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Effectiveness of Safety Countermeasures on Dockless E-Scooter Crashes

Final Report

By

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DISCLAIMER

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Executive Summary

Dockless e-scooter's popularity has yet to wane after the COVID-19 pandemic. Not only that, crash rates across the U.S. have also climbed, with a rise in crash rates by 22% in 2022 compared to 2021. Methods to curb these rates include statewide operation controls, such as banning e-scooters from using the street or sidewalk or forcing the use of helmets depending on age. Yet these regulations lack consistency not only between states, but even within the cities in those states. Paired with the convolutedness of these governmental regulations is the option for these officials to utilize geofencing technologies. These technologies are able to cap e-scooter speeds, or even disallow users from ending their trip in defined no-parking zones. Overall, there is a scarcity of research concerning e-scooter crashes, and even more so regarding geofencing technologies. Paired with a thorough review of government regulations and geofencing case studies, this study addresses the following questions: what are the main reasons behind dockless e-scooter crashes, and does parking or geofencing technologies lower crash rates or injury severities?

Using the University of Texas at Austin (UT) as the case study, researchers utilize injury reports, trips, COVID-19, and weather data to conduct a quantitative and ridge regression analysis. This data was sourced from various outlets, including the University Health Services at UT Austin, City of Austin Transportation Department Shared Micromobility Trips, Texas Department of State Health Services (DSHS), and the National Centers for Environmental Information and spans between the years of 2018-2022, providing a total sample size of 1,726 days.

Using a two-tailed t-test ($t_{critical} = 1.96$), results show that both parking and speed geofence are insignificant at reducing crash rates and injury severities. These results led researchers to focus on predictive rather than inferencing model tactics. Further analysis of the trip and injury data pointed to the year 2019 accumulating the largest number of trips (1045 K trips) and injuries (30 crashes). Notably, the winter season witnessed the highest frequency of crashes, indicating potential issues with road quality during inclement weather. Lastly, the Ridge Regression, with an RMSE of 0.158, demonstrated its superiority as a predictive model for head injuries. By incorporating every data source previously mentioned, the final model identified excessive speeds ($\beta_{ridge,excessvie\ speed} = 0.075$) as the most influential factor in predicting an increase in head injuries. Both the speed and parking geofences showed minimal predictive power regarding head injuries, consistent with the findings of the t-test. Additionally, variables exhibiting a strong negative relationship with head injury prediction included knee and ankle injuries, crashes involving vehicles, and facial injuries. This inverse relationship can be attributed to the prevalence of lower extremity injuries, the nature of vehicle-related collisions resulting in shoulder injuries, and potential discrepancies in data reporting where face injuries may be misreported as head injuries. It is crucial to emphasize that these findings are specific to UT campus data and may vary depending on the study area.

While further research is strongly advised, our findings suggest that city and university officials continue to implement speed geofences, especially in areas with steep inclines where excessive speeds pose a significant risk of head injuries. Secondly, to mitigate injury severity resulting from collisions with other modes of travel, such as pedestrians and cyclists, we propose enforcing e-scooters to operate along designated bike lanes or dedicated e-scooter lanes if feasible. Lastly, promoting helmet use remains a reliable strategy to reduce the likelihood of head injuries among e-scooter users.

Introduction

Background

Dockless e-scooters were introduced to the public around July 2017 (Cross 2020). Accessible for rent through mobile apps, e-scooter operations expanded to approximately 100 major cities across the U.S. by late 2018 (National Association of City Transportation Officials, n.d.). In 2018 alone, riders completed 38.5 million trips on e-scooters, in addition to 36.5 million trips taken in station-based bike share systems (Transportation 2020). The potential benefits of using an e-scooter include shifting trips away from private vehicles, completing last-mile trips, reducing one's carbon footprint, and expanding travel options for underserved communities (Glavić et al. 2021; Sanders, Branion-Calles, and Nelson 2020).

In 2020, the use of e-scooters rapidly declined during the implementation of various local, state, and federal COVID-19 stay-at-home orders aimed at slowing the spread of the virus (Bureau of Transportation Statistics 2021). One study discovered that, despite a decrease in total shared e-scooter trips during the pandemic, partly due to vendors exiting the market, the average trip length increased, and the temporal patterns of this mode did not undergo meaningful changes (Dean and Zuniga-Garcia 2022). By 2022, e-scooter ridership had rebounded to pre-pandemic levels (Brasuell 2022). Since COVID-19, e-scooters have maintained their relevance, with ridership levels rebounding to pre-pandemic figures. However, there has been little to no research conducted on safety mitigation efforts for e-scooter crashes since then (National Association of City Transportation Officials 2022). Most safety investigators believe that the likelihood of injury and the severity of injuries in any crash increase with higher speeds or an increasing speed differential between intersecting bodies (Toofany et al. 2021). Common risk reduction efforts include government intervention by prohibiting e-scooters from using streets or sidewalks, even with the absence of bike lanes. Alternative approaches involve geofencing technologies coupled with impoundment fees.

Using GPS technology, geofences enforce speed reductions that lower speed, turn off the e-scooter throttle, or prevent the user from parking once the user crosses the invisible geographical barrier. By tracking the user, geofencing can force the rider to slow down or come to a complete stop. Consequently, less speed equates to less momentum to be dissipated in the event of a scooter colliding with another object. Another popular geofencing method involves preventing a user from ending their trip within a pedestrian hot spot. This approach compels riders to search for alternative routes or stopping points during their trips, further separating e-scooter users from other modes of travel. Paired with an impoundment fee, this method could prove nearly as effective as the speed geofence in reducing crash rates and severity. As mentioned earlier, there has been little research on e-scooters in general, let alone the effectiveness of geofencing or other safety countermeasures. Therefore, this report aims to fill this gap by addressing the following problem statement:

Problem Statement

As e-scooters become more popular for personal transportation and leisure activities, emergency departments are treating an increase in injuries nationwide (U.S. Consumer Product Safety Commission 2023). With injury rates rising 22% in 2022 from 2021, appropriate safety countermeasures have not been fully assessed (U.S. Consumer Product Safety Commission 2023). E-scooters can reach very high speeds (15+ mph), and users typically have little to no protection, posing a safety hazard and high risk for head injuries (Shichman et al. 2022). Even without an in-depth understanding of the contributing factors to scooter crashes, city officials and university leaders have already taken steps to curb scooter use in high-crash areas through the use of geofences. Yet there is an even greater lack of studies that have measured the impact of geofences toward safety in a meaningful way. Therefore, this analysis aims to unravel the causes behind crashes and gauge the effectiveness of e-scooter safety countermeasures (i.e., speed and parking geofencing restrictions) in reducing crash rates and injury severities.

Objectives

The University of Texas at Austin's campus will act as the location of interest for evaluating scooter crashes. This study will provide a thorough quantitative analysis of injury report data for the before-after safety analysis of the effectiveness of the geofencing technologies. The analysis also evaluates the effectiveness of the speed reduction and parking geofence in lowering crash frequencies and injury severity. The proposed work will address the following CAMMSE research thrust:

1. Conduct a comprehensive literature review on state-to-state e-scooter operation policies, including regulations regarding street versus sidewalk bans, helmet requirements, and the evolution of geofencing technology.
2. Provide a thorough quantitative analysis regarding the causes behind e-scooter crashes and injury retention.
3. Create a machine learning model that predicts head injuries.
4. Provide recommendations for city officials and universities based on these results.

Expected Contributions

The outcomes of this study have pinpointed the primary causes of e-scooter-related crashes. These findings enable city officials to strengthen safety measures aimed at reducing both the frequency and severity of such incidents.

Report Overview

This report begins with a review of existing literature on dockless e-scooter operation regulations across U.S. states, focusing on geofencing technologies and implementation challenges faced by cities. Following this, a qualitative analysis of injury and trip data from the case study is presented, leading into the development of a Ridge Regression model to predict head injuries. Conclusions regarding the effectiveness of various countermeasures in reducing crash rates are drawn, accompanied by recommendations tailored for city and university policymakers.

Literature Review

Research indicates the majority of e-scooter-related crashes happen along streets and sidewalks. While most of these crashes result from the rider falling off the scooter, the second-largest number of incidents occurs when riders collide with vehicles. Mitigation efforts to reduce these crashes involve statewide restrictions on e-scooter riding along streets and sidewalks. The majority of the U.S. allows e-scooters to operate along roadways, yet concerning sidewalks, there is a nearly equal split on banning e-scooters. To address the lack of legal regulation, city officials may seek geofencing technology in areas with high pedestrian or vehicular volumes.

This section will provide additional details on states that have implemented e-scooter restrictions. Following this, there will be a brief discussion of the process of acquiring a geofence and the challenges of navigating the relationship between e-scooter vendors and city officials. Examples of cities grappling with these issues will also be provided. Given that UT Austin serves as the case study for this report, the review will conclude with a description of the City of Austin's timeline of major events and changes from the deployment of e-scooters in Austin to the present day.

E-Scooter Crashes and Safety Countermeasures

E-Scooter Crash Type and Injury Severity

Previous studies consistently state that e-scooter-related crashes primarily occur along roadways. Much of this research attributes these crashes to colliding with a vehicle or falling due to pavement quality, with less emphasis on excessive speed as a contributing factor. Yang et al. (2020) conducted a quantitative analysis of e-scooter crash characteristics using nationwide news reports on e-scooter crash data. Their key findings indicate the majority of reported crashes were located along the travel lane and involved collisions with vehicles. The second-largest collision type was riders falling off their scooters due to uneven pavement or avoiding fixed objects, such as trees. Notably, no crashes were reported in bike lanes, suggesting that riding e-scooters in dedicated facilities may result in fewer conflicts with other transportation modes (Yang et al. 2020).

These findings align with another study conducted by the Austin Public Health report in 2019. The report summarized interviews with 271 people involved in e-scooter-related injuries. It revealed that more than half (55%) of the riders were injured in the travel lanes, one-third (33%) on the sidewalk, and that collisions with vehicles and falling off were the two major types of collisions (Austin Public Health 2019). It is important to note that the Austin Public Health report collected interviews from individuals who visited local hospitals to treat their crash-related wounds, indicating the collection of mostly severe crashes (Austin Public Health 2019). In contrast, Hall, Baumanis, and Machemehl in 2024 collected injury reports from the University Health Services at UT Austin. They found that the majority of crashes (n=54) on UT Austin's campus were due to users falling off their scooters (70%) due to excessive speeds (~50%) (Hall, Baumanis, and Machemehl 2024).

Regarding research associated with e-scooter injuries, head injuries have emerged as the most common injury, with a rate noted to be more than double that of bicycle accidents (Namiri et al. 2020; Trivedi, Liu, and Antonio 2019; Tischler et al. 2023). The study conducted by Hall, Baumanis, and Machemehl in 2024 also provides a helpful depiction of the bodily locations of e-scooter injuries seen at UT's campus, with the face (23%), head (18%), and knee (18%) identified as hot-spot locations for injuries.

