

Truck Stops as Critical Infrastructure: Enhancing Resilience and Driver Safety in Times of Crisis

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ABSTRACT

The COVID-19 pandemic underscored the critical role of truck stops as essential infrastructure for truck drivers, yet little is known about how these facilities supported drivers' evolving needs during such emergencies. This capstone explored the question: what gaps exist in truck stop infrastructure, and what challenges do drivers face under normal and emergency conditions such as COVID-19 and Hurricane Ian? To investigate, spatial analysis was used to analyze truck stop and parking infrastructure density, and topic modeling and semi-structured interviews were used to understand the needs and challenges faced by truck drivers. Key findings indicated a strong nationwide emphasis on the availability and quality of parking, food services, and restroom facilities, with a heightened importance during periods of emergencies. Spatial analysis revealed that 29% of high-risk counties have neither publicly funded rest areas nor facilities operated by the three largest national truck stop chains. Interview participants highlighted systemic parking shortages, lack of real-time communication, and lack of driver-oriented policy as challenges faced by drivers today. The findings suggest a mismatch in infrastructure demand and availability, compounded by a lack of regulations that expose truckers to undue risks, especially during emergencies. There is a need for greater emphasis on driver welfare in policy development and infrastructure planning to ensure they are protected during the delivery of essential goods and services during emergencies.

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1. Introduction

1.1 Motivation and Relevance

The COVID-19 pandemic highlighted the essential role of truck drivers in maintaining the flow of goods across the United States (U.S.). Drivers transported critical supplies, including medical equipment, food, and water, under unpredictable and chaotic conditions. During this time, the U.S. government was not equipped to adapt critical infrastructure to meet drivers' needs. To reduce contact and enforce social distancing rules, many truck stops and rest areas were closed as a precaution (Sperry et al., 2022). This was problematic, as truck stops are essential for breaks, meals, restrooms, and sleep. The increased demand for goods pressured drivers to work longer hours, but with fewer safe and reliable places to stop (Crizzle et al., 2021). Drivers crossing multiple jurisdictions also faced a patchwork of pandemic-related health and safety guidelines. Inconsistent policy guidance made it difficult to understand which protocols to follow, directly affecting their ability to operate safely and effectively (Calacal, 2020). COVID-19 was a crisis event that uncovered vulnerabilities in national infrastructure and policymaking. Truck drivers, often overlooked in emergency preparedness planning, suffered unanticipated consequences as a result.

The logistical pressures felt through COVID-19 motivated further investigation of trucking operations during other types of emergencies, such as hurricanes and wildfires. For example, Hurricane Ian was a storm that hit Florida's southwestern coast in September 2022, leaving severe infrastructure damage in its wake and affecting the state's near-term gross domestic product (GDP) growth (S&P Global Market Intelligence, 2022). Another case was the 2025 Southern California wildfires, which destroyed thousands of homes. The recovery efforts have been constrained by equipment and material backlogs, which contributed to rising rebuilding costs (Rudge, 2025). Meanwhile, the slow pace of recovery had downstream effects on California's agricultural sector, reducing crop production and food supply, and increasing food prices (Ita, 2025).

This capstone aims to provide actionable recommendations to improve truck stop availability and service offerings during future emergencies. Our research is sponsored by the Humanitarian Supply Chain Lab (HSCL) at the Massachusetts Institute of Technology (MIT) Center for Transportation and Logistics (CTL). By focusing on the role of truck stops in emergencies, we seek to inform federal and state policies that promote infrastructure resilience, driver safety, and supply chain continuity.

1.2 Definitions

The terms “truck stops” and “rest areas” are often used interchangeably, but they are distinct in several ways. Truck stops are privately owned and operated refueling stations located along highways and highway exits. They offer essential services to truck drivers, including meals, restrooms, fuel, showers, and parking. Amenities range from basic to premium, which can include services such as laundry, gyms, and entertainment centers. Rest areas are publicly funded and managed facilities that cater primarily to passenger vehicles, offering limited services such as parking and restrooms. Some rest areas provide truck parking, though capacity is often limited. This capstone uses the term “truck stops” to broadly describe both truck stops and rest areas unless otherwise specified.

Crisis events refer to unanticipated, large-scale events, such as pandemics or natural disasters, that place significant stress on infrastructure and communities. The Federal Emergency Management Agency (FEMA) defines emergencies as events that pose risks to life and property on a large scale (FEMA, 1996). Throughout this report, “crisis event” and “emergency” will be used interchangeably.

1.3 The Role of Freight Transportation During Emergencies

Commercial truck transportation is vital to the U.S. economy. In 2023, trucks moved \$13.6 trillion worth of goods, accounting for 74% of all domestic freight movement (Bureau of Transportation Statistics, 2023). Disruptions in trucking operations can quickly destabilize essential services, including healthcare, food distribution, fuel supply, and waste management.

Truck drivers must maintain their physical and mental well-being to perform safely and sustainably. Under normal conditions, they plan rest areas along routes to comply with federal Hours of Service (HOS) regulations, which limit the number of hours drivers may work in a given period to ensure they get adequate rest (FMCSA, 2021). During crisis events, road closures and shifting conditions often disrupt these plans, which may prevent drivers from reaching designated rest areas (Marshall, 2020). These disruptions lead to delivery delays and increase risks to driver safety.

Emergencies place considerable stress on the broader transportation system. The National Academies of Science, Engineering, and Medicine (2024) emphasizes the critical role of transportation “before, during, and after an emergency.” Given trucking’s central function in supply chain operations, truck stops and rest areas are essential nodes that support emergency preparedness and response. Without adequate infrastructure, the delivery of essential goods is compromised.

All major sectors such as healthcare, food, fuel, retail, and waste management rely on timely truck deliveries, and disruptions in freight can cause cascading shortages. Hospitals may run low on oxygen and food within days, grocery store shelves may empty due to just-in-time inventory systems, and fuel shortages can impair emergency response services (Shenoy, et al., 2021; National Academies of Sciences, Engineering, and Medicine, 2020). These effects underscore the need to ensure uninterrupted freight flows, especially during crises.

1.4 The U.S. Truck Stop Industry

The truck stop industry in the U.S. has a combined revenue of \$400 billion and is comprised of approximately 130,000 locations. The top 50 companies represent 40% of industry revenues (First Research, 2025). There are three prominent companies in this market: Love's Travel Stops & Country Stores (Love's), Pilot Travel Centers (Pilot Flying J), and TravelCenters of America (TA). Collectively, these three chains operate less than 1% of all truck stops in the U.S., demonstrating the highly fragmented nature of this industry. However, they are prominent due to their strategic locations along high-traffic interstate corridors, wide variety of offerings, and loyalty programs, particularly their fleet partnerships with major carriers that offer increased convenience for commercial trucking operations (CSP Daily News, 2010). However, some drivers still opt to support independent "mom-and-pop" truck stop operators, which may offer more flexible and more personalized service (Smith, 2013).

Truck stops, commercial or independently operated, offer several amenities such as restaurants, bathrooms, and parking. However, one major distinction between major commercial chains and independent truck stops is the scale at which they offer truck parking. Of the approximately 310,000 truck parking spaces in the U.S., the major truck stop chains collectively comprise of half these spots (FHWA, 2015). Combined with the standardized offerings provided by the major chains, parking makes them attractive to truck drivers who are looking for a place to stop for breaks; as a result, they often fill up faster than the parking lots of independent truck stops (Cannon, 2021).

1.5 Extent of the Truck Parking Crisis

Truck parking shortages remain one of the industry's most critical challenges, undermining both safety and freight efficiency. State observations show that 59% of states report shortages of parking spaces in public rest areas, 31% report parking shortages at designated pullouts or vistas, and another 31% observe deficiencies at private truck stops (FHWA, 2015). This situation is shown by the prevalence of unofficial and illegal parking. Nearly half of state-level Departments

of Transportation (DOTs) report incidents of illegal parking on freeway interchange ramps and highway shoulders, while 94% of state motor carrier safety officials identify at least one location where unlawful parking occurs (FHWA, 2015). These unofficial parking spaces are often located in hazardous or forbidden areas, increasing risks for both drivers and the public.

Drivers' perceptions confirm the severity of the issue. Over 75% of truck drivers and nearly 66% of logistics personnel report regularly experiencing difficulties in finding safe parking when needed. The struggle to find available parking during nighttime hours is of particular concern, with 90% of drivers indicating they face this challenge. This problem is more pronounced during certain time frames: 48% of private truck stops report being more than 100% full between midnight and 5 AM, while 37% see truck parking occupancy rates between 76% and 100% from 7 PM to midnight. Unofficial parking is also more common on weekdays, with 47% of observations occurring during this period, compared to lower rates on weekends (FHWA, 2015). These findings underpin the need to further investigate the parking crisis in relation to truck stops and to quantify the extent of the parking shortage.

1.6 Driver Safety

Krasniuk et al. (2024) identified that a top determinant for drivers selecting a truck stop was the availability of safe and accessible parking. A Federal Highway Administration (FHWA) survey of truck drivers found that 98% of respondents had struggled to find safe parking (2015).

Inadequate parking space forces drivers to use unsafe or unauthorized locations, such as parking on highway shoulders, ramps, or roadsides, which exacerbates congestion, reduces roadway reliability, and heightens safety risks (FHWA, 2022). A salient example of this is the case of Jason Rivenburg, a truck driver who was tragically murdered in 2009 while parked at an abandoned gas station due to a lack of safe parking options. As a result, "Jason's Law" was enacted into federal legislation in 2012 as part of the Moving Ahead for Progress in the 21st Century Act (MAP-21) to address the critical shortage of safe truck parking spaces across the U.S.

The availability and quality of truck stops also directly relates to driver fatigue. Truck drivers are required to comply with federal HOS regulations, which limit their consecutive working hours. The inability to find parking can result in drivers working beyond the number of hours allowed under the HOS regulations, which can increase driver fatigue. For example, the Federal Motor Carrier Safety Administration (FMCSA) mandates a 30-minute rest break within the first eight hours of duty. Yet, according to the American Transportation Research Institute (ATRI), 48% of truck drivers spend over an hour daily searching for parking, leading to lost productivity and

increasing fatigue. A study by Bunn, et al. (2019) demonstrated that longer distances between rest areas correlate with increased accidents involving commercial truck drivers. These findings underscore the importance of accessible and well-maintained truck stops in preventing fatigue-related incidents.

1.7 Problem Statement

Our capstone was defined by the research question: What gaps exist in truck stop infrastructure, and what challenges do drivers face under normal and emergency conditions?

This project's goal was to deliver data-driven insights regarding our research question and provide actionable recommendations regarding emergency preparedness and driver safety during crises. Our report aimed to highlight the importance of truck stops in maintaining supply chain continuity and building network resiliency. As this subject matter has not been investigated in depth, our capstone endeavors to serve as the groundwork for future research.

2. State of the Practice

Current research uses qualitative methods to discuss how truck stops influence driver health and safety and parking availability, but little has been explored regarding their role in emergency response and supply chain resilience (Krasnuik, et al., 2024; Bunn, et al., 2019; Lincoln, et al., 2018). Separately, spatial analysis has been used in transportation and emergency response research, but not specifically to investigate the role of truck stops (Loidl, et al., 2016; Goodchild, et al., 2009; Yuan, et al., 2023). This represents a critical gap in literature, as truck stops play a vital role in supply chain resilience, particularly during crises. The following sections review prior research and how their methodologies were used to advance our work.

2.1 Spatial Analysis

Spatial analysis is about understanding how location influences patterns, relationships, and outcomes. In the context of transportation, it examines how infrastructure, geography, and movement interact across space. This is especially important for freight systems, where the physical layout of roads, rest areas, and facilities directly affects efficiency and resilience. Geographic Information Systems (GIS) make this kind of analysis possible by layering different datasets onto a shared map-based framework. This helps researchers and planners visualize routes, assess vulnerabilities, and identify opportunities for improvement. Our capstone applied these methods to evaluate the U.S. transportation network, using spatial analysis to pinpoint critical truck stops that play a key role during emergencies. In particular, we focused on

uncovering disparities between where truck stops are located and where they are most needed – particularly within high-risk counties.

In 2016, scientists and researchers from Austria and other European institutions utilized GIS for transport modeling to enhance the spatial analysis of mobility systems (Loidl, et al., 2016). Since transportation inherently involves the movement of people and goods across space, accurate geospatial data is crucial for developing reliable models. The researchers found that GIS enables the integration of diverse datasets, such as road networks, land use data, and real-time traffic sensors, allowing real-world spatial dynamics to be incorporated into transport models. Additionally, GIS provides powerful visualization tools that help researchers and stakeholders interpret complex transport data. By visually analyzing travel trends, bottlenecks, and system inefficiencies, decision-makers can identify critical issues and implement targeted infrastructure improvements and policy interventions. These visualization capabilities make GIS an essential tool for optimizing transport systems and enhancing planning processes.

Goodchild, et al. (2009), from the University of Washington, Washington State University, and the Washington State Department of Transportation, leveraged GIS to develop and analyze a statewide network of freight movements. They mapped Washington's freight infrastructure, including highways, railways, waterways, and intermodal facilities, to create a detailed spatial representation of the system. They integrated diverse datasets, such as infrastructure details, traffic volumes, and commodity flows, to provide a comprehensive view of freight movement. Using GIS, they optimized freight routes by analyzing distance, congestion, and travel time, which improved logistics efficiency and reduced costs. GIS also enabled disruption simulations, allowing researchers to assess the impact of road closures and develop resilience strategies. Additionally, they conducted industry-specific case studies, such as agricultural product and diesel distribution, to map supply chains and identify vulnerabilities. By visualizing complex freight data, GIS helped policymakers, planners, and stakeholders interpret insights and make informed decisions. It also supported economic impact analysis by identifying critical freight corridors and prioritizing infrastructure investments.

