2015). Fatal collisions do not exhibit spatial clustering, though many occur in a non-intersection space.

OLS regression results using block groups as the unit of analysis showed that the average road traffic has a negative coefficient, meaning that collisions occur slightly away from areas of high road traffic. The variables for street intersections, bike signs, and mileage bike infrastructure all had negative coefficients. A misspecification of the OLS road network regression may be that speed limits were not one of the explanatory variables, as they are not a part of the KY DOT data set, but in a future study could be spatially joined from another data source.

Using the Strava data enhanced the depths of understanding the spatial and temporal trends of car-cyclist collisions. Strava data could also be a bias of the study, as west Louisville featured limited app use.

The GWR shows there is strong variation across Louisville in how the variables effect collisions. Like was found in the OLS and GWR regressions, bus stop density is commonly found to be associated with cyclist collision events (Chen and Zhou, 2016). The GWR regression would have different results had binary (logistic) been chosen as the model type. Block groups either do or do not contain collisions and could be studied with this division instead of count of collisions.

At intersections the trajectories of cyclists and cars can change. This study found that most car-cyclists collisions occur in intersections. However, stop-sign controlled intersections were found to negatively correlated with collisions and light-controlled intersections were positively correlated with collisions. This study reflects other research that found more stop-sign controlled intersections on a roadway can slow traffic flow and make a roadway safer. The results also reflect research that has found more signalized intersections lead to more collision events (Chen, 2015). It would be helpful for future studies if police report codes could differentiate between these types of intersections.

It is recommended that police data include more coded crash information. A critical aspect of car-cyclist collisions is missing from the current police data: the angle of collision. The car pre-collision action is known in police data but it is not known the location on the car or cyclist which sustained the impact of collision. Police reports may include a drawing of the collision, but this information is not made into a code for a spreadsheet (Lusk, Asgarzadeh, and Farvid 2015). It is not possible to recreate an accident and learn from the crash in relation to the infrastructure, potential blind spots, and conflicting paths with the current coded information available. More detailed road networks (multiple travel lanes, turn lanes, bike lanes) necessitate more detailed reporting.

The underreporting of car-cyclist collisions is a bias in this study. Many collisions go unreported if there is no injury or property damage. There are also many occurrences where a collision is narrowly avoided. It is recommended that Louisville-Jefferson County make their Close Call reporting submission form (“Have”) a GPS-enabled webpage or mobile phone application. This way location information is accurately recorded for a close call, and users could select from fields which share police codes. It is additionally recommended that this data be made available to researchers so that multiple sources of crash data can be compiled for a study. Close calls, or near misses, of collision events should equally be considered in transportation research that studies collisions, as they influence cyclists’ and non-cyclists’ perceptions of safety as much as collisions (Sanders, 2015).

Along with forming perceptions of safety through experience, residents also perceive the safety of cycling in their community is through witnessing others cycle and the existence of infrastructure that is designed for cycling. Both the benefits, and safety, of cycling increase congruently with the cycling population (Delmelle and Thill 2008). The presumption that a method of transportation is safe is the most important factor in method selection (Ha and Thill 2011). Cities that want to see an increase in cyclists and the benefits of a substantial cycling community should improve the safety of cycling.

This thesis also considered the similarities between crime events and collisions. Collisions have contributory factors and are more like crime events than accidents. The same theoretical frameworks used for crime analysis were used to support the spatiality of collisions. There are too few human factors recorded to further utilize situational action theory in the reasoning behind collision events. The other theories discussed can be utilized to explain differences between areas of hot spots and cold spots of collisions. In east Louisville, cold spots of decreased collision events are evident despite there being only proximal bike infrastructure. This area features high cycling activity, pointing to a collective conscience about mobility norms in the area. There is likely safety in the quantity of cyclists present in east Louisville. The high cycling activity has normalized their road presence to the point that spatial and mobility decisions are clearly guided for cars and cyclists.

Looking to social disorganization theory, collisions are more likely to occur in neighborhoods of low investment, or transitional zones. These areas would have low infrastructure investment. Considering neighborhood factors as explanatory variables for collisions removes fault from individuals to a fault of geography. This theory would uphold hotspots with correlations to many built environmental factors. The main built environment factor this thesis tied to collisions were signalized intersections.

It can also be said that collisions are like crime events due to the fear they instill in the public's perception of space. The fear of crime, or the fear of collisions, is the most limiting factor for peoples' choice of use of space. And like crime events, car-cyclist collisions may not align with the way space is perceived (Kamalipour, Faizi, and Mermarian, 2014). Space may be perceived as unsafe when that is not statistically supported. The reality of the reasons for collisions may not align with the collective conscience of the community: shared ideas about where is safe to cycle, where is not safe, beliefs about what causes collisions and who is at fault. Therefore, like crime prevention, reducing collisions must consider social conditions as well as environmental (Kamalipour, Faizi, and Mermarian, 2014). The theoretical framework outlined in this section allows for the humanization of discrete events.

The thesis has implications for the health and safety of cyclists in Louisville. It has analyzed a variety of dependent variables and outline numerous specific places that are risky for cyclists. It has indicated that bike infrastructure can impact space and make it safer. Growing the bike network in Louisville should continue to be a planning priority. It has identified populations at risk. It should be a goal to educate younger populations about cycling safety.

This thesis has considered factors of the built environment to discover if car-cyclist collisions display any patterns that could be used to improve cycling safety. This thesis is significant because it has been the first study to consider cyclist volume as an explanatory variable of the spatiality of car-cyclist dependence. This thesis also put forward recommendations to better the information available to study cyclist collisions, and ways to improve the safety of cyclists in Louisville. It also evaluated the use of third-party sources as exposure measures and explanatory variables. This thesis was successful in its endeavor to learn more about the spatio-temporal trends of car-cyclist collisions.

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