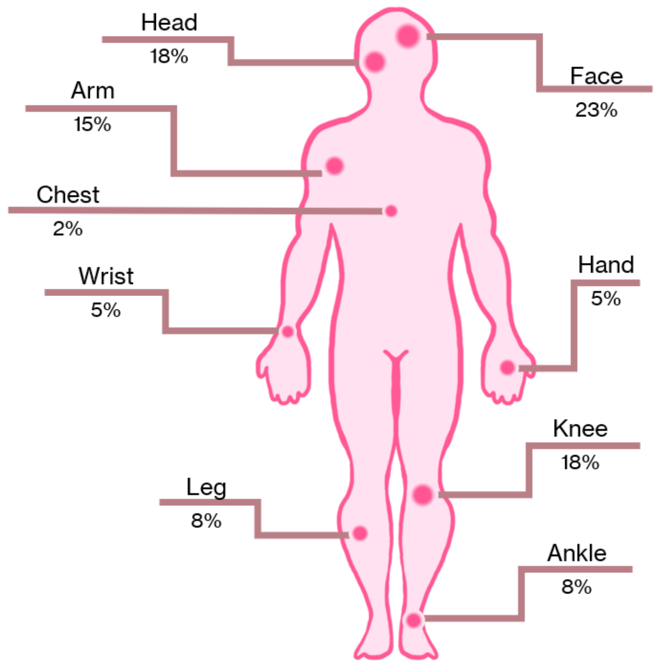

Figure 1: Injury Locations

Further insights into the high number of head injuries could be attributed to the lack of helmet use. Trivedi et al. 2019 reported that out of 193 observed e-scooter-related injuries collected from two urban emergency departments in Southern California, 182 (94.3%) patients were not wearing a helmet (Trivedi, Liu, and Antonio 2019). Common injuries also include fractures of the upper extremity and dislocations (Tischler et al. 2021; Shichman et al. 2022).

Whether it's the rider falling off their scooter or colliding with a vehicle, solutions to curb e-scooter crashes and serious injury, point to countermeasures that separate e-scooter users from other modes of travel. Examples include statewide implementations, such as making e-scooters illegal to use along sidewalks or streets. However, policies vary widely among cities on whether e-scooters should use roads, sidewalks, bike lanes, or multi-use trails (Chang et al. 2019; Fang, Agrawal, and Hooper 2019), and to date, there has not been research evidence available to guide these decisions.

Ban from Sidewalks or Streets

There is a discrepancy in laws and regulations between states, and even among cities in states, regarding whether e-scooters can operate along sidewalks, streets, or both. This mainly depends on the categorization of e-scooters within laws. Many states specify that e-scooters share the same rights and regulations as bicyclists, mopeds, or have created rules specific to e-scooters. Depending on the category an e-scooter user falls under, it can significantly impact where they are legally allowed to operate and whether they are required to wear a helmet.

Figure 2 provides a map of state-by-state regulations for e-scooters, depending on whether there are no legal specifications for e-scooters, if it is legally stated that e-scooters can ride along the street or sidewalk, or if there is a complete ban. Note that the majority of states allow e-scooters to ride along the street, yet when it comes to the sidewalk, the country tends to become more equally split. States like Montana and Delaware have banned e-scooters from operating on both roadways and sidewalks.

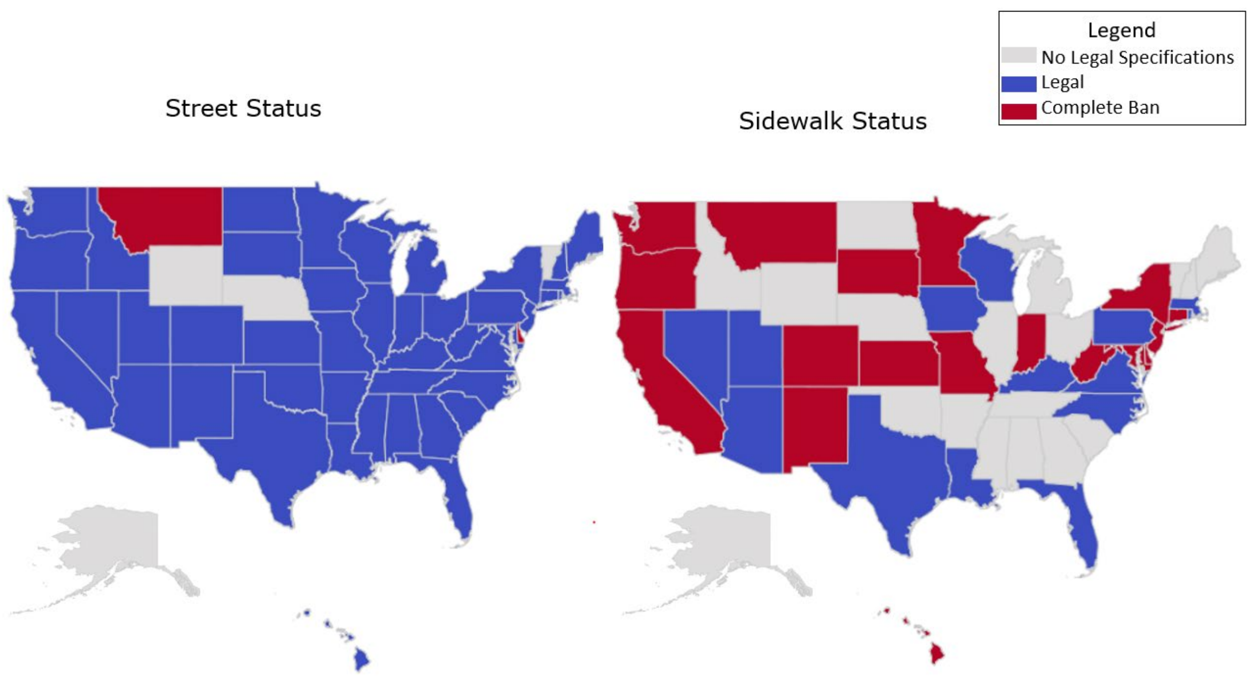

Figure 2: E-scooters Legally allowed to operate Street and Sidewalk per U.S state

Figure 3 identifies the states that specify e-scooter users are required to use helmets while riding. Some states say that *all* users must wear a helmet, but majority specify this is only necessary if the rider is below 16 or 18 years of age (Levy 2023). Helmet regulations are typically enforced if a state categorizes e-scooters as bicyclists, subjecting them to adhere to bicycle laws. These laws often specify age restrictions for helmet use.

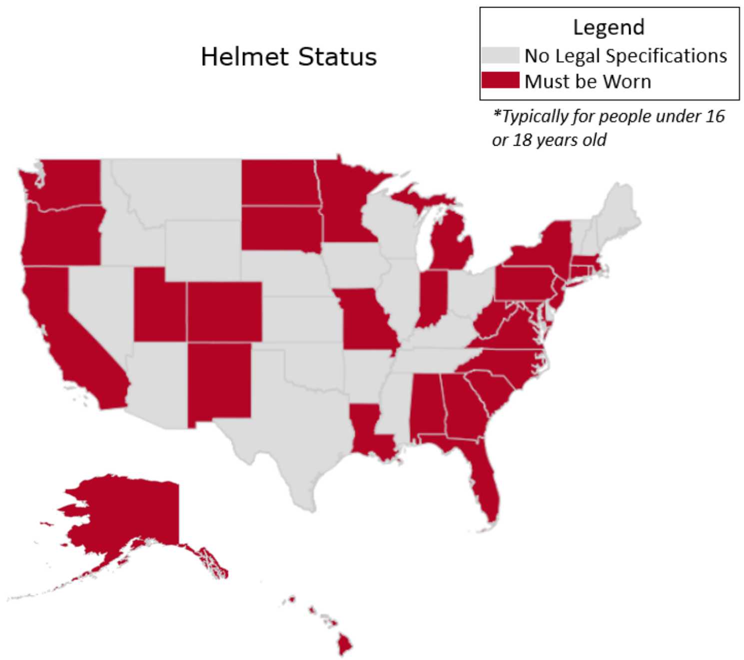

Figure 3: E-scooters Legal Requirement for a Helmet per U.S state

Rules toward e-scooters typically becomes more specific and stringent within local jurisdictions. In Texas, some cities permit e-scooters to be ridden on sidewalks, while others prohibit sidewalk use or have specific regulations in place. In Austin, for example, riding an e-scooter on sidewalks is legal as long as the rider yields to pedestrians and does not operate the scooter in a hazardous or reckless manner (City of Austin, n.d.). Houston, on the other hand, prohibits e-scooters from being ridden on sidewalks in business districts, only allowing their use in residential areas (Sundaram 2019; Levy 2024). Dallas's specific regulations state that e-scooters are not allowed on sidewalks in certain areas, such as the Central Business District or Deep Ellum entertainment district. Outside of these zones, riding an electric scooter on the sidewalk is permitted (Levy 2024). Another safety countermeasure that can compensate for the lack of consistency among statewide legal regulations is geofencing technologies.

Geofencing Technology

Geofencing is an invisible, geographical fence that lowers the speed, turns off the throttle, or prevents the parking of a rental e-scooter once it crosses the fence boundaries. The e-scooter rider is tracked by GPS technology, and enforced speed reductions can either slow down or completely stop the rider (Radcliff 2020). It is important to note that only dockless, rental e-scooters are affected by the geofence, therefore personal e-scooters are not affected.

The objective of geofences is to reduce the crash rates of e-scooters by allowing the user more time to react and avoid danger of colliding with other transportation modal users, such as vehicles and pedestrians. To avoid such collisions, geofences are typically placed along areas with high-pedestrian or vehicle volumes. Examples of these areas include university campuses, tourist areas, parks, and highways.

Geofence operating times do not have to remain static but can change across time, meaning geofences can be activated during nighttime, holidays, festivals, etc. Activating the geofence during nighttime hours along high pedestrian traffic areas, such as downtown, could greatly reduce the number of intoxicated individuals using e-scooters, whereas activation during holidays can reduce e-scooter-related collisions in areas with high pedestrian or vehicular traffic. The Portland Bureau of Transportation used this feature after a violent clash between right-wing groups and leftist adversaries on August 22nd, 2021. To avoid further violence during this time of political scrutiny and extremism, the city stated that "e-scooters will not be available to ride in downtown Portland or Waterfront Park" from noon on Aug. 22 to 6:01 am on Aug. 23 (Smith 2021). This alert was released to users who opened the Lime Scooter app in that area.

Implementation Process

The installation process of geofences begins with a request by city officials to e-scooter vendors. Once the vendors agree to the request, they create the bounds of the geofence. Vendors have the ability to change these bounds at any moment in time and do not need the approval of city officials (Transportation 2020). This can lead to confusion among riders when different companies' e-scooters stop functioning at different geographical borders. Once again in Portland, Oregon, this issue appeared when two companies, without warning city officials, significantly reduced their service areas during winter, making traveling outside downtown via e-scooter difficult for people who relied on e-scooters as their year-round, first-choice mode of transportation (Transportation 2020).

Lack of Geofence Research

Research regarding geofences is lacking overall, especially over the safety benefits that come with geofencing. A paper written by Moran in 2021, analyzed the geofences in San Francisco from 2017-2019 via manual digitization of all geofences. Moran found that each e-scooter vendor geofences expanded with time, starting in the northeast quadrant of the city, yet with little to no expansion into western neighborhoods (Moran 2021). Moran also reviewed permit guidelines and applications submitted to e-scooter vendors which indicated San Francisco's regulations for geofences have been limited and inconsistent, which may have contributed to the concentration of services in one section of the city, as well as disconnected geofence "islands" (Moran 2021).