GIS plays a pivotal role in analyzing and optimizing network infrastructure. Yuan, et al. (2023) highlighted how a GIS-based method is effective at identifying critical links in urban road networks with benefits at the micro, meso, and macro levels. Experts suggest that GIS analysis can be an effective tool in navigating the complexities of modern supply chains, allowing multi-faceted analyses of economic, environmental, and social impacts, and enabling contemporary approaches to transportation modeling, such as dynamic visualization, network optimization, and predictive analytics (FHWA, 2022).

Our capstone used GIS methods because it uniquely integrated spatial and infrastructural data, enabling us to model truck stops locations and evaluate parking density. This method allowed us to visualize critical gaps and identify where critical infrastructure is most needed in vulnerable areas.

2.2 Topic Modeling and Advancements through BERT

Topic modeling is an unsupervised ML text mining method that is commonly used to extract semantic themes from large bodies of text (corpora). This method groups frequently co-occurring words or phrases into topics, but the computer does not understand the topics themselves; interpretation is left to the researcher. However, the ability to analyze large corpora and identify themes is a powerful method used in a range of contexts (China, 2023). Topic modeling falls within text mining, a discipline within data science that is focused on extracting insights from large amounts of unstructured text, such as transcripts, emails, or social media posts. It involves converting linguistic data into a structured format that allows computers to analyze and identify patterns, relationships, and themes. Text mining techniques can be categorized into supervised or unsupervised machine learning (ML), where the former involves human intervention to guide pattern identification, and the latter allows the computer to make connections and infer meaning without human intervention (University of Delaware, 2024). For the purposes of this capstone, topic modeling allowed us to analyze the thoughts and sentiments of truck drivers in a corpus of truck stop reviews. Without the application of topic modeling techniques, this would be a highly manual process that would require reading each review and categorizing it by theme. Topic modeling advances this process significantly through advanced ML algorithms, making the process more efficient without sacrificing accuracy.

Treiblmaier and Mair (2021) applied several text mining techniques to interviews to explore the applicability of these methods for logistics and operations research. They conducted 19 semi-structured and partly narrative interviews with supply chain experts, which were transcribed, cleaned, and processed for the application of five textual analysis methods: word clouds, sentiment analysis, topic modeling, correspondence analysis, and multidimensional scaling. The use of sentiment analysis identified emotions and perceptions by assigning a polarity score to topics, which indicated the positive, neutral, or negative nature of a topic. Topic models identified the most important clusters of words to each company to compare organizations. Word clouds were a quick yet powerful device to communicate frequently mentioned words. Treiblmaier and Mair's research established the exploratory yet versatile nature of textual methods and how they can effectively identify patterns and trends hidden in corpora. They argued these techniques are

fast and effective for exploratory analysis and assist in finding further topics for investigation. However, researchers must exercise some creativity and interpretation to make sense of the outputs.

Recent advancements in natural language processing (NLP) have quickly surpassed traditional approaches to topic modeling. The most common traditional method is Latent Dirichlet Allocation (LDA), which is a generative probabilistic model that assigns explicit probabilities to topics and words based on frequency. It assumes that each corpus is a combination of user specified latent topics, and that each word is generated by a topic (Pykes, 2023). It takes a “bag-of-words” approach where word order is ignored, and topics are identified based on word co-occurrence. Recent advanced embeddings-based models offer a more semantically rich approach.

Embeddings are numeric vector representations of words that capture semantic relationships more effectively than traditional models like LDA, and are a foundational component of modern NLP (Liang, 2024). Early embeddings-based models such as Word2Vec assign words to a single vector, regardless of context. For example, the word “bank” would be assigned the same vector, whether it’s referring to “river bank” or “bank account”. It can capture general semantic relationships but cannot distinguish between different meanings of the same word or adapt to sentence context (Yadav, 2024).

The field of NLP experienced a major breakthrough with the introduction of deep learning models, significantly improving the ability to understand context and meaning (purpleSlate, 2024). One such model is the Bidirectional Encoder Representations from Transformers (BERT), an advanced model developed for NLP and pre-trained on rich, contextual, multilingual data. BERT’s innovation lies in its ability to conduct bidirectional processing, meaning it reads entire sentences forwards and backwards, and can capture a rich understanding of a single word based on the words surrounding it (Yadav, 2024). BERT’s ability to understand nuance makes it a state-of-the-art model that is highly effective for text mining. The development of BERT has widely transformed NLP-based technologies, including search engines, voice assistants, and chatbots (Muller, 2022). It has also sparked the development of further models for specific use cases, such as BERTopic, an advanced topic modeling technique.

Egger and Yu (2022) conducted a comparison of four topic modeling methods on efficacy analyzing Twitter data, and particularly how each handle noisy, unstructured, and short-form text. It included two traditional models: LDA and Non-negative Matrix Factorization (NMF), and two embeddings-based models: Top2Vec and BERTopic, all of which were analyzed on performance, interpretability, topic coherence, and relevance of findings. They found that BERTopic and NMF

performed the best on short-text Twitter data. Specifically, BERTopic captured novel insights using its embeddings-based approach, whereas NMF generated distinct but uninteresting topics. In contrast, LDA was not recommended, as the topics generated were too general or irrelevant. Top2Vec generated some novel insights, but overall topics were irrelevant and hard to interpret. Egger and Yu concluded that the BERTopic method presented the most potential to generate useful insights on short-form text analysis. They highlighted the model's ability to capture context that may remain obscured with other models.

The BERTopic model is built upon four sub-components: transformer-based word embeddings, dimensionality reduction, clustering, and cluster representation (Briggs, 2023). Transformer models, such as BERT, encode text into dense semantic vector representations. The choice of transformer model is critical, as it affects the quality of embeddings, and low-quality vectors result in low-quality clusters. However, transformer models typically produce high-dimensional vectors, meaning each data point is described by potentially hundreds of dimensions. Dimensions are descriptive features of data, and when excessive features are included, lead to complex and uninterpretable results. Therefore, dimensionality reduction is used to compress dimensions such that important structures and patterns are retained while reducing computational power and generating interpretable clusters (Allaoui, et al., 2020). BERTopic utilizes the Uniform Manifold Approximation and Projection (UMAP) method for this purpose, which is a technique capable of preserving both local and global data structures better than earlier algorithms (Borrelli, 2021). Once dimensionality has been reduced, clustering is performed with Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN), which is a clustering algorithm that expands prior methods to more effectively handle outliers, noisy data, and irregularly shaped clusters (Panjabikesan, 2023). Finally, BERTopic uses the class-based Term Frequency and Inverse Document Frequency (c-TF-IDF) method to label clusters, which is a technique that identifies the most representative words per cluster by adapting the traditional TF-IDF weighting scheme to the cluster level (Briggs, 2023). The combination of these four techniques result in interpretable and semantically significant clusters that are an improvement upon existing topic modeling methods.

This is demonstrated through An et al.'s (2023) research comparing modeling approaches on Korean e-commerce consumer reviews to extract insights regarding purchase motivations and product insights. The objective was to compare the efficacy of traditional models (LDA and K-Means) against newer models (BERTopic and Modified Deep Clustering Network [DCN] BERTopic) on topic coherence, word coherence, and topic diversity. The researchers found that newer models exhibited better performance than traditional models, with default BERTopic (which

used UMAP and HDBSCAN) showing the highest scores in topic diversity. The LDA and K-Means-based models exhibited relatively low topic diversity and a high degree of overlap across topics, making results less semantically meaningful. The DCN BERTopic performed well, but the researchers ultimately recommended the default BERTopic as the use of HDBSCAN for clustering was more effective at filtering out noisy reviews, boosting overall model performance.

One limitation of the BERT model is that human validation is still required to fully interpret topics. Eklund and Forsman (2022) conducted topic modeling on 10,000 English news articles and visualized the output on a custom web application named STELLAR. The model used a standard BERTopic approach: generating BERT embeddings, applying UMAP for dimensionality reduction, clustering with HDBSCAN, and representing clusters with c-TF-IDF. The objective was to have three subject-matter experts (SMEs) validate the topics that came from the BERTopic model and evaluate metrics such as keyword quality and topic coherence. Of the 63 topics generated, 52 (82%) were considered coherent by the SMEs, with an overall 87% agreement on focus topics. Keyword quality was considered acceptable, but with room for improvement. However, because topic coherence required unanimous SMEs agreement on a focus topic, only 57% of articles were considered coherent. Challenges faced with incoherent topics included subjects with multiple focus topics or emphasizing emotional or stylistic elements. The researchers concluded that while BERTopic was viable for industry applications, human oversight was still needed, especially when dealing with trend-driven or nuanced topics.

Our capstone used topic modeling to efficiently uncover themes and sentiments from a large corpus of truck stop reviews, a task that would be prohibitively time-consuming to do manually. This method allowed us to identify patterns in driver experiences and concerns, providing insights critical for understanding infrastructure needs during emergencies.

2.3 Semi-Structured Interviews

Semi-structured interviews have been used widely to assist researchers in exploring qualitative perspectives on a subject. Unlike surveys, semi-structured interviews provide participants with the opportunity to express thoughts, emotions, and experiences more freely. Semi-structured interviews are guided by a facilitator and a pre-determined list of questions to ensure consistency across interviews while allowing flexibility to follow up on topics of interest (Kallio, et al., 2016). The conversational style encourages deeper and more candid responses, fostering richer insights that might not surface through other data collection methods. One key advantage of semi-structured interviews is their ability to reveal unexpected themes, offering

nuanced and unique viewpoints that extend beyond the topics outlined in the original research guide (Sage Research Methods, 2004).

In 2022, researchers from Michigan State University and Clemson University used virtual focus groups to capture actionable insights into how the COVID-19 pandemic affected the trucking industry (Sperry, et al., 2022). By engaging participants across multiple organizational levels, including drivers, supervisors, and upper management, they gathered diverse perspectives on business adaptations, workplace safety, and driver experiences. Using a semi-structured protocol, they asked targeted questions about pandemic-related challenges, including supply chain disruptions, changing consumer demand, and new safety measures. Truck drivers detailed real-world obstacles, such as closed rest areas, reduced social interaction, and increased health risks, while company leaders explained strategic responses. Researchers systematically coded and analyzed the qualitative data using thematic analysis, identifying patterns and key takeaways. These insights provided practical recommendations for improving business operations, enhancing driver safety, and strengthening industry resilience during crises. Overall, the interviews provided a rich source of information that contributed to the study's findings and actionable recommendations for the trucking industry during and after the COVID-19 pandemic.

The advancement of Large Language Models (LLMs) has enabled partial automation of thematic analysis, a process traditionally reliant on human interpretation. To investigate whether LLMs could effectively perform this activity, De Paoli (2023) used GPT-3.5-Turbo to analyze themes for two datasets: interviews with video game players, and interviews with university lecturers of data science. The LLM was able to successfully identify several themes recognized by human researchers, particularly within the gaming dataset, even if different wording was used. However, the LLM struggled at capturing nuanced psychological themes and occasionally hallucinated new themes. De Paoli concluded that LLMs should be used to assist with thematic analysis but not replace human interpretation. Specifically, a human and artificial intelligence (AI) collaboration model was recommended, where AI generated themes for humans to interpret, refine, and validate.

Our capstone used semi-structured interviews to gather in-depth, qualitative insights from truck drivers and industry stakeholders that might not emerge from quantitative methods alone. This approach allowed participants to share personal experiences and unexpected themes, enriching our understanding of the transportation system's challenges during crises.

3. Methodology

Our research adopted a mixed-methods approach to address the research gap in truck stops. First, we applied spatial analysis to identify at-risk truck stops and parking density. Second, we conducted topic modeling to identify drivers' needs and sentiments across time, region, and vulnerability to risk. Finally, we facilitated expert interviews to validate our findings and identify policy improvements. By combining these approaches, our study introduces a new perspective on truck stops as critical infrastructure in disaster response.

3.1 Spatial Analysis of the U.S. Freight Network

To identify the most critical truck stops in the U.S. freight network, we visualized the data sources in Table 1 on a geospatial map using ArcGIS to identify relevant networks, nodes, and potential bottlenecks. All maps are stored in ArcGIS Online and data is housed in GitHub (Cafaro & Hsiang, 2025).

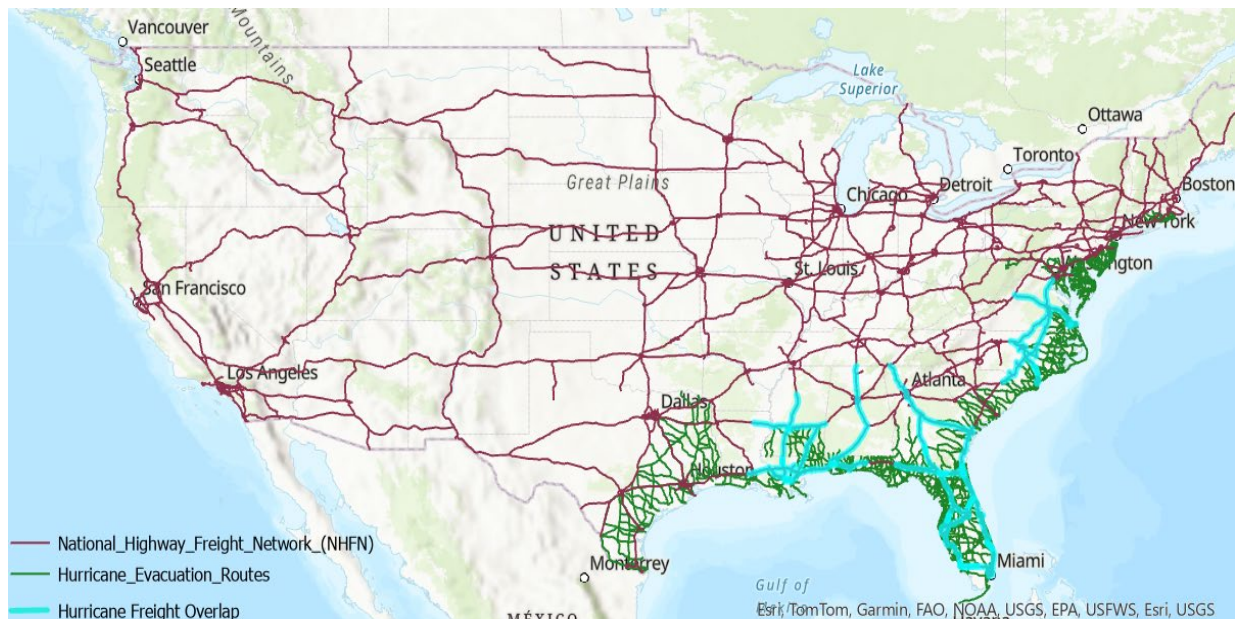
Three types of geospatial data were considered. First, roadways were included as they represent the primary infrastructure through which freight flows. The National Highway Freight Network (NHFN) map shown in Figure 1 provides an overview of the primary transportation corridors that facilitate the movement of goods across the country. These routes are essential for commercial trucking and maintaining supply chain operations. Areas with a high concentration of freight corridors correspond with manufacturing and major logistics hubs, such as the Midwest, Northeast, and Southern California.

Figure 1. National Highway Freight Network (NHFN)



To better understand where the freight system was most vulnerable, hurricane evacuation routes from the Federal Emergency Management Agency (FEMA) were layered with the NHFN to identify zones of compounded risk and reflect infrastructure specifically designed for crisis response, as shown in Figure 2. Coastal regions in the Southeastern U.S. emerge as particularly critical areas where high freight volumes and high disaster risk converge. According to the U.S. Department of Transportation, there are more than 49,000 miles of designated hurricane evacuation routes across 23 coastal states. Many of these routes overlap with interstate highways that form the NHFN as they are designed to rapidly move residents away from high-risk coastal areas during severe storms. This intersection creates a key vulnerability: during hurricane evacuations, freight mobility can be severely disrupted by congestion, lane reversals, or road closures. These disruptions can delay the timely delivery of essential goods such as food, fuel, and medical supplies, especially to regions that are at the highest risk of needing it most.

Figure 2. NHFN and FEMA Hurricane Evacuation Route Overlap



This exploration led to the selection of two crisis events for further investigation using topic modeling and semi-structured interviews: the COVID-19 pandemic and Hurricane Ian. COVID-19 was a worldwide pandemic that began in March 2020, and it was chosen for its nationwide impact on freight movement and infrastructure access, affecting truck stops across multiple high-risk regions. Hurricane Ian was a major tropical storm that landed in Florida in September 2022, and it was selected due to its profound and lasting impact on the state's supply chain (S&P Global Market Intelligence, 2022). As demonstrated by Figure 2, the intertwined nature of freight flows and disaster response on major highways in the Southern region, made Hurricane Ian a valuable case study to understand infrastructure gaps and network resiliency.

The second kind of geospatial data used was truck stop nodes, which were represented through the inclusion of major commercial truck stops and public rest areas, sourced from corporate websites and the National Highway System (NHS), respectively. These nodes were essential for understanding the location, proximity, and availability of parking relative to the national roadway network. Due to the fragmented nature of the truck stop industry and lack of centralized parking supply data, we used the top three national truck stop chains by total number of locations—Love's, Pilot Flying J, and TA—as a proxy for private parking infrastructure. Collectively, these companies account for over 50% of the nation's truck parking capacity (FHWA, 2015). Public rest areas were added using data from the NHS, providing a more complete view of parking availability across both private and public sectors. Combining these nodes enabled us to calculate parking density by region, including the number of truck parking spots per square

mile. Although individual parking spot counts were not visualized on the map, they enabled analysis of parking density. This metric expressed how equitably parking infrastructure is distributed across different parts of the U.S. In doing so, we aimed to identify whether high-risk regions were underserved relative to their infrastructure demands.

The third type of geospatial data used were areas vulnerable to risk as defined by the National Risk Index (NRI). Our map incorporated regional risk exposure by incorporating FEMA's NRI framework, which categorizes every U.S. County by its vulnerability to 18 natural hazards, including hurricanes, wildfires, floods, and tornadoes (FEMA, 2025). It assigns each county a risk level ranging from "Very Low" to "Very High", enabling regional comparisons. The NRI is calculated using two main components: Expected Annual Loss and Community Risk Factor. Expected Annual Loss estimates the average annual economic and human losses caused by natural hazards, including damage to infrastructure, agriculture, and health. The Community Risk Factor adjusts this estimate based on local social conditions. It combines two subcomponents: Social Vulnerability and Community Resilience. Social Vulnerability measures how susceptible different population groups are to harm during emergencies. Community Resilience captures how well a community can prepare for, respond to, and recover from disasters. FEMA assessed 3,231 counties, of which 144 are classified as either "Relatively High" or "Very High" risk. Our spatial analysis focused exclusively on these counties, which we refer to throughout our capstone as "high-risk counties."

In the event of a crisis, these regions are most likely to suffer from damage to their freight infrastructure or require additional support to maintain access to food, fuel, and medical supplies. Including high-risk counties in our spatial analysis allowed us to prioritize regions most vulnerable to risk and disruption. Table 1 summarizes the data sources used in our spatial analysis.

Table 1. Data Sources Used in Spatial Analysis

Dataset	Data Source	Description
<i>Roadways</i>		
U.S. Interstate Network	FHWA	All major interstate highways and roadways used to transport freight.
Hurricane Evacuation Routes	FEMA	Major corridors to be used for evacuation in the event of a hurricane.
<i>Truck Stops and Rest Areas</i>		

Truck Stops	Corporate websites of selected chains	Locations of top three major truck stop chains (Love's, Pilot Flying J, TA).
Rest Areas	National Highway System (NHS)	Rest areas funded and managed by federal and state governments.
<i>Areas Vulnerable to Risk</i>		
National Risk Index (NRI)	FEMA	A framework developed by FEMA to categorize U.S. counties by "Very Low" to "Very High" vulnerability to risk, based on expected loss resulting from natural disasters and community risk factors.

Finally, our map used U.S. Census Bureau-defined regions and divisions to segment the country and allow analysis of regional differences in infrastructure availability. This regional classification enabled more consistent comparisons in truck parking availability across the Northeast, Midwest, South, and West, such as the normalization of total parking capacity by square mile. This approach allowed us to quantify regional disparities and prioritize areas for targeted infrastructure support and calculate parking density metrics that revealed which areas may be over- or under-resourced relative to others. The regions are shown in Appendix L.

3.2 Topic Modeling of Truck Stop Reviews

We conducted topic modeling of truck stop reviews to assess how truck driver preferences varied under crisis versus normal conditions. This component of our methodology allowed us to analyze key topics and evaluate how drivers may have perceived services and infrastructure during emergencies. All code is available in GitHub (Cafaro & Hsiang, 2025).

3.2.1 Data Collection

We received truck stop rating and textual review data from a leading navigation software provider, whose app is used primarily by North American truck drivers. The data spanned two time periods: August 2019 to January 2021, and February 2022 to March 2023. These two time periods capture several months before and after the initial onset of COVID-19 and Hurricane Ian, respectively.

The dataset includes reviews of privately-owned truck stops that span the U.S. and Canada. Canadian truck stop reviews were removed, as well as duplicate rows, leaving 270,810 unique reviews. Reviews were segmented by time period (i.e., before or after onset of a crisis event), region, and whether it was present in a high-risk county, as defined by the NRI. Our objective was to obtain up to 12 months of data for each time period, but this was only possible for the time period before Hurricane Ian. Remaining reviews outside the time periods of interest were dropped, resulting in 170,676 unique reviews that were included in our analysis. As two crisis events were selected for investigation, there are 32 possible segments that reviews may be mapped to, as shown in Table 2. The reviews segmented into high-risk counties represent 22% of total reviews, and the remaining 78% represent reviews from non-high-risk counties.

Table 2. Review Count by Time Period, Region, and Vulnerability to Risk

In a High-Risk County					
Region	Pre-COVID-19 Onset	Post-COVID-19 Onset	Pre-Hurricane Ian	Post-Hurricane Ian	Total
	<i>Aug 2019 – Mar 2020 (7 months)</i>	<i>Mar 2020 – Feb 2021 (11 months)</i>	<i>Sept 2021 – Sept 2022 (12 months)</i>	<i>Sept 2022 – Aug 2023 (11 months)</i>	
West	2,759	5,202	3,766	2,830	2,495
Midwest	508	854	693	440	617
Northeast	121	228	152	116	19,156
South	3,807	5,832	4,999	4,518	14,557
Total Reviews	7,195	12,116	9,610	7,904	36,832

Not In a High-Risk County					
Region	Pre-COVID-19 Onset	Post-COVID-19 Onset	Pre-Hurricane Ian	Post-Hurricane Ian	Total
	<i>Aug 2019 – Mar 2020 (7 months)</i>	<i>Mar 2020 – Feb 2021 (11 months)</i>	<i>Sept 2021 – Sept 2022 (12 months)</i>	<i>Sept 2022 – Aug 2023 (11 months)</i>	
West	2,595	4,739	4,800	3,199	34,645
Midwest	6,312	10,753	10,533	7,047	8,458
Northeast	1,586	2,734	2,452	1,686	75,408
South	14,088	22,540	22,331	16,449	15,333
Total Reviews	24,581	40,766	40,116	28,381	133,844

Segmenting by time, region, and vulnerability to risk allowed exploration of each segment to better understand truck drivers' needs and preferences under different conditions. Within each of the thirty-two segments, the reviews were further grouped by ratings (i.e., rating out of five stars) to reflect whether they contained positive, neutral, or negative sentiment. Although reviews

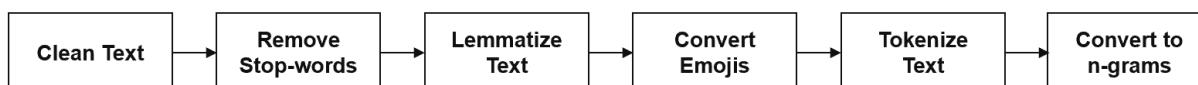
may have had nuanced emotions, this was a simple segmentation strategy that allowed us to separate the topics that emerged across reviews in aggregate.

3.2.2 Data Preprocessing

To prepare the truck stop review data for analysis, the corpus was cleaned and preprocessed according to the steps outlined in Figure 3. First, the process of text cleaning ensured text standardization and consistency, such as setting all text to lowercase, removing special characters (e.g., punctuation, extra spaces, URLs), and expanding contractions (e.g., “don’t” expanded to “do not”). Stop-word removal ensured that common but uninformative words were removed (e.g., “the”, “a”, “is”). Lemmatization reduced words to their basic form (e.g., “happiness” converted to “happy”), which consolidated similar words and improved model efficiency. Emojis were converted into words to retain emotional cues in reviews (e.g., a sad face emoji converted to “:sad_face:”).

Tokenization is the process of splitting a string of text into smaller parts, also referred to as tokens. For example, a sentence with five words would be split into five tokens. This step was necessary to standardize the structure of our data and generate clean word embeddings. From these tokens, n-grams (a sequence of n consecutive words) could be generated. This step was crucial to having semantically rich clusters. Early iterations of our model experimented with clustering single keywords, bigrams (two-word sequences), trigrams (three-word sequences), and fourgrams (four-word sequences), but trigrams resulted in the most coherent and semantically rich clusters. For example, single keywords often produced generic topics such as “parking”, bigram clustering generated broader concepts such as “parking lot”, while clustering with trigrams produced more precise topics such as “small parking lot”. Clustering with fourgrams often introduced unnecessary noise and resulted in less interpretable cluster labels.