Another study by Liazos et al. in 2022, created a methodological tool for decision-making in regulating e-scooter usage in urban areas. In other words, this paper aimed to maximize the extent of geofences in an urban area for the sake of maximizing road safety, while considering travel time impacts for users (Liazos et al. 2022). Utilizing a Non-Dominated Sorting Genetic Algorithm, NSGA-II, researchers were able to conduct a case study in downtown Athens, Greece (488 edges). Researchers used cost (travel time) and safety (geofence length) as their measurements of effectiveness. The length of a geofence was used as a measure of safety, it was assumed that the greater the length, the greater the safety impacts. Results found that the cost-wise best solution features 46.3 vehicle hours, at a geofenced length value of 10,700 m. On the other hand, safety-wise, the best solution is achieved when the geofence covers 14,100 m at a high cost of 68 vehicle-hours. Evidently, there are notable differences between the two solutions, which differ by almost 40% in terms of total geofenced length and 30% in terms of user cost (Liazos et al. 2022). Once more, Liazos assumed that geofence length resulted in greater safety impacts, they did not use other safety measures, such as crash rates, to assess the effect of geofences on user safety.

One of the first studies solely focusing on the safety benefits of geofencing is Hall, Baumanis, and Machemehl in 2024. This paper presented a multi-faceted analysis of e-scooter data to determine whether geofences have a causal relationship in reducing crashes at UT Austin's campus (Hall, Baumanis, and Machemehl 2024). Utilizing crash data from UT Health Services, e-scooter trip data, and COVID-19 viral spread within the geofenced area around campus, which forced riders to operate at a maximum speed of 8 mph and limited them to certain parking areas, researchers used causal mediation analysis to understand the impact of these geofences on crash rates between September 2018 and October 2022 ($n = 208$). The results indicate parking restriction geofences and the pandemic indirectly contributed to a decrease in the number of reported e-scooter injuries. Moreover, these mediators partially mediated the relationship between the number of trips completed and the number of e-scooter injuries reported, with parking geofences accounting for the most significant proportion of mediation (50%), and the COVID-19 pandemic accounting for 30% mediation (Hall, Baumanis, and Machemehl 2024). Indirect can be interpreted as the parking restriction geofences preventing the exposure of e-scooter riders to injuries. Riders notice the unavailability of parking near their final destination, deterring them from using rental e-scooters reach that particular destination. Conversely, for riders looking to start their trip on campus, if there is a scarcity of scooters nearby, they were less motivated to choose it as their mode of travel (Hall, Baumanis, and Machemehl 2024).

Overall, research regarding geofences is limited, leading to an even greater lack of research on the review of geofence effectiveness in terms of safety. Moran's 2020 study highlighted policy issues associated with implemented geofences, while Liazos et al. in 2022 merely considered geofence length as an assumed measure of increased safety. Hall, Baumanis, and Machemehl's 2024 research stands out as the only study that conducted a before-after analysis of injury rates post the creation of a geofence. Its findings indicate parking geofences reduce e-scooter crash rates by indirectly discouraging e-scooter use overall. To reaffirm these results regarding the use of parking geofences over speed, this report will utilize the same data and case study area.

Cities with Geofencing Technologies

As previously noted, there are discrepancies in U.S statewide regulations on where e-scooter users can ride. Cities that lack statewide regulations are left with the choices of creating their own rules or implementing geofencing technologies within high-risk areas. This section serves as a review of some of the cities that installed geofencing technologies. Major details such as where the geofence was placed, and what ensued after the installment of the geofences ae provided.

San Diego, CA

September 2018 San Diego city officials created geofence boundaries as well as designated parking locations along the beach boardwalk and downtown. Their stated purpose of the geofence and parking spaces was to prevent access of e-scooters to certain areas, prevent vehicles from being locked, and limit the number and locations of vehicles parked together in downtown. The geofence reduces speeds from 15 mph to 8 mph or even 3 mph, depending on the user's location (Cutter 2020). Furthermore, the city of San Diego is one of the few cities that uses location data from user's cellphones to track the progress of the geofences (Cutter 2020). Unfortunately, this trip data is not available to the public.

Issues

Overall, city officials claim the geofenced boundaries generally work as expected and consistently across all vendors. Yet they noted some challenges their agency has experienced related to the limitations of GPS and to cellphone issues. Cellphones present challenges when riders switch their phones to Airplane Mode to prevent being detected in geofenced areas (Cutter 2020). This allows the users to continue to reach up to 20 mph along the boardwalk (Nieto-Gregorio and Coronado 2019).

Los Angeles, CA

August 2019, the Los Angeles Department of Transportation (LADOT) began their geofence program. This program includes basic speed reductions and designates parking areas. The geofence locations include local roadways, trails, or paths. Once the user reaches the geofence they are either subjected to a maximum speed of 15 mph, or 0 mph, depending on the area (Garcetti 2021). E-scooter users can ride on surface streets and are encouraged to ride in bike lanes if available (Cutter 2020). Furthermore, the LADOT requires a cap on how many e-scooter users a company can operate within city boundaries. Additionally, the company must also have liability coverage, provide community outreach and education programs, and share all trip data with the city (Cutter 2020). Like San Diego, LADOT also uses location data from user cellphones. This data is not available to the public.

Issues

LADOT claimed geofence boundaries typically work across all vendors, yet there have been claims of GPS location "ping-rate" and tracking errors. The GPS "ping-rate" is the automatic release of location information to vendor servers. Once the location is captured and notified that the user is within a geofenced area, the servers send a signal back to the scooter which lowers its speed. The issue is that these location signals differ depending on the vendor and company that operate a scooter (Cutter 2020). This could cause some scooters to take longer to decelerate. There have also been issues with GPS location inaccuracies. Moreover, the app claims a scooter is within a geofenced area when, in reality, it is traveling alongside or near a geofenced area (Cutter 2020). The latter circumstance results in an unnecessary change in vehicle speed.

Tallahassee, FL

Beginning in July 2019, the Tallahassee City Commission implemented a three month program through October 2019 to evaluate whether e-scooters were a good fit for the city (Chapter 2019). Scooters can be ridden at various locations around the city, with one caveat. The scooters may not be used on the campuses of Florida State University, Florida A&M University, and Tallahassee Community College. The companies are required to implement geofencing to stop scooters from operating on campus. If a scooter enters a campus, the scooter's speed would be gradually slowed to a stop.

Issues

As soon as five days after the e-scooters were allowed to operate within the city, issues with the geofencing immediately arose. College, university, and city officials claimed it to be overall ineffective, with no evidence of speed reductions occurring on campuses (Casey 2019). Each vendor, including Lime, was required to remove all scooters from the streets until the geofences were operating (WTXL Tallahassee 2019). After retesting the boundaries, the e-scooter vendors redeployed the scooters in late July (Ogles 2019). There have been no other complaints of the geofences malfunctioning.

Portland, OR

Portland Bureau of Transportation (PBOT) initially released a 120-day pilot program in July 2018, which was followed by a second one-year pilot program in April 2019. This second program was to gather additional data about e-scooter operations and test management strategies to address the issues identified during the first pilot (Transportation 2020). The results from the second pilot-programs resulted in the creation of geofences that slow e-scooters from 15 mph to 12 mph, 3mph, or even 0 mph. The speed cap is dependent on the location. Most of the geofences are located along trails, paths, parks, and other non-roadways (Cutter 2020; Transportation 2020).

The areas with the 12-mph cap include Waterfront Park, the Eastbank Esplanade, and the Springwater Corridor. North and South Park Blocks are where e-scooters speeds are 3 mph, and the 0 mph geofence includes natural areas like Forest Park, parks with playgrounds, and other areas of concern (Transportation 2020). The goal of the geofences is to prevent access to specific areas, limit device speed, and designate scooter parking areas. Another caveat to the relationship between PBOT and the e-scooter vendors is PBOT is authorized to provide geofence shapefiles for vendors to employ and update. This effort is to standardize geofencing boundaries across all e-scooter companies (Cutter 2020).

Issues

PBOT noted the geofencing technology functions inconsistently across e-scooter vendors. Additionally, these inconsistencies even appear within a single e-scooter company. These inconsistencies may be related to the ability to draw geofence boundaries given relatively low or variable geographic information system (GIS) accuracy (Cutter 2020).

Summary

Past research has revealed the majority of e-scooter-related crashes occur along travel lanes and involve incidents such as riders falling off their scooters due to pavement quality issues or colliding with vehicles. These crashes often result in serious injuries, particularly to the head or face. To mitigate such incidents and enhance the separation of e-scooters from other modes of travel, state leaders enact laws and regulations specifying where e-scooters can operate—whether on the street or the sidewalk. While most U.S. states permit e-scooters on the street, opinions on sidewalk usage are more divided. Helmet-use regulations are generally sparse and often only mandate riders under the age of 16 or 18 wear one. Adding to the complexity of e-scooter regulations, cities can establish their own rules. For instance, in Texas, while e-scooters are technically allowed on both streets and sidewalks, Houston prohibits them from sidewalks within business districts (Sundaram 2019; Levy 2024).

Alternatively, cities may employ geofences to reduce collision rates between e-scooters and other modes of travel. However, this solution has its own drawbacks. Ambiguity surrounds the placement and removal of geofences, predominantly managed by private e-scooter companies. Government officials are thus subject to the operational decisions of these companies. Moreover, there is a clear deficiency in research regarding the safety impacts of geofences.

Reviewing several city's experiences with geofencing technologies reveal consistent issues with GPS and speed enforcement. Table 1 provides a summary of these issues. The GPS limitations include tracking errors, such as location inaccuracies, and discrepancies in "ping-rate" across vendors. Other issues were seen to occur with the speed reduction performance. These major shortcomings reinforce the need for more research in measuring the overall benefits of geofences.

The City of Austin has implemented several geofence boundaries and acts as the focus of this study. The following section will provide a synopsis of the timeline and details regarding the e-scooter deployment in Austin, Texas, the geofences and pilot programs that were put in place, and how these events will play into the before-after safety analysis of the geofence, as well as other e-scooter safety installations.

Table 1: Geofence Issues throughout Cities

City	Geofence Type	Issues
San Diego, CA	Reduces Speed to 15-3 mph depending on area	GPS tracking errors from Airplane Mode on cellphones
Los Angeles, CA	Reduces Speed to 15-0 mph depending on area	GPS limitations on "ping-rate", and tracking errors
Tallahassee, FL	Reduces Speed to 0 mph when entering state universities	Geofence failure to operate
Portland, OR	Reduces Speed to 15-0 mph depending on area	Geofencing functions inconsistently across e-scooter vendors

Methods

This report seeks to investigate the characteristics of dockless e-scooter crashes and understand the role of speed and parking geofences toward crash rates and injury severities. Similar to the Hall, Baumanis, and Machemehl 2024 research, this report will use the UT Austin campus, which employs a speed and parking geofence, as the case study area, as well as a plethora of other data including weather, and COVID-19 viral spread. This section will provide the timeline and journey of e-scooters within the Austin area, the data collection, cleaning and statistical analysis, and a description of Ridge Regression.

City of Austin E-scooter Timeline

As one of the first cities in the U.S. to host the initial wave of e-scooter rentals, the City of Austin developed its own responses, pilot studies, and adaptations to manage the e-scooter fleet. This section will cover significant events that could have influenced e-scooter usage, subsequently impacting injury occurrence and severity.

April 2018: *E-scooter Rentals First Deployment*

In April 2018, the company Bird was the first to begin operations and release rentable e-scooters in the City of Austin (Jankowski 2021). Soon after, their chief competitor, Lime, entered the scene, releasing more than 200 rentable e-scooters (Wear 2018). Struggling to regulate the sudden incursion of scooters, city officials began to develop regulations and enforce impoundments on improper usage and parking for these dockless e-scooters.

May 2018: *City of Austin Emergency E-scooter Regulations*

A month after the release of the scooters, City of Austin officials worked quickly to release emergency regulations to regulate, enforce and govern dockless mobility technology. This rule describes licensure requirements relating to: (1) definitions; (2) dockless mobility units; (3) service area and size of fleet; (4) safety; (5) parking; (6) operations, and customer service; (7) data reporting and sharing; (8) insurance, performance bonds and fees; and (9) general (City of Austin Manager 2018). Some main takeaways are:

- Users are not allowed to ride into unauthorized areas such as private property, parkland, state-owned land,
- Users are only allowed to park in designated areas that are defined as the following:
    - Hard surface (e.g., concrete, asphalt) within the landscape/furniture zone of a sidewalk so long as there is at least 3 feet of clear walking space;
    - Within a public bike rack;
    - Other designated areas that are enforced via geofence, marked parking boxes or other methods (City of Austin Manager 2018).

March 2019: *The University of Texas at Austin Campus Speed Geofence*

March 2019, UT's Parking and Transportation Services (PTS) set up a geofence around defined areas throughout campus that required Bird, Jump, Lime, and Lyft scooter users to operate at a maximum speed of 8 mph (The University of Texas at Austin 2019). Other safety recommendations suggested users:

- Wear helmets and follow other safety guidance
- Only operate in areas where bicycle traffic is allowed
- Only operate at low speeds if a bicycle or pedestrian traffic is present
- Be aware of geofencing areas
- Park in designated areas or at bicycle racks (The University of Texas at Austin 2019).

Figure 4 reveals the defined geofenced areas throughout campus and the designated parking zones (Hall, Baumanis, and Machemehl 2024). This map also highlights areas throughout campus and within the nearby city where scooters are allowed to operate at 15 mph.

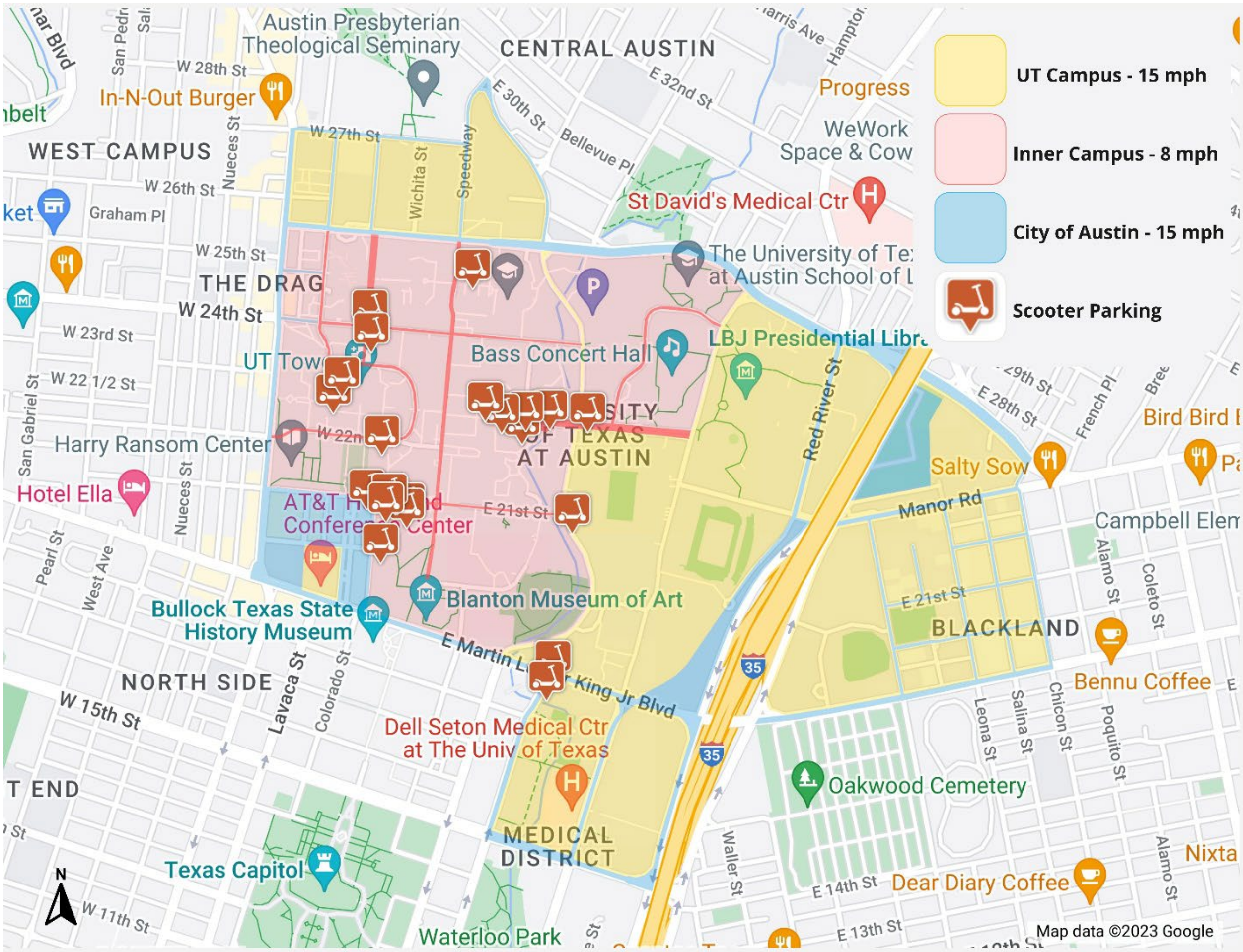

Figure 4: Geofenced Areas and Parking Locations through UT Austin's Campus

***May 2019:** Adopted City Regulations and Fines*

The city's safety rules and regulations were adapted, with some rules loosened, while others were tightened with ticketing fines. This includes:

- Lifting a rule allowing e-scooters to ride along certain areas of downtown, and users are directed to operate their scooters in a "reasonable and prudent manners" (Jankowski 2019).
- Austin police officers will also be able to ticket those who violate rider rules. First-time violations will carry a fine of $20, where subsequent violations will cost $40 (Jankowski 2019).
- Requiring anyone under 18 to wear a helmet while operating a scooter or dockless mobility device

Left unaddressed was the question of allowing e-scooters to operate on trails. The city council chose to address this question after the completion of the Austin's parks and trails pilot program (Jankowski 2019).

***January 2020:** E-Bike and E-Scooters Austin Trails Pilot Program*

The City of Austin's Parks and Recreation Department (PARD) collaborated with Public Works, Austin Transportation (ATD), and the Law Department to conduct a yearlong pilot program from

January 2019 to January 2020. The objective of this study was to assess the safety and effectiveness of allowing e-scooter users on specific parkland trails (City of Austin 2020). During the pilot program, both e-scooters and electric bikes were permitted on paved parkland trails. In the program's final month, geofencing was introduced along these trails, restricting the speed of rented e-scooters to less than 8 mph. Participants who used the trails were invited to complete a survey, revealing that two-thirds of respondents found micro-mobility to be a convenient and swift means of transportation. Additionally, people expressed a preference for riding in protected bike lanes or on urban trails (City of Austin 2020). Unfortunately, specific survey results related to the geofence have not been publicly disclosed. Furthermore, it remains unclear whether e-scooters are still permitted on the trails or if the geofences are still in effect.

UT Campus Parking Geofence

In January 2020, UT Austin augmented their existing e-scooter regulations, initially implemented in March 2019, by introducing more stringent impounding fees and a parking geofence. This reinforcement emphasized the requirement for scooters to be parked only in designated areas or bicycle racks. Failure to adhere to proper parking procedures would incur a $150 impound fee. Improper parking locations include leaving scooters at university events or in undesignated areas such as doorways, ramps, stairways, or anywhere that obstructs ADA access or parking. This fee is also applicable to scooters left on Speedway or the Main Mall (The University of Texas at Austin 2020). For users renting dockless e-scooters, a geofence was implemented to restrict users from concluding their trips outside the designated parking zones. In essence, users are unable to end their trip until they have relocated to one of the campus's approved parking zones.

March 2020*: The COVID-19 Pandemic*

The first case of COVID-19 in Travis County appeared March 13, 2020 (Adams 2021). On the same day, Governor Greg Abbott declared a state of emergency for Texas, and by March 24th, the stay-at-home orders for the Austin area came into effect. This led to a complete shift in day-to-day travel behaviors, with people transitioning to working from home and only undertaking essential trips.

April 2020: *Lyft Leaves Austin*

The shift in travel behavior due to the pandemic resulted in businesses, including e-scooter operators, to experience a drastic decline in demand. As a consequence, Lyft, one of the primary operators in the city, chose to cease their operations in Austin in April 2020, removing their fleet of 2,000 e-scooters (Bradshaw 2020). Other mobility app companies, such as Lime, Wheels, Spin, and JUMP, temporarily halted operations and withdrew their devices from Austin's rights-of-way. Bird reduced its fleet on March 27, 2022, but continued to provide a small number of devices for essential workers (Bradshaw 2020). Research conducted during the pandemic revealed a decrease in total shared e-scooter trips, attributed, in part, to vendors exiting the market. However, there was an increase in average trip length (Dean and Zuniga-Garcia 2023).

Present Day

At present, Austin has four e-scooter rental operators, some of which also offer bicycles and sit-down e-scooters. These providers, listed in order of fleet size, are Lime, Bird, LINK, and Wheels (City of Austin 2023). Lime boasts the largest fleet, comprising 3,500 scooters and 500 bicycles, while Bird follows closely with a fleet of 3,000 scooters (City of Austin 2023). Table 2 presents a detailed breakdown of the current fleet size for each company.

Table 2: E-scooter Providers Fleet Sizes

Provider	E-scooter Fleet	Bicycle Fleet	Sit-Down E-scooter Fleet
Lime	3,500	500	-
Bird	3,000	-	-
LINK	2,000	-	-
Wheels	-	-	1,750

As for the current trip frequency, an average 7,100 trips are completed per day within the City of Austin (Ride Report 2023). Figure 5, provided by Ride Report's Global Micromobility Index, illustrates hot-spot locations for e-scooter usage throughout Austin. Popular locations include downtown, the eastside, and South Congress. Downtown serves as the central business district with offices, museums, public art, nightlife, and shopping. The eastside is considered one of the fastest-growing neighborhoods in Austin, featuring concert venues, bars, restaurants, and a younger crowd. The South Congress area is an iconic district offering views of the Texas Capitol, mainly filled with shopping and dining. Given Austin's expanding population, its status as a tourist attraction, and the rising public concern about the presence of e-scooters, it's no surprise that the City of Austin and the Austin-Travis County EMS departments released an e-scooter injury report in October 2023 (Swiatecki 2022; Leffler 2019).