Figure 3. Text Preprocessing Workflow



3.2.3 Model Development

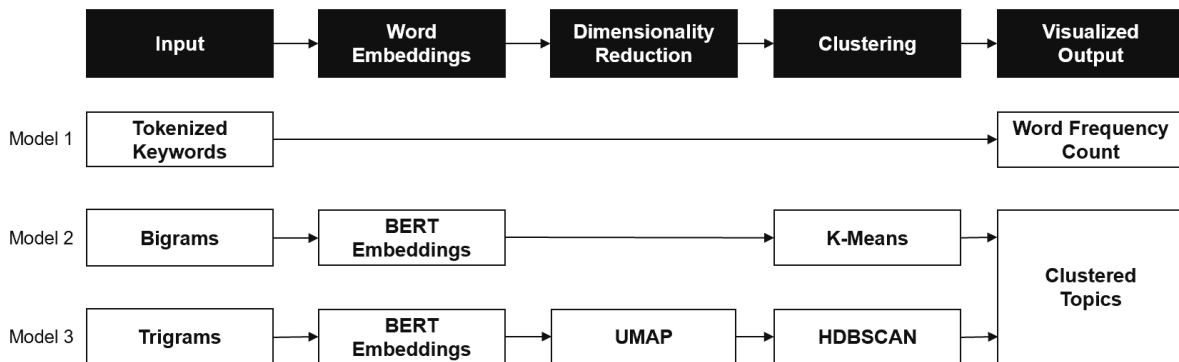
Three models were run as part of this capstone as shown in Figure 4, with the trigram model as our primary one. First, a simple word frequency count was conducted to establish a baseline understanding of the most common words in the corpus. Second, a simple K-Means model was used to cluster bigrams and illustrate improvement upon the simple word count. Bigrams were generated and embedded with the BERT SentenceTransformer model (all-MiniLM-

L6-v2), which is a state-of-the-art, pretrained model for sentence, text and image embeddings. Our primary model structurally followed the standard BERTopic workflow described in Section 2.2. This included embedding trigrams with SentenceTransformer, reducing high-dimensional data features through UMAP, and clustering topics through HDBSCAN. However, custom configurations were made to the standard BERTopic workflow for the unique needs of our dataset. This included adjusting the UMAP “n_neighbors” parameter and creating custom data visualization outputs.

One of the primary UMAP algorithm parameters is n_neighbors. The n_neighbors parameter determines the number of data points to consider when learning the structure of a dataset. It is typically set as a value between 2 and 100, where smaller n_neighbors values prioritize local data patterns and high values capture broader patterns. For example, n_neighbors=30 represents each data point considering its 30 nearest data points when examining relationships between them. The standard BERTopic workflow designates n_neighbors=15, but our model set n_neighbors=5, as truck stop reviews are typically short-form texts that have nuanced differences. For example, the phrases “no parking after 9 pm” and “lot fills up fast at night” are locally similar, and a low n_neighbors value helps them stay grouped, whereas a high n_neighbors value may lead to both being lost within larger topics about parking.

The second modification was creating custom visualizations for the model output. Our desired output was a frequency visualization of trigrams for each segment to maximize interpretability and comparison across the dimensions of time, region, vulnerability to risk, and sentiment. The standard BERTopic workflow uses c-TF-IDF for cluster representation, but since our main objective was frequency visualization and the trigrams were sufficiently informative, and we omitted this part of the standard workflow.

Figure 4. Model Workflows



3.3 Trucking Industry Expert Interviews

We conducted ten qualitative semi-structured interviews with stakeholders embodying the personas shown in Table 3. The interviewees represented a diverse range of experiences within the trucking industry, including FEMA disaster relief support, policy advocacy, corporate fleet management, and independent owner-operators. Most geographies were represented, with a slightly higher representation of interviewees based in Southeastern U.S. states.

Table 3. Interview Personas

Persona	Areas of Experience	Geography Covered	Number of Participants
Drivers & Owner-Operators	Long-haul trucking, disaster relief, HOS compliance, dispatch, route planning	National, focused on Southern & Southeastern U.S.	3
Industry Associations & Policy Leaders	Advocacy, policy development, safety standards, regulatory engagement, industry representation	National, Southeastern U.S.	3
Infrastructure & Operations Stakeholders	Facility management, corporate logistics, tech solutions, emergency operations	Midwest, Nationwide	3
Public Sector & Academic Researchers	Freight planning, safety research, system resilience research, public-private coordination	Eastern Corridor, West Coast	1
Total			10

Interviews were facilitated according to the interview guide in Appendix A. The guide was designed to supplement gaps in public data by exploring infrastructure accessibility, amenity availability, regulatory flexibility, and technology limitations from the perspective of those with on-the-ground experience. Our aim was to understand how truck drivers and industry leaders navigate crises and where infrastructure improvements could be most impactful. All interviews were recorded, transcribed, and analyzed thematically with an LLM.

4. Results and Discussion

Our mixed-method analysis yielded three key findings regarding truck stop infrastructure in high-risk counties. Spatial mapping revealed that 29% of FEMA-designated high-risk counties

lack either public rest areas or facilities operated by major truck stop chains, with notable infrastructure gaps in densely populated regions including areas surrounding San Francisco, Austin, New York, and New Orleans. Topic modeling of driver reviews identified parking availability (23% of topics), food services (12%), and restroom facilities (11%) as the predominant concerns, with sentiment analysis indicating more negative experiences in high-risk counties. These quantitative results were corroborated by expert interviews, which confirmed widespread parking shortages and highlighted communication failures during emergencies that compound infrastructure limitations for drivers navigating disaster zones. Together, these methods enabled a robust assessment of infrastructure capacity and challenges faced by drivers, and highlighted gaps in current policy and emergency readiness.

4.1 Spatial Analysis

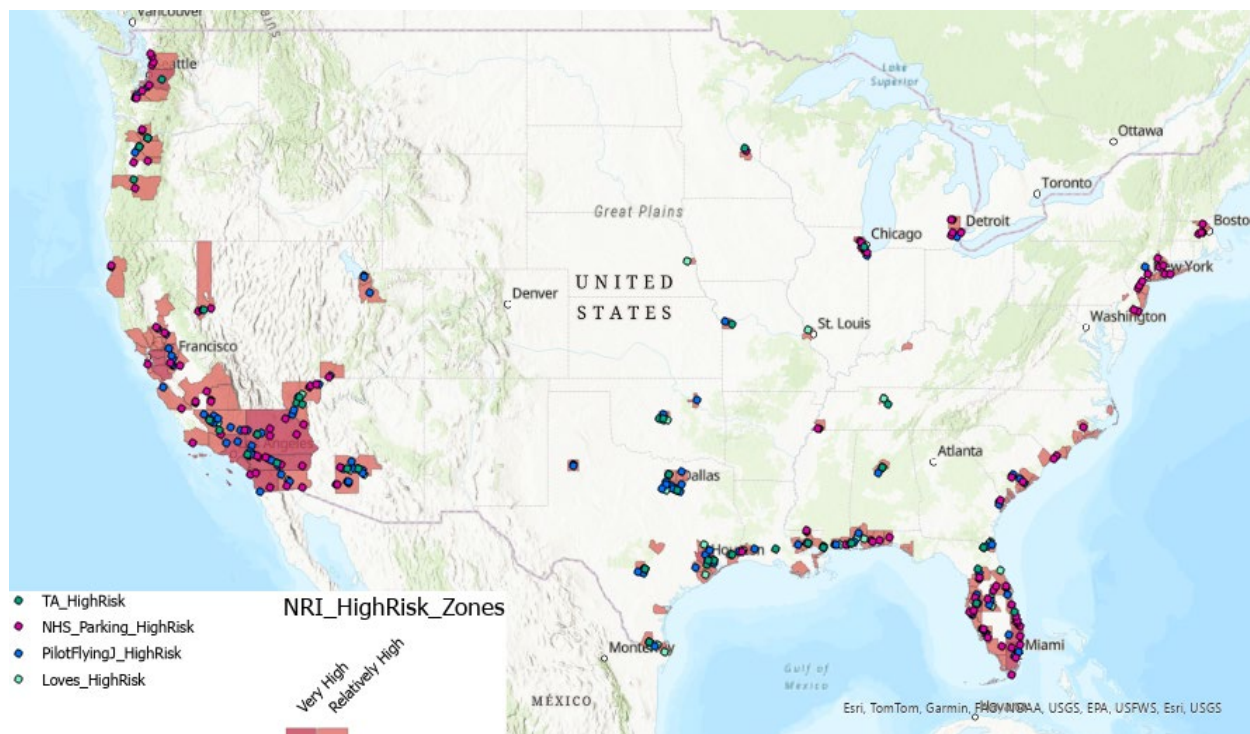
Our spatial analysis centered on three interrelated dimensions: the distribution of truck stops in high-risk counties, the identification of “truck stop deserts” (i.e., counties that have no truck stops from major commercial providers), and the spatial relationship between truck stops and critical transportation corridors. This three-pronged framework enabled a systematic evaluation of freight infrastructure's capacity to support driver needs and maintain supply chain resilience during emergencies.

As illustrated in Figure 5, our analysis integrated NRI hazard exposure data with truck stop availability to pinpoint regions where gaps may hinder freight mobility and emergency response efforts. Our results showed that 29% of FEMA-designated high-risk counties lack either publicly funded rest areas or facilities operated by the three largest national truck stop chains. Notable truck stop deserts emerge in densely populated regions, including counties surrounding San Francisco, Austin, New York, Philadelphia, and New Orleans. Particularly concerning is Florida's infrastructure gap despite its acute hurricane vulnerability, five of the state's 28 counties deemed “High-Risk” by FEMA lacked major national chain truck stops and public rest areas. This disparity highlighted critical infrastructure deficiencies in disaster-prone regions.

Through geospatial mapping, we assessed alignment between truck stop locations, critical freight routes, and emergency routes. While truck stops were typically clustered along interstate highway corridors, we identified multiple high-risk counties with sparse coverage along emergency routes. These truck stop deserts expose drivers to safety and regulatory risks, especially if they have exceeded daily driving time as defined by HOS regulations and cannot find a place to rest. In times of crisis, such gaps create dangerous chokepoints that could impede evacuation efforts and relief operations.

The results reveal stark geographic disparities. Southern California's high-risk counties contain a high-density cluster of 71 rest areas and truck stops along key freight corridors, reflecting robust infrastructure support. In contrast, regions with high population densities and freight activity – including New York, Long Island, Washington, D.C., and the San Francisco Bay Area – show limited commercial truck stop availability. The analysis identifies 42 high-risk counties lacking facilities from the three largest commercial operators, concentrated in densely populated states like New York and New Jersey, along with hurricane- and flood-prone regions of North Carolina and South Carolina.

Figure 5. Truck Stops and Rest Areas in High-Risk Counties



Expanding on the previous analysis, Figure 6 includes truck stops with reviews in our dataset to add qualitative insight into infrastructure performance in high-risk zones. By incorporating trucker review data, we identified 675 additional truck stops located in high-risk counties that were not captured in the original dataset of NHS public rest areas and the top three commercial truck stop chains. These independently reported locations – not consolidated from any existing infrastructure databases – reveal how existing datasets significantly underrepresent the facilities that drivers rely on in practice. Figure 6 illustrates the geographic distribution of truck stops in high-risk counties across U.S. census regions, using the enhanced dataset. The South contains the highest number of truck stops in high-risk counties (609), followed by the West (376),

despite the West having a much larger land area. In contrast, the Midwest and Northeast show far fewer truck stops, with only 71 and 45 respectively, raising concerns about infrastructure scarcity in these regions. The chart highlights clear regional disparities in infrastructure density, which may affect how effectively drivers can find safe and legal parking during disruptions. Together, the FEMA high-risk counties and augmented dataset demonstrate the value of supplementing official data with on-the-ground insights to more accurately assess coverage gaps and support freight resilience.

Figure 6. NHS Rest Areas, Major Commercial Truck Stops, and Truck Stop Review Locations in High-Risk Counties