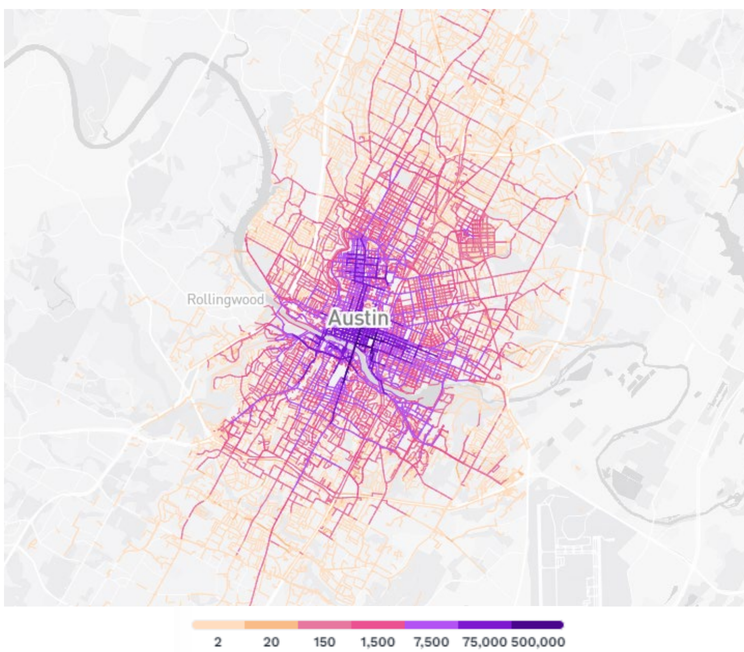

Figure 5: Current Ride Report Map of Total E-Scooter Trips Completed in Austin, TX

This report did not sound alarm bells, as per Austin-Travis County EMS estimates, which stated that there were only 48 accidents involving e-scooters from July to September, out of the 29,423 patients its medics attended during that period (Seipp 2023). The EMS Division Chief, Kevin Parker, also noted that 'e-scooter accidents have a very minimal impact on the community and on our EMS system.' He further stated that 'the majority of the cases are only impacting the person riding the scooter… [they're] not having a larger impact on bystanders or other people who may be around them' (Seipp 2023).

It is essential to consider the historical context of dockless e-scooters in the City of Austin and UT's campus. Throughout this study, researchers will consistently highlight the dates of the two UT geofences (speed and parking) and the onset of the COVID-19 pandemic. The use of these dates is deliberate, as crash data was obtained from UT health services, and researchers hypothesize the parking restriction and the pandemic may have an equal, if not greater, impact on user safety compared to the geofencing technologies.

Data Collection

To address the major characteristics of dockless e-scooter crashes and understand the effectiveness of speed and parking geofences in lowering crash rates or injury severities, the study collected data on e-scooter injury reports, trips, COVID-19, and weather within the case study area of UT's geofence (refer to Figure 4). The data was sourced from various outlets, including the University Health Services at UT Austin, City of Austin Transportation Department Shared Micromobility Trips, Texas Department of State Health Services (DSHS), and the National Centers for Environmental Information. The data spans from April 2018 (around the initial release of e-scooters in Austin) to December 2022, providing a total sample size of 1,726 days for this analysis. This section will provide the cleaning tactics, statistical backings, and summary of the variables that will be used within the predictive model.

E-scooter Trip Cleaning

Trip frequency data was sourced from the City of Austin Transportation Department of Shared Micromobility portal, which documented a total of 15 million trips completed by users renting e-scooters from Lime, Uber, and Bird within the City of Austin. The cleaning of e-scooter trip data followed the method outlined by Younes et al. 2020 involving the exclusion of all trips that did not either begin or end within UT Austin's campus. In summary, the researchers excluded trips meeting the following criteria:

- Distance is shorter than 0.02 mile or longer than ten miles,
- Average travel speed is above 20 miles per hour,
- Duration is less than two minutes or longer than 90 min, and
- The trip did not begin or end within the census tracts that cover UT Austin campus.

Statistical Significance of Geofences

To establish a robust statistical foundation for constructing an inference model to measure the effectiveness of geofences on campus e-scooter crash rates and injury severity, we must commence with a basic t-test. T-tests are a common inferential statistic employed to determine if there is a significant difference between the means of two groups. They are applicable for datasets that follow a normal distribution and possess an unknown variance. The equation used for the t-test is as follows:

$$\boldsymbol{t = \frac{\bar{x} - \mu}{\sigma/n}}$$

Where:

- $\bar{x}$ = sample mean
- μ = assumed mean
- σ/n = standard error

Injury severity will be measured by the rate of head injuries. Furthermore, it is important to note that we normalized crash rates, as well as head injuries by e-scooter trips completed on campus. This practice is a common method utilized by the Federal Highway Administration (FHWA) and will allow us to account for crash anomalies that occurred during the COVID-19 pandemic (Federal Highway Administration 2011). The null and alternative hypothesizes for the four geofence t-tests is:

Crash Rates:

Ho: There is no difference in the number of e-scooter
crashes after the activation of the [speed or parking] geofence at UT campus

Ha: There is a difference in the number of e-scooter
crashes after the activation of the [speed or parking] geofence at UT campus

Injury Severity:

Ho: There is no difference in the number of head injuries from e-scooter
crashes after the activation of the [speed or parking] geofence at UT campus

Ha: There is a difference in the number of head injuries from e-scooter
crashes after the activation of the [speed or parking] geofence at UT campus

Table 3 presents the results of the four t-tests. Organized with the left side representing the speed geofences crash and injury severity tests, observe that the t-stat (0.27 and -1.46) falls within the two-tail range of $\pm$1.96. This implies that we fail to reject the null hypothesis, suggesting no difference in crash rates or head injuries after the activation of the speed geofence on UT's campus. The same conclusion applies to the parking geofence. On the right side of the table, the t-stat for crash rates is 1.10, and -0.46 for injury severities. Both fall within the two-tail range of $\pm$ 1.96, leading to the same conclusion—we fail to reject the null hypothesis, indicating no significant change in crash rates and head injuries after the activation of the parking geofence.

Based on these results, we can conclude that for this particular sample the speed and parking geofence are not significant toward reducing crashes rates or injury severity. Therefore, we will abandon statistical inferencing, and focus now on predictive power through machine learning models. More specifically with the goal of understanding which variables are best for predicting the rate of head injuries.

Table 3: Crash Rates and Injury Severity t-tests

Speed Geofence			**Parking Geofence**	
Crash Rates	**Before Activation**	**After Activation**	**Before Activation**	**After Activation**
Mean	2.20E-05	1.97E-05	2.67E-05	1.62E-05
Variance	1.08E-08	5.93E-08	1.71E-08	6.90E-08
Observations	355	1371	655	1071
df	1363		1665	
t-stat	**0.27**		**1.10**	
t-critical two tail	1.96		1.96	
Head Injuries	**Before Activation**	**After Activation**	**Before Activation**	**After Activation**
Mean	2.62E-06	1.17E-05	7.52E-06	1.12E-05
Variance	1.14E-09	4.90E-08	8.50E-09	5.79E-08
Observations	355	1371	655	1071
df	1578		1503	
t-stat	**-1.46**		**-0.46**	
t-critical two tail	1.96		1.96	

Data Summary

Table 4 lists a basic description, as well as an attribute summary of the mean, standard deviation, the minimum and maximum values for all the variables that will be used within the predictive model. The variable with the largest mean of 2020 is the year, whereas the lowest are the binary variables, such as injuries, and crash location, and therefore only have means of around 0 to 0.01.

Table 4: Data Description and Attribute Summary

n =1726					
Feature Variable	Description	mean	std	min	max
	Weather				
DailyAverageDryBulbTemperature	Daily average dry bulb temperture (F°)	72.02	14.71	17.00	95.00
DailyAverageWindSpeed	Daily average wind speed (mph)	4.61	2.09	0.20	12.60
DailyPrecipitation	Daily precipitation (in.)	0.10	0.34	0.00	3.73
DailySnowfall	Daily snowfall (in.)	0.00	0.14	0.00	5.40
	E-scooter Trips Completed within UT's Campus				
total_scoot_trips_day	Total number of dockless e-scooter trips	1316.73	1470.33	0.00	19379.00
	E-scooter Crash Injury (0 or 1)				
InjuryLocation_NoInjurySustained	No Injury Sustained	0.00	0.05	0.00	1.00
InjuryLocation_Shoulder	Shoulder	0.00	0.02	0.00	1.00
InjuryLocation_Head	Head	0.01	0.09	0.00	1.00
InjuryLocation_Face	Face	0.01	0.09	0.00	1.00
InjuryLocation_Elbow	Elbow	0.00	0.04	0.00	1.00
InjuryLocation_Arm	Arm	0.00	0.06	0.00	1.00
InjuryLocation_Wrist	Wrist	0.00	0.04	0.00	1.00
InjuryLocation_Hand	Hand	0.00	0.04	0.00	1.00
InjuryLocation_Leg	Leg	0.00	0.05	0.00	1.00
InjuryLocation_Knee	Knee	0.01	0.09	0.00	1.00
InjuryLocation_Ankle	Ankle	0.00	0.05	0.00	1.00
InjuryLocation_Chest	Chest	0.00	0.02	0.00	1.00
InjuryLocation_foot	Foot	0.00	0.02	0.00	1.00
	E-scooter Crash Location (0 or 1)				
CrashLocation_Roadway	Roadway	0.01	0.12	0.00	1.00
CrashLocation_Sidewalk_Curb	Sidewalk or Curb	0.00	0.04	0.00	1.00
	Modes Involved in Crash (0 or 1)				
ModesInvolved_Vehicle	Vehicle	0.01	0.07	0.00	1.00
ModesInvolved_Pedestrian	Pedestrian	0.00	0.05	0.00	1.00
ModesInvolved_Bicycle	Bicycle	0.00	0.04	0.00	1.00
ModesInvolved_Scooter	Scooter	0.00	0.04	0.00	1.00
	Other Reasons for Crash (0 or 1)				
ModesInvolved_ExcessiveSpeed	Excessive Speed	0.01	0.10	0.00	1.00
ModesInvolved_SystemMalfunction	System Malfunction, brakes failing	0.00	0.03	0.00	1.00
ModesInvolved_Other_RoadSurfaceQuality	Poor Road Surface Quality	0.01	0.08	0.00	1.00

ModesInvolved_Other_Intoxication	Intoxication	0.00	0.03	0.00	1.00
ModesInvolved_Other_Object	Hitting an Object, i.e., pole	0.00	0.05	0.00	1.00
	E-scooter Rental Brand (0 or 1)				
RentalType_Lime	Lime	0.01	0.11	0.00	1.00
RentalType_Bird	Bird	0.00	0.02	0.00	1.00
	Time				
Year	Year	2020.11	1.37	2018.00	2022.00
Month	Month	6.77	3.37	1.00	12.00
Day	Day	15.77	8.80	1.00	31.00
Weekday	Weekday (1, 2, 3... 7)	3.00	2.00	0.00	6.00
Season	Season (1, 2, 3, 4)	2.56	1.11	1.00	4.00
	Geofence Activated (0 or 1)				
Geofence_Speed	Speed geofence activated (lowers speed to 8 or 15 mph, depending on location)	0.79	0.40	0.00	1.00
Geofence_Parking	Parking geofence activated (restricts available parking)	0.62	0.49	0.00	1.00
Daily_COVID	Total daily COVID-19 Cases in Travis County	159.20	335.38	0.00	5068.00

Shifting our focus to prediction, this analysis is not bound by the rules of ordinary least squares (OLS). Consequently, it is not necessarily straightforward for an analyst to determine which variables to retain. Traditional inference-based thinking emphasizes removing multicollinearity and retaining significant variables, which does not align with the primary goal of prediction (Baumanis, Hall, and Machemehl 2023). Moreover, the strong correlations observed in the predictive variables of Figure 6 are not a concern for this comparison because multicollinearity alone does not affect the predictive ability of a model (Farrar and Glauber 1967). The strongest correlations are exhibited by those with coefficients between ± 0.50 and ± 1.0, and moderate correlation is observed in those within the range of ± 0.30 and ± 0.49.

Table 5 highlights the strongest correlations, and it demonstrates e-scooter trips completed on UT campus are negatively correlated (-0.56) with the parking geofence. In other words, when the parking geofence was activated, less trips were completed on campus. The parking geofence most likely limited users' ability to end their trip near their desired destination, inevitably deterring them from utilizing a dockless e-scooters. Another noteworthy correlation is between someone crashing and obtaining a face injury (0.50) to the scooter they were riding being a Lime. This relationship can be explained by the larger presence of the Lime scooters within the Austin area compared to Bird or other scooter companies (refer to Table 2).

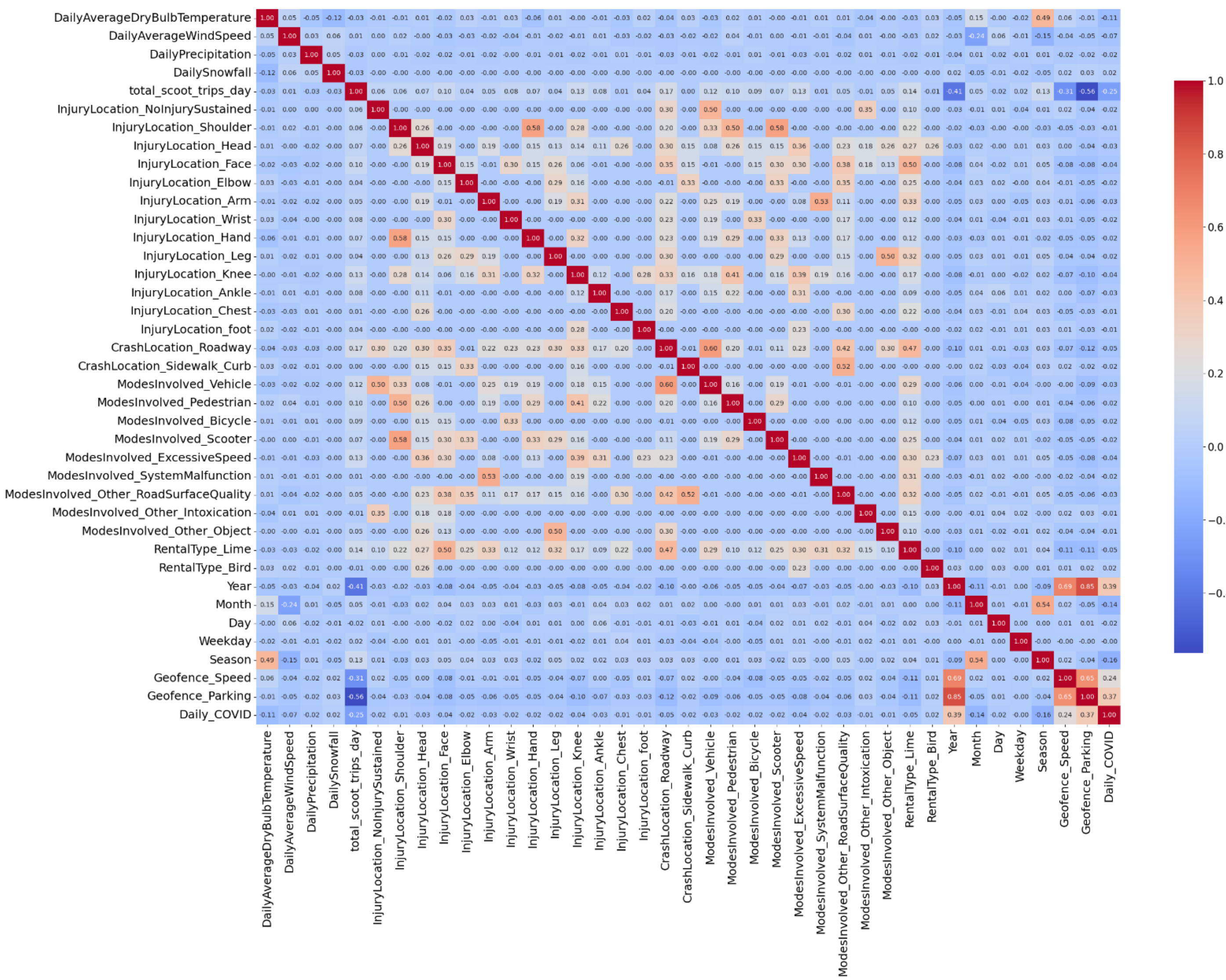

Figure 6: Correlation Matrix of Final Dataset

Table 5: Variables with Strong Correlations

Variable 1	Variable 2	Correlation
total_scoot_trips_day	Geofence_Parking	-0.56
InjuryLocation_Face	RentalType_Lime	0.50
CrashLocation_Sidewalk_Curb	ModesInvolved_Other_RoadSurfaceQuality	0.52
InjuryLocation_Arm	ModesInvolved_SystemMalfunction	0.53
Season	Month	0.54
InjuryLocation_Shoulder	InjuryLocation_Hand	0.58
InjuryLocation_Shoulder	ModesInvolved_Scooter	0.58
ModesInvolved_Vehicle	CrashLocation_Roadway	0.60
Geofence_Speed	Geofence_Parking	0.65
Year	Geofence_Speed	0.69
Year	Geofence_Parking	0.85

Ridge Regression

Ridge regression, or commonly known as L2 regularization, is a technique for analyzing regression data that suffers from multicollinearity and overfitting. In the presence of multicollinearity, least squares estimates remain unbiased; however, their variances increase significantly, leading to a potential deviation from the true value. To address this, ridge regression adds a penalty term to the traditional least squares objective function, introducing a regularization parameter (α) that controls the strength of the penalty. A larger the α, the stronger the regularization and shrinking of coefficients toward zero. This discourages the model from relying too heavily on any one predictor variable, thus mitigating multicollinearity issues. The objective function of the ridge regression is:

$$L_{ridge}\left(\hat{\beta}\right) = \sum_{i=1}^{n}(y_i - x_{ij}\widehat{\beta_J})^2 + \alpha \sum_{j=1}^{m} \widehat{\beta_J} \tag{1}$$

Where the coefficients represent:

- n = the number of observations,
- y_i = the target variable (head injuries),
- x_{ij} =feature variables (weather, scooter trips, time, etc.),
- $\widehat{\beta_J}$ = feature variable coefficients,
- α = regularization parameter.

We employed the k-fold cross-validation (CV) method to determine the optimal α value. K-fold CV is a standard technique for evaluating a model's performance on unseen data. The dataset was divided into 10 equal k-folds, with one serving as the validation set. The model was trained and validated K times, where each iteration involved holding out a different fold as the validation set while using the remaining K-1 folds for training. This process was repeated K times, and the results were averaged to obtain a robust performance estimate, specifically the mean squared error (MSE). K-fold cross-validation helps reduce variability in model performance that might arise from a single train-test split. This CV process was repeated for each potential value of α.

Summary

The chosen case study area, encompassing the city of Austin and UT, has witnessed various events related to dockless e-scooters. This section initiates by outlining these events, deemed crucial for the initial data collection in this report. Commencing the research segment from April 2018 to December 2022, with a focus on the UT campus, it details the data collection and cleaning procedures. Moreover, the statistical analysis revolves around gauging the impact of geofences on e-scooter crashes and head injuries. Adhering to the standard of normalizing crash rates by e-scooter trips, a basic t-test was executed to evaluate the significance of the speed or parking geofence activation in reducing these rates. Failing to prove significance, the focus shifts from inference to creating a predictive model using ridge regression. This robust machine learning model is well-suited to handle multicollinearity. Subsequent sections will delve into the model's limitations, results, and discussions.

Limitations

Limitations exist in the absence of precise crash report locations. The reports, obtained from the University Health Services on campus, lack specific crash locations, thus we assume that the crash occurred within UT's campus. Additionally, it is acknowledged the reported crash numbers likely underestimate the actual total of e-scooter-related crashes in the area. Research indicates only about 50% of crashes involving micromobility, including pedestrians, bicyclists, and e-scooters, are reported (Stutts and Hunter 1998). Lastly, it's crucial to note the COVID-19 data represents cases in Travis County, not specifically within the UT campus area. Due to the unavailability of UT Health Services' COVID-19 data, we assume UT exhibited a trend similar to the county.

Data Analysis and Results

This section provides an analysis of the e-scooter trips and injury report data, as well as the Ridge Regression model's results. The model results will be compared to a basic linear regression model in order to demonstrate its robust predictive capabilities.

E-scooter Trip Data

Figure 7 illustrates the daily e-scooter trips undertaken within UT's campus in the defined time frame, totaling around 15 million trips. As previously mentioned, the activation periods of the speed and parking geofence, along with the occurrence of the first confirmed COVID-19 case in the Austin area, are marked by the red and green-yellow dashed lines. The impact of geofences on trips is unclear, but the pandemic clearly resulted in a decrease in number of trips, nearly reaching 0 daily trips for two months. Notably, a substantial spike in e-scooter trips is observed during the UT vs. Louisiana State University (LSU) football game on September 7th, 2019.