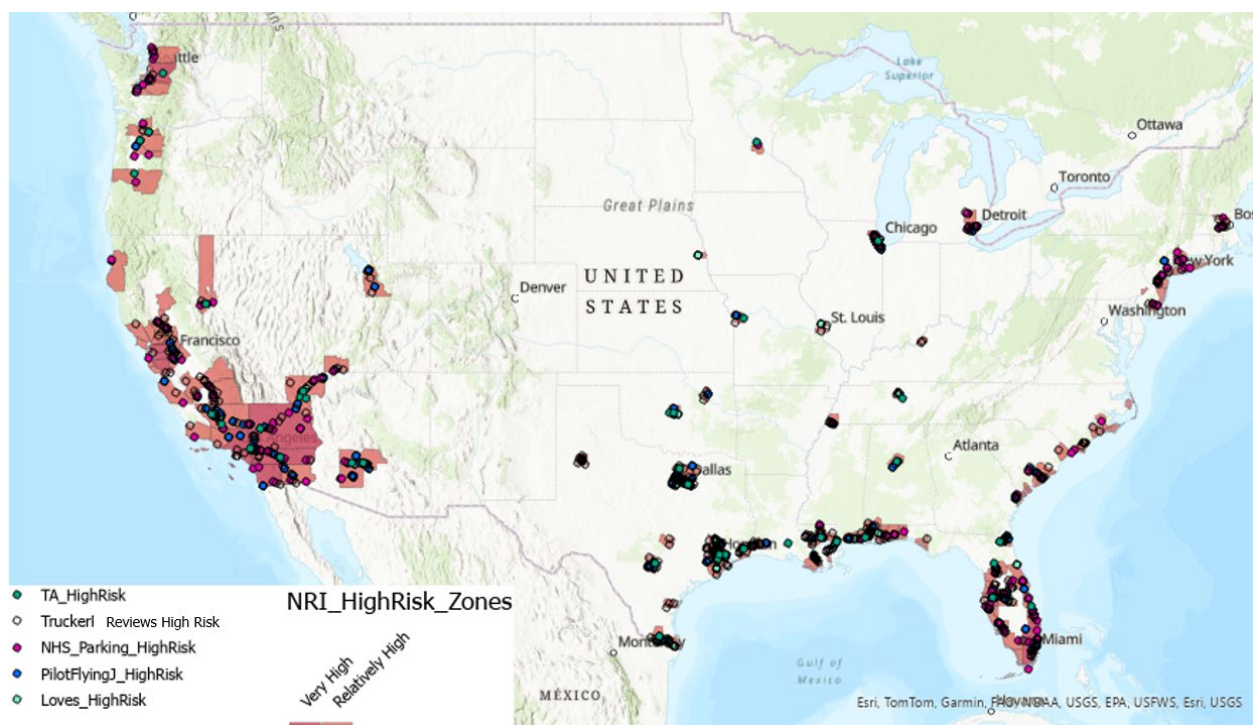
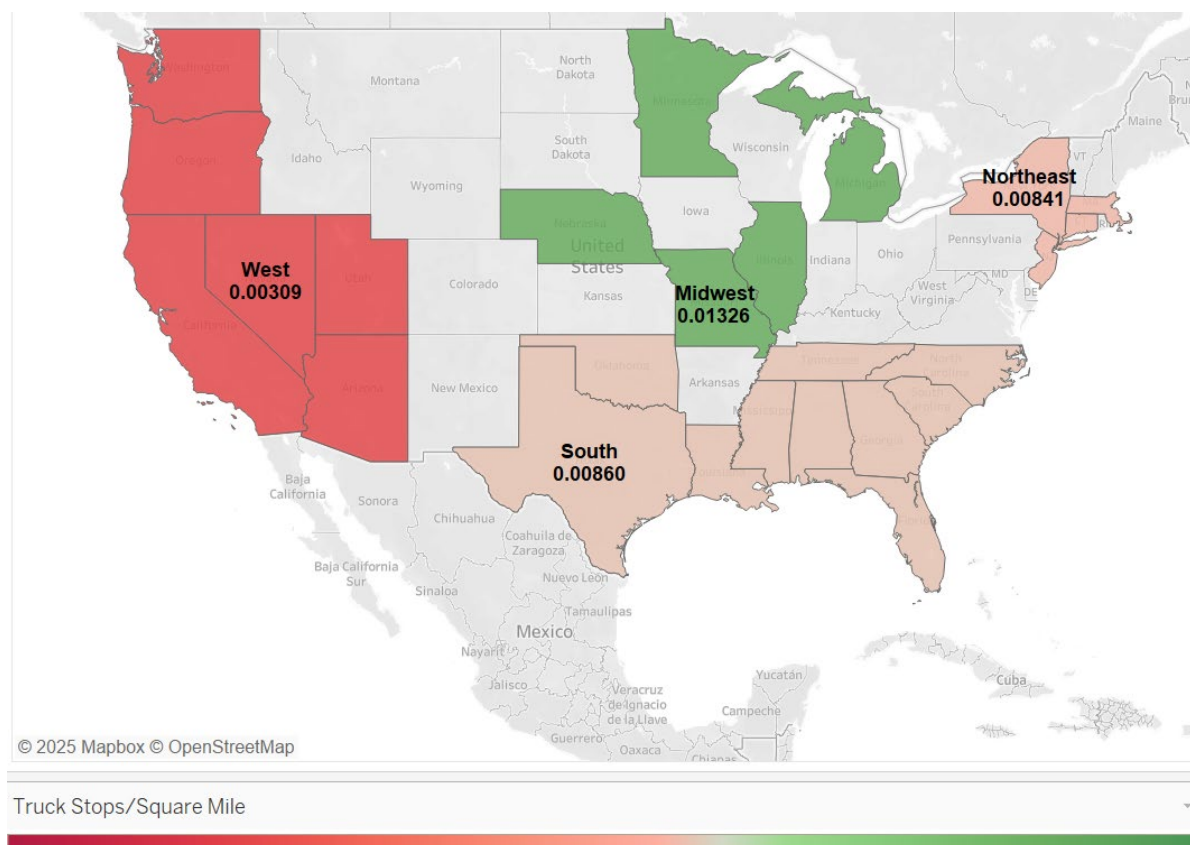


Figure 7 shows truck stop density per square mile of FEMA-designated high-risk areas across U.S. regions. Density varies widely: the Midwest has the highest (0.01326 stops per square mile), followed by the South (0.00860 stops per square mile), Northeast (0.00841 stops per square mile), and West (0.00309 stops per square mile). The Midwest's high density reflects its concentration of freight corridors, logistics hubs, and infrastructure, especially in Illinois and Minnesota. This supports better driver access to services even in high-risk areas. The West, despite major freight activity in California and nearby states, has the lowest density due to its vast geography and sparse infrastructure outside urban centers. This limits driver access to critical services during emergencies. The South and Northeast fall in the middle. The South combines

developed freight corridors with large rural zones lacking infrastructure. The Northeast's relatively high-density stems from dense population centers, smaller land area, and major freight routes.

Figure 7. Truck Stops per Square Mile of High-Risk Area, by Region



4.2 Parking Density Analysis

Literature reviews, topic modeling, and expert interviews repeatedly emphasized the lack of safe, accessible, and available parking as one of the most urgent and widespread challenges for truck drivers, especially during emergencies. Unlike other concerns – such as limited access to food or restrooms – parking shortages emerged as both a daily operational burden and a serious safety risk. These shortages often force drivers to violate HOS regulations or rest in unsafe conditions. Given how frequently these concerns appeared, we conducted a more detailed analysis of parking density using geospatial datasets from NHS rest areas and the top three commercial truck stop chains. While there is no comprehensive dataset that captures amenities like the number of showers or restaurants nationwide, we were able to obtain data on the number of parking spaces at these public and commercial truck stops. This allowed us to quantify parking availability and assess how equitably it was distributed across the U.S. We then evaluated

coverage by county, census division, and region to determine whether spatial data confirmed the concerns raised in interviews and topic modeling of truck stop reviews.

Figure 8 shows the total area (in square miles) of high-risk counties by census division. The Pacific division stands out, with over 94,000 square miles of high-risk land – more than double the next highest division, the South Atlantic (41,617 square mile). This high spatial area exposes these places to substantial logistical pressure on emergency routes, especially when compounded by diverse topography and long distances between nodes. Other regions with substantial high-risk land area include the Mountain and West South-Central divisions, which may be a result of widespread seismic risk. This indicates that Western and Southern states may require more resilient and expansive truck stop infrastructure.

Figure 8. Regional Exposure: Area of High-Risk Counties

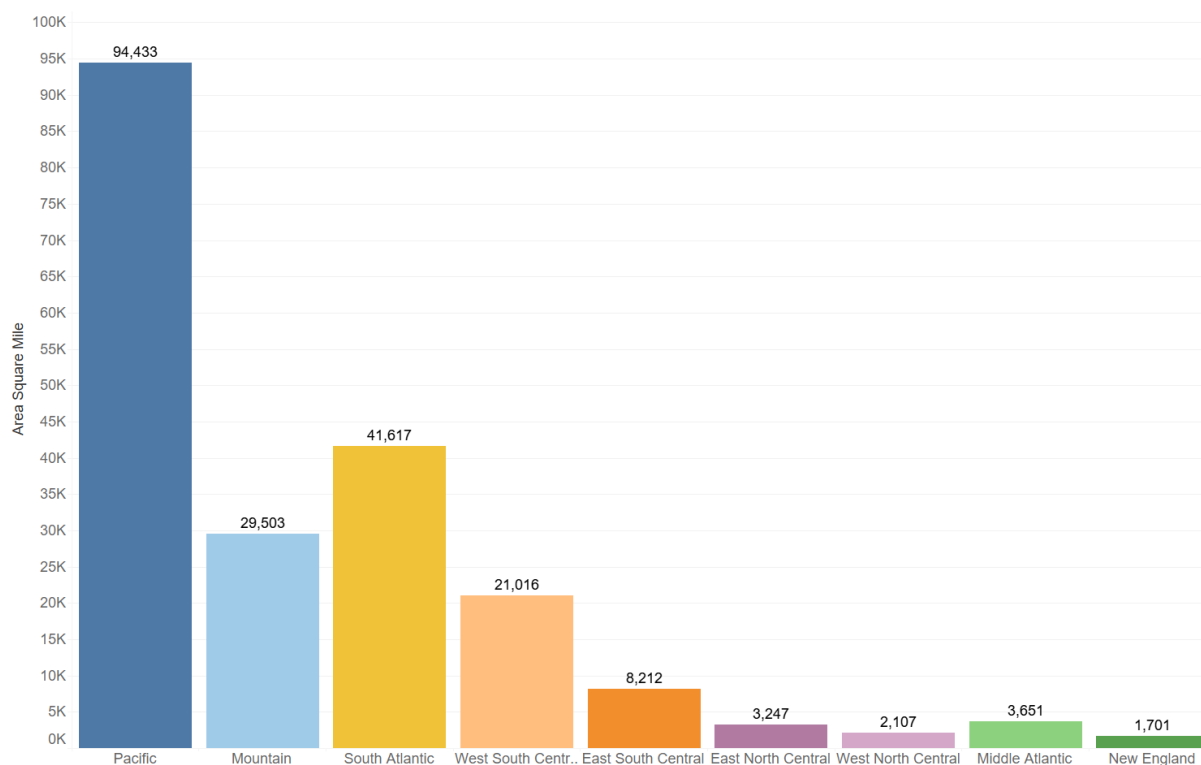


Figure 9 represents the number of truck parking spaces located in high-risk counties. The Pacific division again leads with 9,729 spaces, followed by the West South-Central division (7,462 spaces) and South Atlantic (5,741 spaces). However, absolute parking spot counts were deceiving when not normalized by geographic area. For example, the Mountain division has nearly 30,000 square miles of high-risk land but fewer than 4,000 truck parking spaces. This imbalance suggests limited accessibility during emergencies and could force drivers into unsafe or informal parking situations in already hazardous regions.

Figure 9. Parking Supply: Spaces in High-Risk Counties

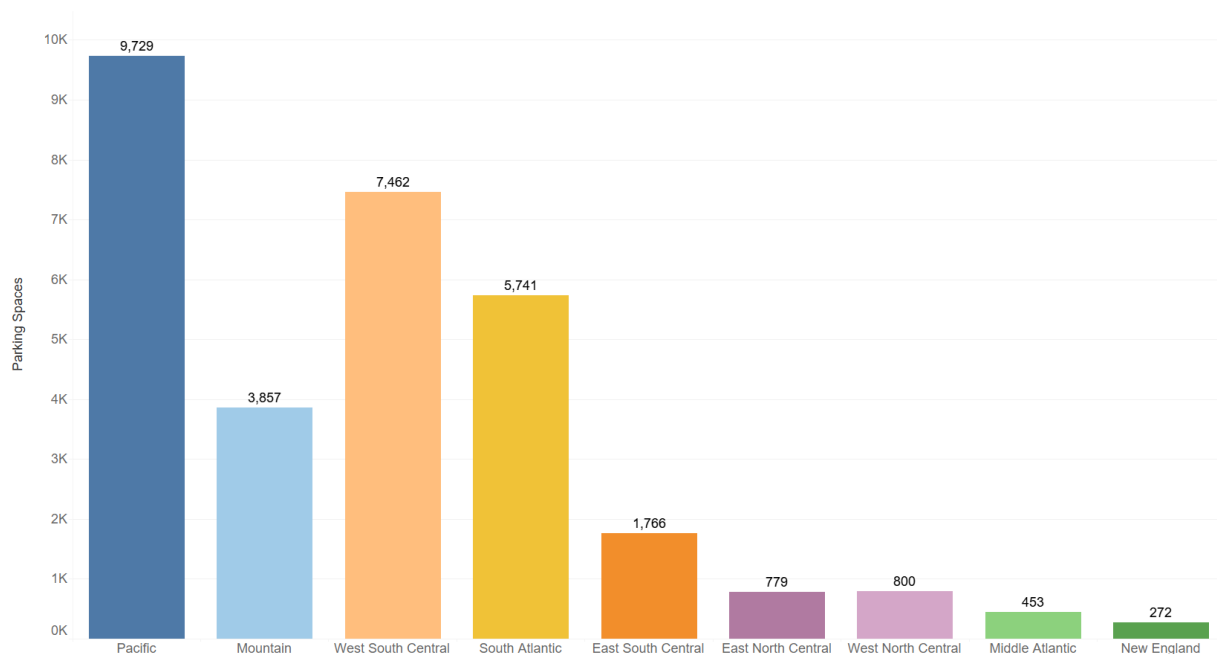
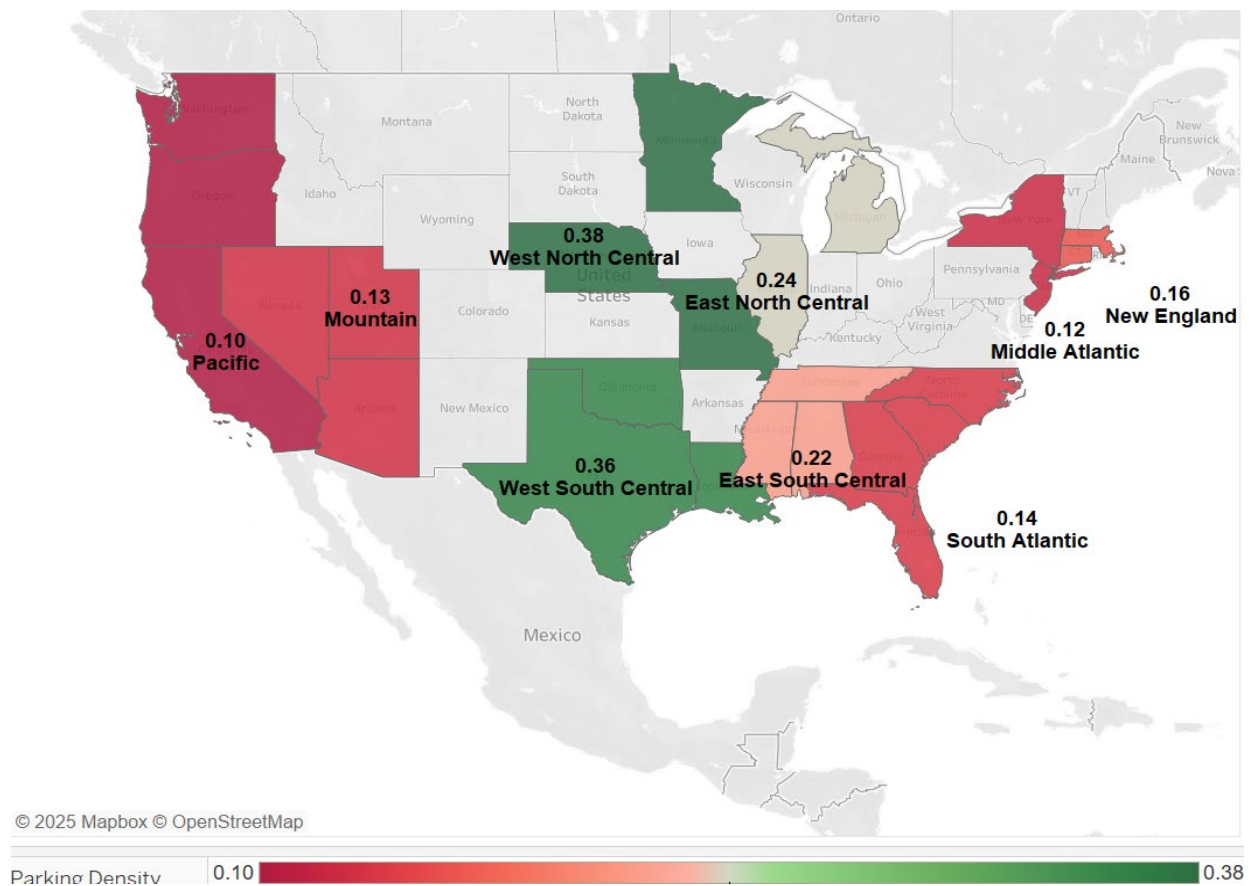