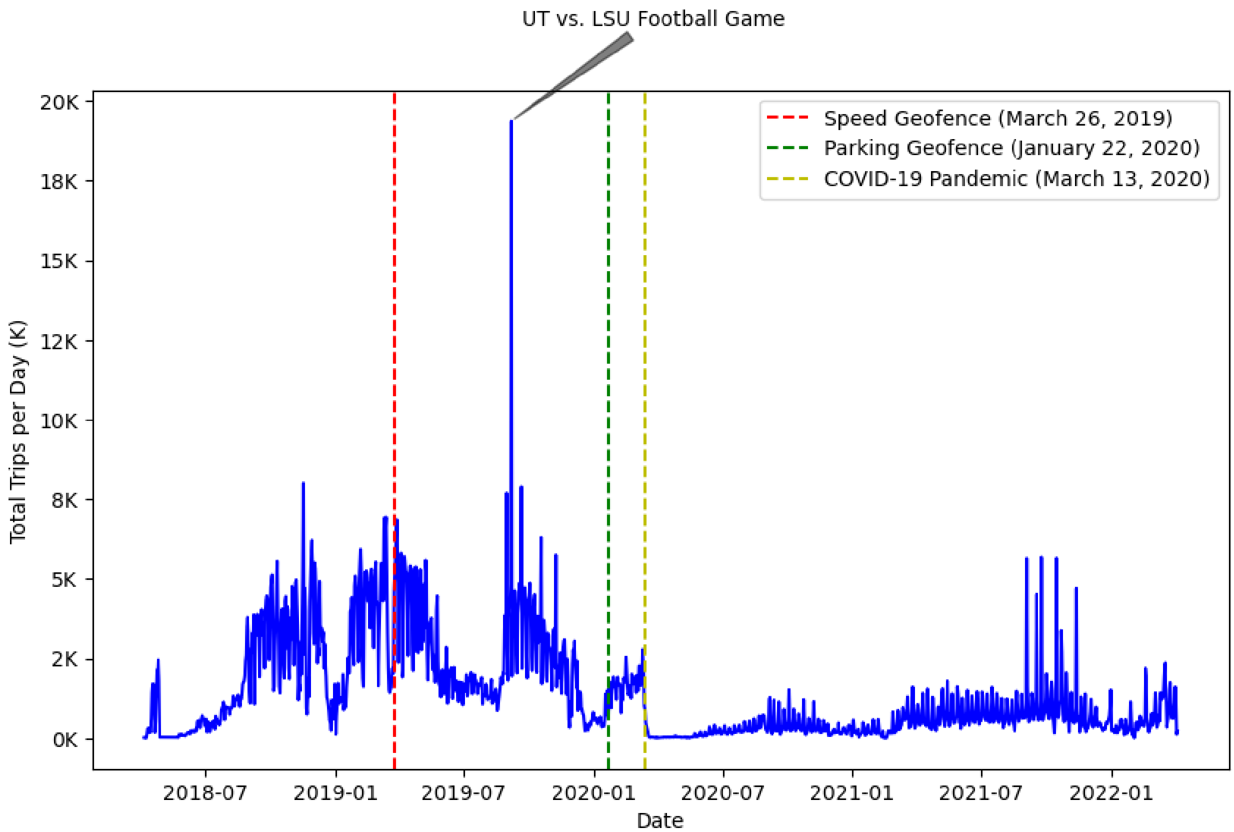

Figure 7: Daily E-scooter Trips at UT Austin

To delve deeper into the temporal patterns, Figure 8 offers a detailed analysis of trip distributions over time, presenting the total sum of trips per year, season, and day of the week at UT. In 2019, the highest number of trips was recorded (1045 K trips), while 2020 marked the year with the fewest completed trips (174 K trips). Additionally, the Fall season saw the most significant number of completed trips, contrasting with the Winter season, which had the lowest. Examining days of the week, Saturday emerged as the day with the highest trip count, indicating that recreational trips were the most favored mode of travel with e-scooters.

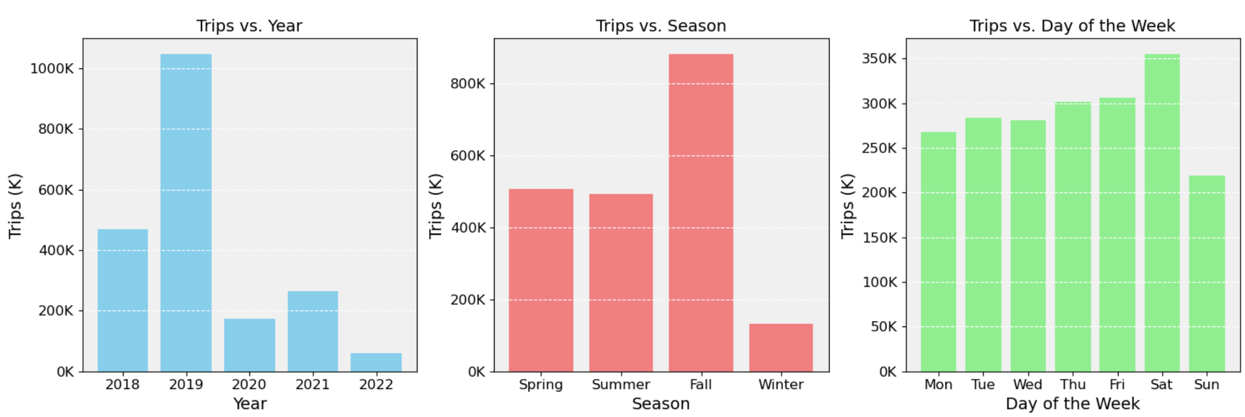

Figure 8: Trips per Year, Season, and Day of the Week at UT Austin

E-scooter Injury Report Data

E-scooter injury crash reports were obtained from UT University Health Services, located on campus and mainly serving the student population. These reports cover incidents where individuals sought aid after crashing on an e-scooter between the analysis time period of April 2018 and December 2022 (n = 54 incident reports). Notably, 95% of all injury reports involved rented e-scooters, with the remaining incidents related to privately owned scooters. The reports include details such as the incident date, injury type, crash location, reasons for the crash, modes involved, and injury location(s) on the body.

In a separate study, our team conducted a UT community mode choice survey during Spring 2023 to understand post-COVID-19 travel patterns on campus. The survey revealed that 1.4% of undergraduate and graduate students use an e-scooter to commute to campus. Considering the total enrollment of 51,913 students at UT in Fall 2023, a minimum sample size (n = 22) provides a 95% confidence level that the real value is within ±5% of the measured sample. Notably, our sample size of 54 student injury reports well exceeds the minimum required for statistical significance.

Figure 9 breaks down the temporal changes in crashes per year, season, and day of the week. In 2019, UT recorded the highest number of e-scooter-related crash reports (30). Surprisingly, it wasn't the pandemic that resulted in the lowest number of crashes; that occurred in 2021. Additionally, during the winter season, the majority of crashes took place, indicating potential issues with road quality. Lastly, Mondays and Fridays had the highest concentration of crashes.

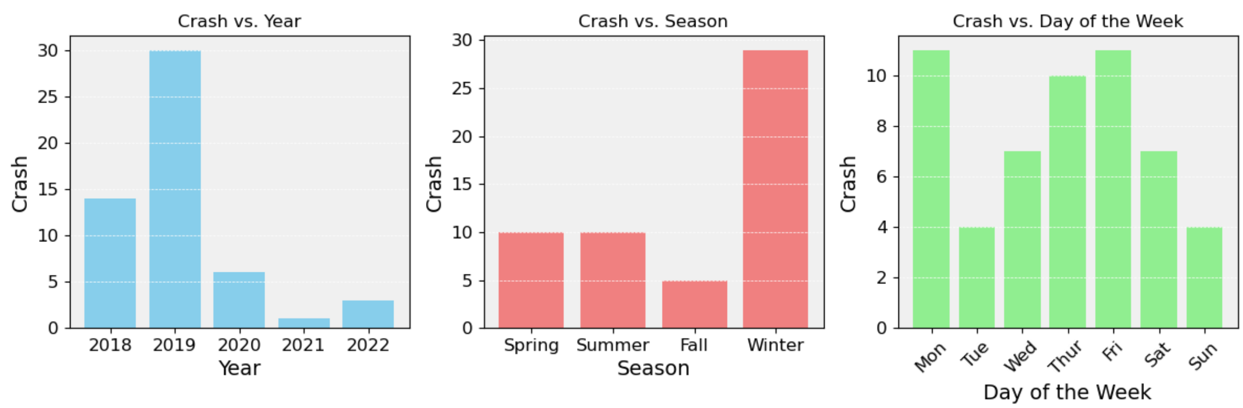

Figure 9: Crashes per Year, Season, and Day of the Week at UT Austin

Ridge Modeling Results

With the target variable being head injuries and the feature variables including trips, reasons for crashes and weather, the final model identified crashes due to excessive speeds as the most important variable for predicting a head injury.

Before creating the Ridge regression, we conducted k-fold cross-validation, which found that an α value of 10 produced the smallest mean squared error (MSE). To demonstrate the predictive power of Ridge Regression, we compared the root mean squared error (RMSE) of Ridge against a basic ordinary least square (OLS) or linear regression model. As shown at the bottom of Table 6, the RMSE of linear regression is 0.168, whereas Ridge's RMSE is 0.158, indicating that Ridge is better at predicting head injuries. Table 6 also compares the Ridge and linear regression estimates, along with the linear regression's 95% upper-lower confidence intervals and p-values. Note the boldened p-values represent p-values less than 0.05. While a researcher could pick out the most significant variables or those that increase R^2, those would not necessarily be the most predictive variables. Prediction and inference are different aspects, sometimes conflicting, and they each have their place. However, an accurate prediction of head injuries is crucial for understanding the cause and impact of safety countermeasures, such as geofences.

Table 6: Ridge and Linear Regression Coefficients

Feature Variable	Ridge Coefficient	LR Coefficient	LR 95% Upper CI	LR 95% Lower CI	p-value
ModesInvolved_ExcessiveSpeed	0.075	0.078	0.102	0.055	**0.01**
InjuryLocation_Arm	0.054	0.057	0.081	0.033	**0.05**
ModesInvolved_Scooter	0.043	0.048	0.071	0.025	0.09
ModesInvolved_Bicycle	0.041	0.042	0.058	0.025	**0.04**
ModesInvolved_Other_Intoxication	0.040	0.041	0.061	0.021	0.09
ModesInvolved_Other_Object	0.036	0.038	0.066	0.009	0.27
ModesInvolved_Pedestrian	0.030	0.030	0.055	0.006	0.31
ModesInvolved_Other_RoadSurfaceQuality	0.020	0.022	0.046	-0.003	0.47
InjuryLocation_Shoulder	0.020	0.019	0.044	-0.001	0.43
InjuryLocation_NoInjurySustained	0.019	0.022	0.048	-0.009	0.57
InjuryLocation_Wrist	0.017	0.019	0.036	0.003	0.34
CrashLocation_Sidewalk_Curb	0.015	0.015	0.038	-0.009	0.60
InjuryLocation_Chest	0.015	0.014	0.040	-0.010	0.62
CrashLocation_Roadway	0.014	0.015	0.042	-0.015	0.69
Geofence_Speed	0.003	0.003	0.029	-0.021	0.90
RentalType_Lime	0.003	0.004	0.027	-0.021	0.92
Weekday	0.001	0.001	0.025	-0.023	0.97
DailyPrecipitation	0.000	0.000	0.025	-0.025	1.00

Season	0.000	0.000	0.024	-0.024	1.00
RentalType_Bird	0.000	0.000	0.000	0.000	0.01
DailyAverageDryBulbTemperature	0.000	0.000	0.028	-0.029	1.00
DailySnowfall	0.000	0.000	0.024	-0.024	0.99
Day	0.000	0.000	0.024	-0.024	0.99
Geofence_Parking	0.000	0.000	0.023	-0.024	0.99
DailyAverageWindSpeed	0.000	-0.001	0.023	-0.024	0.98
Daily_COVID	-0.001	-0.001	0.022	-0.023	0.98
total_scoot_trips_day	-0.001	-0.002	0.023	-0.026	0.96
Year	-0.002	-0.002	0.022	-0.026	0.95
Month	-0.003	-0.004	0.025	-0.032	0.92
InjuryLocation_foot	-0.004	-0.003	0.020	-0.027	0.90
InjuryLocation_Elbow	-0.011	-0.013	0.011	-0.036	0.65
ModesInvolved_SystemMalfunction	-0.020	-0.021	0.008	-0.049	0.55
InjuryLocation_Face	-0.020	-0.023	0.001	-0.045	0.44
InjuryLocation_Hand	-0.021	-0.022	0.000	-0.046	0.41
InjuryLocation_Leg	-0.028	-0.031	-0.002	-0.059	0.37
ModesInvolved_Vehicle	-0.038	-0.042	-0.017	-0.067	0.16
InjuryLocation_Ankle	-0.043	-0.045	-0.027	-0.063	**0.04**
InjuryLocation_Knee	-0.051	-0.055	-0.032	-0.077	**0.04**
RMSE	0.158	0.168			

Figure 10 provides a graphical representation of the Ridge Regression's feature variables from most to least important, with excessive speeds being the most influential variable in predicting an increase in head injuries ($\beta_{ridge,excessvie\ speed} = 0.075$). This result reinforces previous research on the relationship between speed and injury severities, as well as the basic physics theory that the faster you are traveling, the more force and power you accumulate, leading to more severe injuries due to centripetal force (Toofany et al. 2021). This could result from someone riding downhill or simply speeding. Other variables important for predicting an increase in head injuries include arm injuries, crashes with a scooter, crashes due to intoxication, and crashes due to road surface quality. The least important variables mostly consist of temporal and seasonal variables such as weekday, precipitation, and season. The speed and parking geofences had little to no predictive power in predicting a head injury, aligning with the t-test results.