Figure 10 illustrates the parking density (spaces per square mile) of truck parking infrastructure across different divisions, revealing significant disparities in how infrastructure is distributed relative to land area. The West North-Central and West South-Central divisions have the highest densities at 0.380 and 0.355 spaces per square mile respectively, supporting driver accessibility and mitigating unsafe parking. Despite having the highest total number of parking spaces, the Pacific division has the lowest density at 0.103 spaces per square mile, indicating that parking is spread thinly over vast geographic areas. This mismatch reduces practical utility, especially during emergencies such as wildfires, earthquakes, or other crises, when evacuation or rerouting pressures increase. Together, these findings highlight that truck parking infrastructure in many high-risk counties is not proportionate to land area or crisis risk. The Pacific and Mountain divisions face compounded vulnerabilities due to wide geographic risk zones, low infrastructure density, and increased pressures from emergency evacuations and freight rerouting. From a planning perspective, improving truck parking infrastructure in these regions requires not only adding parking spaces but strategically locating them along high-volume freight corridors and within counties experiencing the greatest vulnerability to risk.

Figure 10. Parking Density by Division



4.3 Topic Modeling

The identification of truck stops in high-risk counties allowed the truck stop review data to be segmented into high-risk and non-high-risk counties and enabled topic modeling across dimensions of time, region, and vulnerability to risk. The truck stop review data was fed into three models, with the trigram model resulting in the most semantically useful clusters, which was consistent with early experimentation clustering different n-grams as described in Section 3.2.3.

For each data segment (as defined in Section 3.2.1), all models were configured to visualize the most frequently occurring topics in a bar chart for positive, neutral, and negative reviews. As such, each data segment produced three bar charts. This output allowed clear and nuanced interpretation of the most common topics in each segment of data. For example, in the Western U.S., pre-COVID-19, and high-risk segment, truck stop reviews were categorized by positive, neutral, and negative sentiment. A separate bar chart was created for each sentiment category. In each chart, each bar represents a group of n-grams that the model identified as describing the same topic, with one representative n-gram used to label the topic.

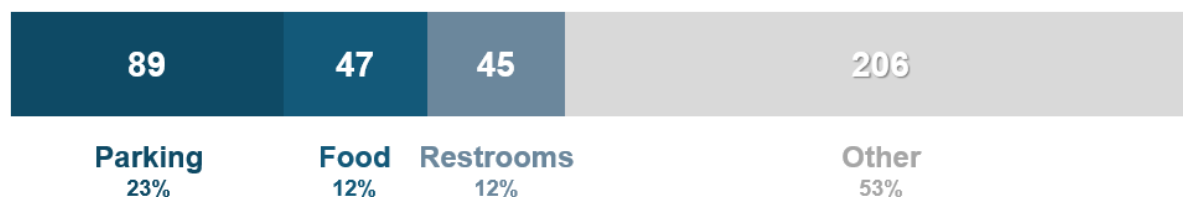
The results of the word frequency count model, shown in Appendix B and Appendix C, gave predictable and uninformative results, with words such as “parking”, “shower”, and “truck” appearing frequently. Although it was valuable to understand the frequency of words, they were uninformative as they lacked context. The second bigram-based model, shown in Appendix D and Appendix E, combined words that commonly occurred together, such as “parking” and “lot”, which was a marginal improvement on the first model. In the word frequency model, these words would have appeared separately when they were likely used in conjunction given the context. However, these labels still were not informative enough to explain why “parking lot” was resurfacing so often.

The trigram model was able to rectify this issue by providing the most informative cluster labels without introducing excessive noise, the results of which are shown in Appendix F and Appendix G. This improvement is mostly attributed to conducting dimensionality reduction (according to Section 3.2.3) and clustering with HDBSCAN.

By reducing the default value of the `n_neighbors` parameter, this ensured that local semantic patterns in truck stop reviews were preserved. This is demonstrated by the nuanced references to themes such as parking, where the model considered trigrams such as “big parking lot” and “small parking lot” distinct. Clustering with HDBSCAN also improved results by dropping outliers (i.e., trigrams that did not belong to any topic), automatically determining the number of clusters (i.e., relevant topics within a segment), and accommodating irregularly shaped clusters (i.e., grouping semantically related trigrams that may not appear obviously similar) – all key advantages for semantic data analysis. Because the model determined the number of topics, each bar chart contains a different number of bars, and similar topics may appear together in the same chart. For example, one bar chart might include both “big parking lot” and “parking food shower” as separate, yet thematically related, trigrams. The full results are available in Appendix F and Appendix G, with sensitive topics or references to individuals removed.

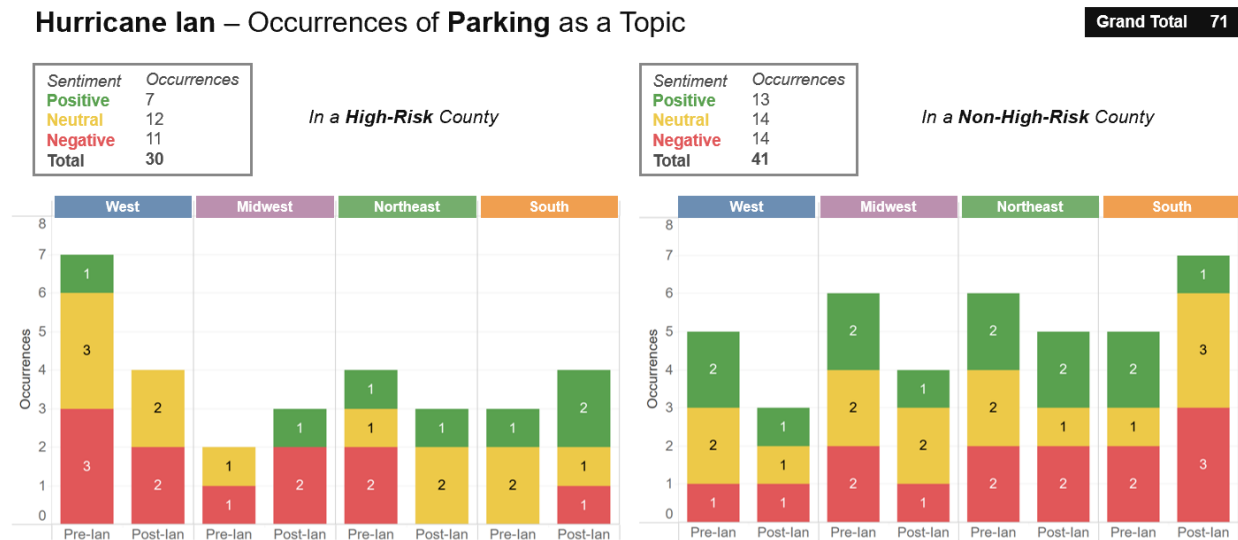
After reviewing all trigrams and grouping similar topics, three themes emerged: parking, restrooms, and food. Topics that were not semantically useful or uninterpretable (e.g., “hard earn money”, “great sunglass read”) were categorized as “other” and excluded from our analysis. The main themes and their relative proportions are shown in Figure 11.

Figure 11. Themes from Topic Modeling by Frequency of Occurrence



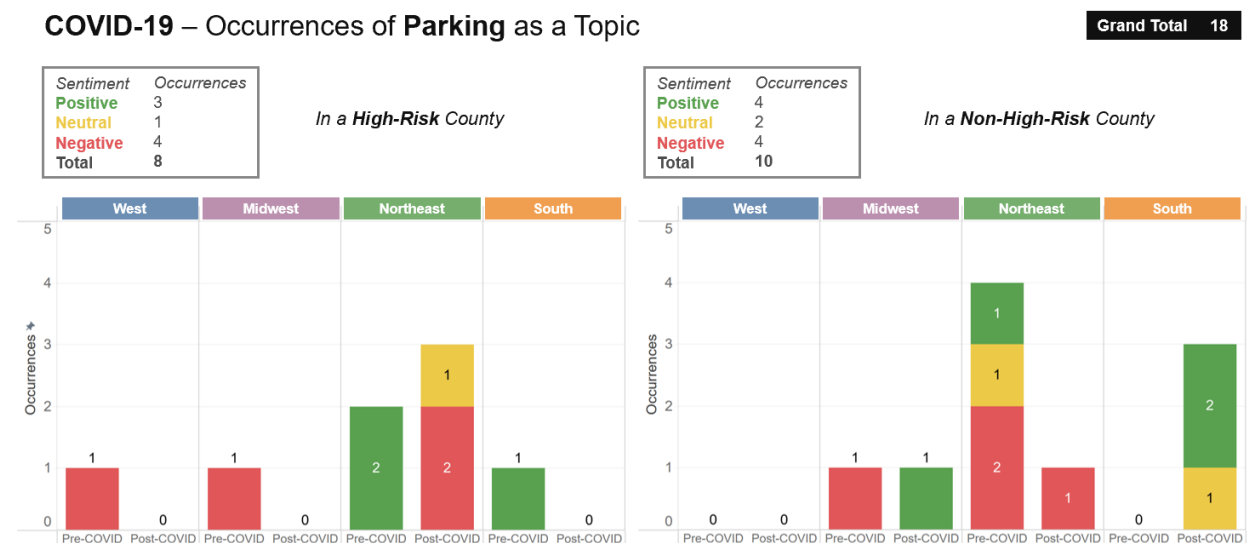
Parking was the common topic discussed, representing 23% of all topics generated by the trigram model. In the Hurricane Ian dataset, parking appeared 71 times, appearing more frequently in non-high-risk counties (41 times) than in high-risk counties (30 times) – these results are available in Figure 12. However, the frequency of occurrence in parking related topics indicates its importance to truck drivers across the U.S., regardless of regional vulnerability to risk. In high-risk counties, sentiments toward parking skewed more negatively than in non-high-risk counties. Deeper investigation revealed that the phrase “big parking lot” was responsible for 35% of positive mentions about parking, and “small parking lot” and “paid parking” were responsible for 24% of negative mentions about parking – this is summarized in Appendix H. This indicates that drivers gave higher scores to truck stops with large parking lots, and lower scores for truck stops with small or paid parking lots. Regionally, Western and Southern U.S. discussed parking the most. Since Hurricane Ian directly impacted the Southern U.S. region, it is reasonable that the demand for supplies and disaster relief translated into higher demand for freight services, and subsequently, truck parking.

Figure 12. Occurrences of Parking as a Topic Before and After Hurricane Ian, in High-Risk and Non-High-Risk Counties



Parking was also the top theme in the COVID-19 dataset but appeared at a lower frequency compared to Hurricane Ian (18 times) – the results are shown in Figure 13. Sentiment was mixed but fewer neutral reviews were seen, indicating more polarized opinions on truck stops during this period. As shown in Appendix I, references to “big parking lot” accounted for 43% of all positive mentions of parking, and “paid parking” accounted for 50% of all negative mentions of parking, a similar effect as seen in Hurricane Ian. These findings are consistent with the severe parking shortage in the U.S., as drivers prefer parking lots that are free and available over the opposite. Regionally, most discussion of parking was concentrated in the Northeastern region, which was also a region that experienced truck stop closures throughout COVID-19 (National Safety Council, 2020; Sperry et al., 2022). The overall lack of parking discussion compared to Hurricane Ian could reflect volatile market conditions during COVID-19, disrupting predictable demand patterns for trucking services and subsequently, the demand patterns for parking (Karam, et al., 2022).

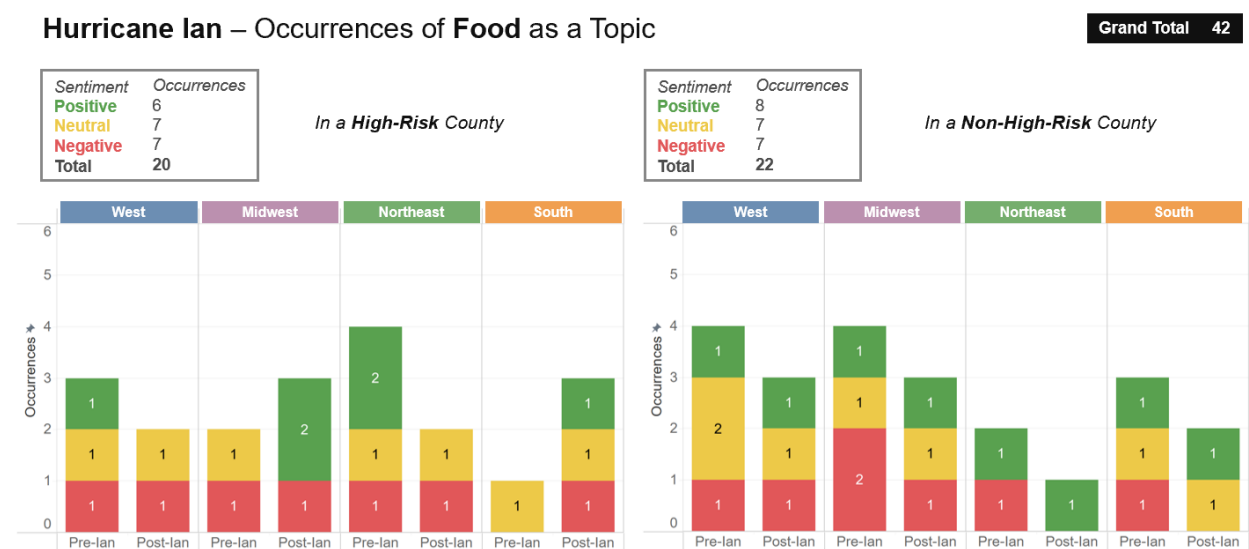
Figure 13. Occurrences of Parking as a Topic Before and After COVID-19, in High-Risk and Non-High-Risk Counties



Food was the second most discussed topic in our dataset, representing 12% of all topics discussed. Trigrams used to describe food were not as informative compared to parking. References to parking provided specific information about the size and cost of parking lots, where most food-related references were general (e.g., “parking food shower”), or regarding specific establishments (e.g., “burger king dunkin”, “carl’s jr”). During Hurricane Ian, food-related topics occurred almost equally across high-risk and non-high-risk counties, with a balance of positive, neutral, and negative sentiment. The Western and Midwestern regions discussed food-related

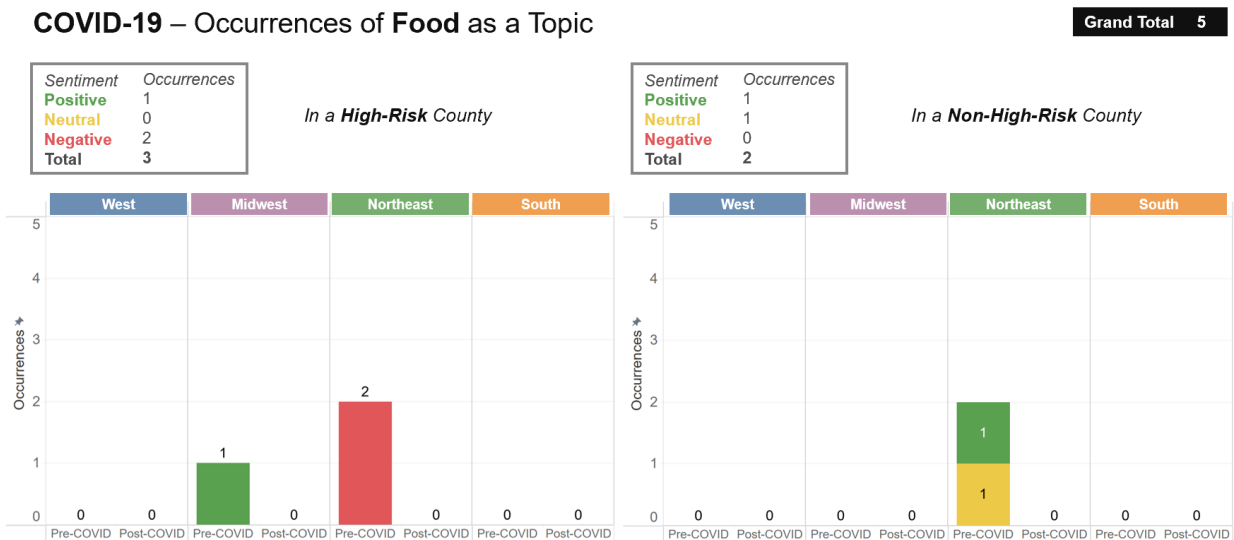
topics the most, with the West specifically seeing a reduction of food-related discussion after Hurricane Ian. Interestingly, this same trend was exhibited across all regions in non-high-risk counties. Food does not appear to be a distinct topic of discussion in the South, where Hurricane Ian directly impacted. Less food-related discussion post-Hurricane Ian or in the South could be a result of fewer drivers on the road due to safety concerns, fewer establishments being open, or drivers preparing their own meals due to the uncertainty of infrastructure access. Two isolated references were helpful in understanding what food-related preferences drivers had, such as positive reviews referencing “hot food inside” and food optionality (e.g., “plenty food option”). These results are summarized in Figure 14. The consistent references to food across high-risk and non-high-risk counties indicate equal importance placed on food regardless of vulnerability to risk during Hurricane Ian.

Figure 14. Occurrences of Food as a Topic Before and After Hurricane Ian, in High-Risk and Non-High-Risk Counties



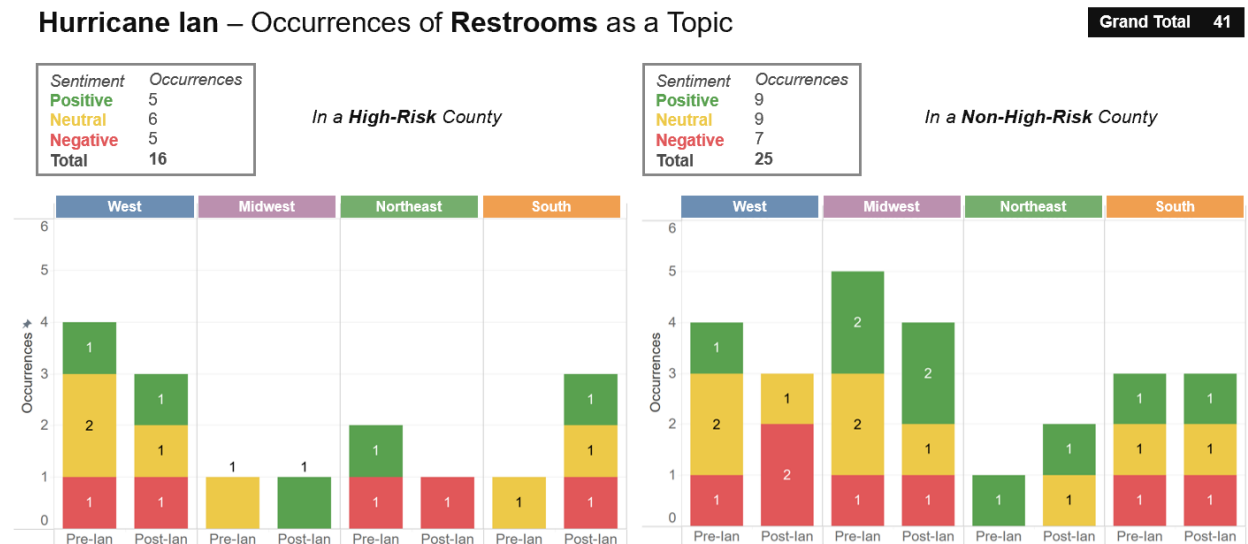
In the COVID-19 dataset, food-related topics appeared a few times, but only within the regions of the Midwest and Northeast. Further examination of the food-related trigrams revealed one negative topic that was informative – “food glanced grossness” – which could indicate a decline in food quality during this period. The results of food-related discussion in the context of COVID-19 are shown in Figure 15.

Figure 15. Occurrences of Food as a Topic Before and After COVID-19, in High-Risk and Non-High-Risk Counties



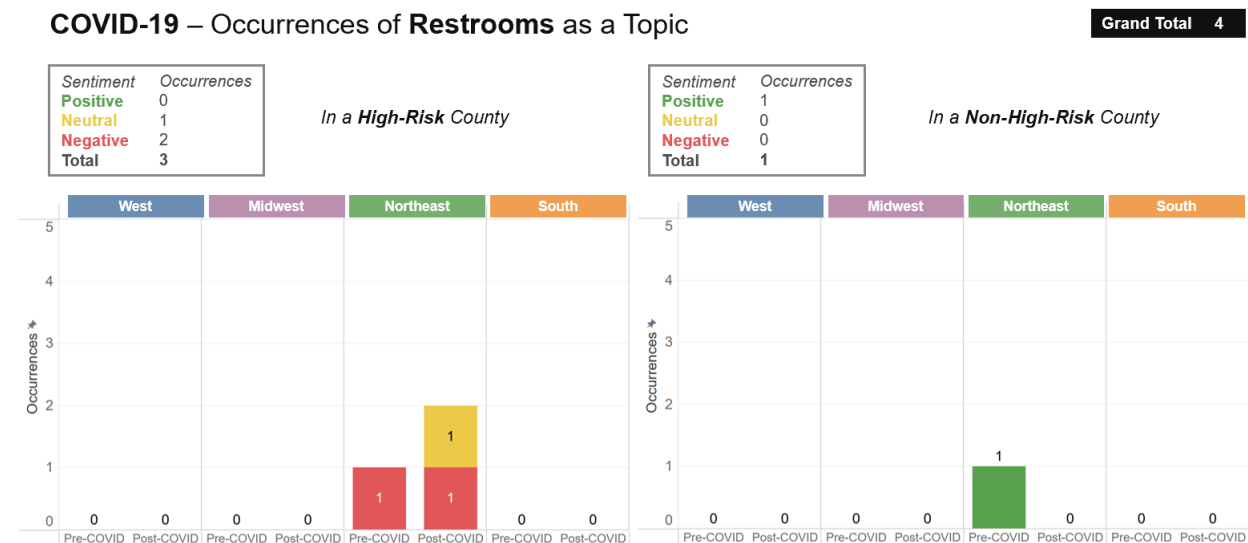
Restroom facilities were the third most discussed topic in our dataset, appearing 45 times. Showers were the most common amenity discussed but there were also references to bathrooms. The Hurricane Ian dataset contained most topics related to restrooms, with 25 occurrences in non-high-risk counties and 16 occurrences in high-risk counties, indicating that restrooms may be of greater importance in non-high-risk counties. Sentiments in non-high-risk counties were more positive compared to high-risk counties, which could indicate better serviced facilities in non-high-risk counties. Regionally, most discussion of restrooms were in the Western U.S., and no clear patterns were observed in the South as a result of the hurricane. However, investigation of trigrams revealed that facility cleanliness explained 29% of positive mentions about restrooms, with trigrams such as “clean shower good” appearing as a positive topic. This aligns with truck drivers’ needs, as truck cabs typically do not have restrooms, and clean facilities are a necessity for personal hygiene (Krasniuk, et al., 2024). There were also three isolated references to shower quality (e.g., “good water pressure”, “shower hot water”) that may inform a need for high quality bathing facilities. These results are shown in Figure 16.

Figure 16. Occurrences of Restrooms as a Topic Before and After Hurricane Ian, in High-Risk and Non-High-Risk Counties



The COVID-19 dataset only discussed restrooms four times, with half of the instances being direct references to facility cleanliness. The lack of discussion surrounding restrooms aligns with social distancing policies implemented during this period, which resulted in many shower facilities being closed or reduced in operational hours (Crizzle, et al., 2021). These results are shown in Figure 17.