Feature variables at the end of the spectrum with a large and negative estimate value can be interpreted as indicating an inverse relationship between the target and feature variable, i.e., a decrease in head injuries. In other words, the larger the negative coefficient, the stronger the inverse relationship. Variables with a strong negative relationship to decreased head injuries include injuries to the knee ($\beta_{ridge,knee} = -0.051$), ankle ($\beta_{ridge,ankle} = -0.043$), (any lower extremity injuries), crashes involving a vehicle ($\beta_{ridge,vehicle} = -0.038$), and injuries to the face ($\beta_{ridge,face} = -0.020$). If an individual were to experience a crash resulting in injury to their lower extremities, it stands to reason that they would be less likely to suffer a head injury as a result. For vehicular crashes, there was a surprisingly high correlation of no injuries being sustained (0.50), and shoulder injuries (0.33) (refer to Figure 6). Vehicle crashes and head injuries only had a correlation of 0.08. Facial injuries could be interpreted as data reporting issues, where the person might have mistakenly noted a face injury rather than a head injury. It is important to reiterate that this model is specific to UT Austin and will likely produce different results with a new dataset.

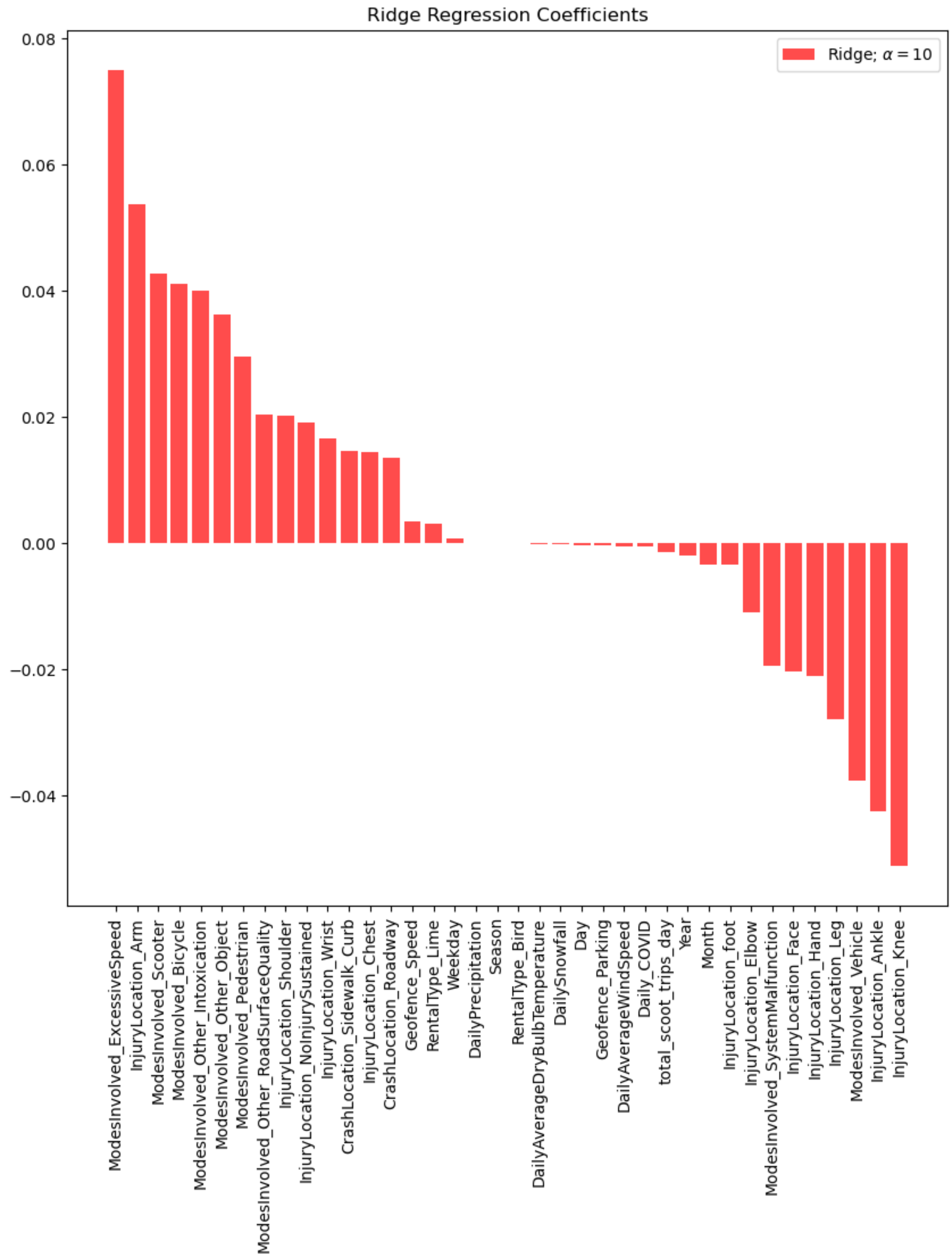

Figure 10: Ridge Regression most to least important coefficients

Discussion and Conclusion

Since 2017, dockless electric scooters, or e-scooters, have taken the transportation infrastructure by storm. Marketed as a solution to completing last mile-trips, reducing one's carbon footprint, and opening the door for more travel options for underserved communities. Just a year after their release to the public, e-scooter trips racked up 38.5 million trips in 2018 (Transportation 2020). Like most modes of travel, e-scooter trips significantly dropped during the COVID-19 pandemic, during which companies began to remove their operations, which was seen in the City of Austin as Lyft, one of the main dockless e-scooter operators, decided to remove their fleet of 2,000 e-scooters (Bradshaw 2020). Yet by 2022, e-scooter ridership levels rebounded to pre-pandemic levels, and are most likely here to stay in the coming future (Brasuell 2022).

Although their presence is boding, research has struggled to keep up, especially regarding the characterization of e-scooter related injuries and the effectiveness of safety countermeasures. A small number of reports have concluded that most e-scooter related crashes occur along the street and sidewalks. Although most of these crashes are caused by the rider falling off the scooter, the second largest number of crashes were due to the rider colliding with a vehicle. Mitigation efforts to curb these crashes include statewide restrictions on e-scooters riding along streets and sidewalks. Majority of states allow e-scooters to operate along the roadway, yet states become more split once it comes to allowing e-scooters along sidewalks. Rules become even more convoluted if a state claims e-scooters must adhere to bicycle rules and regulations, which is pertinent if a state requires e-scooter users to wear a helmet, or if city e-scooter regulations differ significantly from state rulings. An even more finite, and defined combatant, cities can implement is geofencing technology, speed or parking restrictions, along areas with high pedestrian or vehicular volumes.

There is an overall scarcity of research concerning e-scooter crashes, and even more so regarding the effectiveness of geofencing technologies toward crash mitigation. To address this gap, the report conducted a quantitative and ridge regression analysis of injury, trip, weather, and COVID-19 data from 2018 to 2022 with The University of Texas at Austin (UT) serving as its case study. Data was sourced from various outlets, including the University Health Services at UT Austin, City of Austin Transportation Department Shared Micromobility Trips, Texas Department of State Health Services (DSHS), and the National Centers for Environmental Information.

To understand the factors contributing to e-scooter crashes and to assess the effectiveness of safety measures in reducing crash rates and severity, we initiated our study by conducting a t-test on the parking and speed geofences implemented on UT's campus. The parking geofence prevents dockless e-scooters from ending their trips outside designated parking zones, while the speed geofence limits speeds to 8 or 15 mph, depending on the location within the campus. Normalizing crash rates by the number of trips completed on campus, the t-test results indicated that neither the parking nor the speed geofence significantly reduced crash rates or serious injuries. Consequently, we shifted our focus from inference-based modeling to prediction.

Upon reviewing the trip data within the campus, distinct temporal patterns emerged. The year 2019 recorded the highest number of accumulated trips, with a noticeable surge coinciding with the UT vs. Louisiana State University (LSU) football game on September 7, 2019. Moreover, the majority of trips occurred during the fall season and on Saturdays, suggesting a preference for recreational travel. Over the period from 2018 to 2022, a total of 54 crashes were recorded, with the highest number occurring in 2019 (30 crashes). Notably, the winter season witnessed the highest frequency of crashes, indicating potential issues with road quality during inclement weather. Lastly, Mondays and Fridays had the highest concentration of crashes.

With an RMSE of 0.158, Ridge Regression demonstrated its superiority as a predictive model for head injuries. By incorporating feature variables such as trips, crash reasons, and weather conditions, the final model identified excessive speeds ($\beta_{ridge,excessvie\ speed} = 0.075$) as the most influential factor in predicting head injuries. Interestingly, both the speed and parking geofences showed minimal predictive power regarding head injuries, consistent with the findings of the t-test. Additionally, variables exhibiting a strong negative relationship with head injury prediction included knee and ankle injuries, crashes involving vehicles, and facial injuries. This inverse relationship can be attributed to the prevalence of lower extremity injuries, the nature of vehicle-related collisions resulting in shoulder injuries, and potential discrepancies in data reporting where face injuries may be misreported as head injuries. It is crucial to emphasize that these findings are specific to UT campus data and may vary depending on the study area.

While further research is strongly advised, our findings suggest several recommendations for city and university officials. First, considering the lack of statistical significance in the use of geofencing and the impact on crash rates and injury severity, we suggest implementing speed geofences, especially in areas with steep inclines where excessive speeds pose a significant risk of head injuries. Second, we propose enforcing e-scooters operate along designated bike lanes or dedicated e-scooter lanes if feasible to mitigate injury severity resulting from collisions with other modes of travel, such as pedestrians and cyclists, Last, promoting helmet use remains a reliable strategy to reduce the likelihood of head injuries among e-scooter users.

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