Figure 17. Occurrences of Restrooms as a Topic Before and After COVID-19, in High-Risk and Non-High-Risk Counties



Outside the three major themes, there were several intriguing but scarce trigrams that were informative in learning drivers' needs. Customer service-related trigrams (e.g., "friendly staff

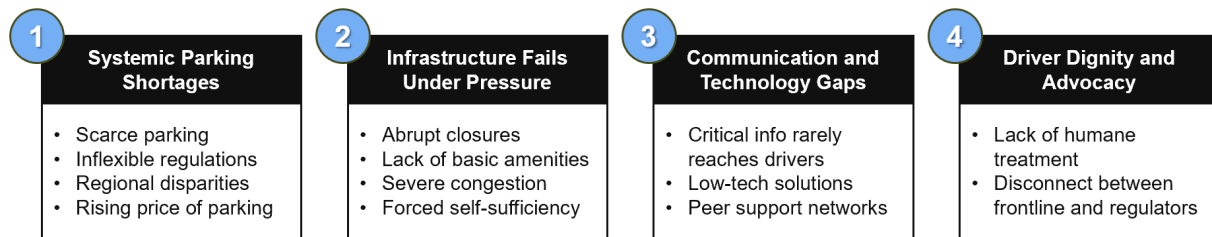
clean”, “horrible customer service”) showed up only six times overall, despite truck stops being a service-based business. It may indicate that staff friendliness and quality of service is a lesser factor in truck stop selection and appeal. Health-related trigrams (e.g., “copay doctor visit”, “doctor visit med”, “driver license health”, “insurance month deductible”), were concentrated only in high-risk counties in Pre- and Post-COVID-19 segments, primarily in the South. Although there were only four mentions overall with no clear affiliation to sentiment, their concentration in COVID-19 time periods indicated a heightened importance towards health-related services. The bigram model also contained a single isolated cluster labeled “wear mask” in a Post-COVID-19 segment, which further adds to the narrative of health importance in the months after pandemic onset. This aligns with healthcare initiatives implemented during COVID-19, such as mobile testing and vaccination sites deployed to truck stops in Philadelphia and mobile health clinics operated at select Pilot Flying J locations in the U.S. (Kellner, 2020; Stinson, 2020).

Three singular references also caught our attention due to their unique and informative nature: “woman ‘s bathroom” associated with positive reviews, “park outside shoulder” associated with neutral reviews, and “accept fleet card” associated with positive reviews. The first trigram could indicate a need for safer or cleaner washrooms for female truck drivers, which is consistent with literature regarding a systematic lack of safe facilities for women in trucking (Huffman and Shirk, 2024; Brooks, 2025). The second trigram may be referencing a lack of parking resulting in drivers needing to park illegally, although the neutral sentiment does not point to a clear conclusion. The last trigram could indicate drivers’ desire to use truck stops that accept corporate fuel cards, which is consistent with a survey of truck driver preferences stating that fuel card acceptance is a key factor in truck stop selection (Toner, 2023).

4.4 Expert Interviews

Findings from topic modeling analysis confirmed the importance of key services – parking in particular – and highlighted notable trigrams for further investigation. These insights informed our interview guide and selection of interview candidates. Our expert interviews validated several findings and added depth to the topics surfaced through topic modeling, as shown in Figure 18.

Figure 18. Key Interview Themes



The primary issue that our interviewees discussed was an overwhelming lack of parking infrastructure. Interviewees with first-hand trucking experience validated the difficulty associated with finding parking in the status quo. Even under normal conditions, drivers must carefully plan their routes around scheduled stops. This is largely due to strict federal regulations, including HOS limits and the mandatory use of Electronic Logging Devices (ELDs), which track key engine data and enforce driving time restrictions. These rules reduce a driver's flexibility to find parking on short notice, making prior planning essential. There can be regional disparities in parking offerings – Southern states such as Texas were named as having more spots, whereas mid-Atlantic states had inconsistent quality and availability. Brent Hutto, Chief Relationship Officer at Truck Parking Club, said that when truckers are parked on the side of roads, it is usually out of need. This is due to legal parking spots being full and driving time being exhausted for the day (personal communication, April 11, 2025). Finally, some interviewees described the decline of free parking spots as paid parking was implemented in several commercial chains, some of which have surge pricing during peak demand. Company drivers are particularly frustrated by this trend as their parking fees may not be reimbursed (personal communication, March 6, 2025).

Drivers that choose to park illegally are exposed to the risk of being towed or fined when their decision may not be out of choice, but necessity. One issue raised by participants is the emergence of predatory towing practices, as some experienced or witnessed commercial vehicles being towed in areas that have historically accommodated trucks without issue. As regulations tighten, participants fear that some parking locations are becoming profit centers for aggressive enforcement. A senior fleet operator shared, “There are places drivers parked for 20 years, now they’re getting towed. I recently had a truck towed — cost \$20,000” (personal communication, March 7, 2025). Such excessive fees can have devastating financial consequences, especially for independent owner-operators and small fleets with limited margins. The escalating enforcement of informal parking areas not only adds economic strain but also exacerbates the stress and operational uncertainty drivers already face in a constrained parking environment.

Drivers with experience transporting FEMA loads stated this problem becomes more severe during disasters, largely due to the unpredictable and chaotic nature of crises. Many truck

stops were closed abruptly during COVID-19 and parking lots cordoned off, leaving drivers stranded without access to basic services or safe places to stop. Drivers transporting emergency supplies may be subject to even more volatility. One driver who hauled for the Red Cross reported camping in their truck for days or weeks, with limited access to bathrooms and food (personal communication, April 21, 2025). During emergencies, affected areas suffer from heightened congestion, making it logistically challenging to access truck stops or parking lots, even if they are available. Should an area lose power, it would render an entire region non-functional – including any available truck stops. Participants stated that truck stop parking lots also become inaccessible during this time, as stores without power are likely closed, along with the lots themselves. This forces drivers to be self-sufficient by preparing food, tools, and emergency supplies in anticipation that their surrounding infrastructure and amenities will be unavailable. Although emergency preparedness is a valuable skill, this places immense pressure on the people responsible for transporting critical goods to communities in need. It was stated that HOS constraints are sometimes relaxed during this period, making it possible for drivers to have flexible hours given the unpredictability of a crisis situation. However, this is not the norm and not uniformly enforced across states (personal communication, April 21, 2025).

Another topic of discussion was the need for consistent and reliable communication, especially during emergency operations. Participants stated that during crises, key information often fails to reach drivers in time. One participant emphasized that during COVID-19 and Hurricane Sandy, which was a tropical storm that devastated the Mid-Atlantic region in October 2012, there was no real-time communication to truckers when facilities shut down or roads were closed, which left many drivers stranded without options. Although new software and applications continue to be developed, they are criticized for lacking real-time information, such as when truck stops reach capacity or are unexpectedly closed. This leads to inaccurate route planning decisions and places drivers in compromising situations. Due to the failures in centralized communications and lack of reliable tools, drivers must be resourceful to ensure their safety and preparedness. This has enabled the creation of peer support networks, often supported by simple yet reliable technologies such as citizens band (CB) radios. As CB radios work in remote areas with poor cell service, it serves as a lifeline during emergencies. Drivers will share crucial information such as parking availability, road closures, and delays with those in their vicinity. As Jess Graham, a seasoned owner-operator and industry veteran, says, “CBs are still how we talk. Apps are fine when they work, but in a disaster? It’s old-school radio that keeps you safe” (personal communication, April 21, 2025).

The last theme that emerged was the need to acknowledge truck drivers' crucial role in infrastructure planning and policy decisions. Despite truck drivers being essential to maintaining supply chains, they often operate under conditions that lack basic respect for their time, safety, and well-being. From limited access to safe and legal parking to the absence of essential services during emergencies, many aspects of the current freight system neglect the human side of logistics and everyday realities faced by drivers. This is most evident during crises, when drivers delivering life-saving supplies may be forced to sleep in trucks without reliable access to power, hygiene facilities, or food. Graham states, "Anytime you lock us out of the building, that means that we are pushed into less than humane circumstances... when you're denied a basic human right and you're out here trying to do a service for the community, it kind of feels disheartening" (personal communication, April 21, 2025). Her words speak to a broader reality where drivers are often treated as expendable, despite performing essential public service work. Concerns were also raised about the unique challenges faced by female truck drivers, particularly the lack of suitable amenities, which contribute to unsafe conditions. Alix Miller, the President and Chief Executive Officer of the Florida Trucking Association, says that "unsafe or poorly lit parking areas, inadequate restroom facilities, and harassment concerns deter many women from entering or staying in the profession" (personal communication, March 11, 2025). Her comments showcase the gendered barriers faced in trucking, which are only exacerbated during emergencies.

4.5 Discussion

As essential workers, truck drivers deserve safe, functional, and dignified working conditions – but unlike traditional workplaces, their "office" spans highways, rest areas, and truck stops, where standards of safety and support are highly inconsistent. If drivers are expected to deliver on their job responsibilities, their work environment must be in a safe and humane condition. Currently, there are no federal standards that regulate truck stop quality or availability. Although HOS rules exist to regulate when breaks must be taken, this increases demand for safe and accessible truck stops but does not regulate truck stops themselves. The federal Surface Transportation Assistance Act (STAA) mandates that states must allow commercial motor vehicles (CMV) reasonable access from highways to food, fuel, lodging, and rest facilities, but does not regulate any component of these facilities (49 U.S.C. § 31114, n.d.). As such, truck stop service offerings vary greatly, which include the availability of services (e.g., parking, food, restrooms), pricing (e.g., use of surge pricing), and cleanliness of facilities.

Our findings confirmed the importance of parking as an essential service for truck drivers nationwide, juxtaposed by a fundamental mismatch in infrastructure availability. Topic modeling

confirmed parking as a key discussion topic in driver reviews, with large, free parking lots receiving positive mentions and small or paid lots drawing criticism. In high-risk counties, negative sentiments about parking were particularly common, highlighting how infrastructure scarcity forces drivers into difficult trade-offs between regulatory compliance and personal safety. During a crisis, these negative perceptions about lack of parking may deter truck drivers from entering damaged areas or supporting disaster relief movements out of concern for their own safety.

Spatial analysis revealed that 29% of FEMA-designated high-risk counties are not serviced by either a public rest area or one of the three largest national truck stop chains as shown in Figure 5. Areas lacking truck stops are not limited to remote regions; they surround densely populated urban centers such as San Francisco, Austin, New York, Philadelphia, and New Orleans, as well as disaster-prone areas like Florida, where five high-risk counties lacked any national chain or public rest areas. This may be due to the lack of land availability in densely developed urban areas, resulting in fewer major truck stop chains and rest areas. These gaps exemplify the infrastructure shortfall in regions that are highly populated, vulnerable to natural disasters, and economically vital, where disruptions could quickly ripple through national supply chains and the overall economy.

Although our dataset does not reflect the presence of smaller, independently operated truck stops in these areas, national chains account for half of truck parking capacity in the U.S. and serves as a proxy for measuring true parking availability. The absence of truck stops within high-risk counties – especially those near major freight and population centers – raises serious concerns about the resilience and equity of the current infrastructure network. Compounded with inconsistent service availability and quality, these systems crumble during emergencies and expose drivers to undue risk and dangers while performing an essential service.

Unfortunately, the consequences of these infrastructure gaps typically fall on the driver. If a load is delayed, parking regulations are violated, or an accident occurs due to fatigue, it is the driver that bears most of the legal, financial, and safety risks. Current policies intended to protect drivers lack a practical, human-oriented view that addresses drivers' needs, especially in emergencies. If existing infrastructure becomes unavailable, basic provisions such as shelter, food, water, and fuel must be ensured. The freight network must be resilient to disruptions, ensuring that central communication systems can effectively disseminate critical, real-time information. Additionally, backup power supplies should be available at key stopping points to maintain operations during emergencies. These protections are necessary to ensure the safety and well-being of truck drivers and ensure the continuity of disaster relief and supply chain operations.

No stakeholders in the trucking ecosystem have a clear obligation to provide humane treatment or sufficient infrastructure. Advocacy efforts – often led by drivers themselves – highlight the disconnect between frontline experiences and institutional responses. Organizations such as the Owner-Operator Independent Drivers Association (OOIDA) and Real Women in Trucking, as well as independent voices in our interviews, have called for policies that prioritize human dignity alongside operational efficiency. Lewie Pugh of OOIDA captured the consequences of misaligned regulation, stating, “We’re passing laws that make [drivers] work like a machine. And of course, people are not machines” (personal communication, March 31, 2025). These rigid rules, such as strict HOS enforcement and limited parking options, often fail to accommodate the unpredictability and demands of long-haul driving. Delia Moon Meier, owner of Iowa 80 – otherwise known as the World’s Largest Truck Stop – further emphasized the human aspect of the industry, saying, “It’s a people business, and when you take the people out of it, you don’t necessarily get the best result” (personal communication, April 16, 2025). Elevating drivers’ voices in transportation planning is not just a matter of fairness – it is essential to building a more resilient, humane, and effective freight network. Policies shaped without the insights of those on the ground risk perpetuating systemic inequities and inefficiencies that compromise both driver welfare and the overall stability of supply chains.

The disconnect between expectations placed on drivers and operational realities not only compromises driver safety, but also weakens supply chain resilience, public safety, and a resilient workforce. Reframing the trucking workplace as a shared responsibility requires urgent action. Solutions must include expanding and modernizing the parking infrastructure, mandating minimum operating standards for truck stops, and involving drivers in infrastructure and policy development. Without these reforms, the industry will continue to externalize its risks onto drivers — a model that is unsustainable for both workers and the freight networks they support.

Ultimately, our capstone highlights a critical but often overlooked component of logistics: the humans who underpin freight systems. Truck drivers are essential workers who keep goods moving during both normal operations and crisis events. If they lose access to rest, information, or fuel, the freight network will fail — regardless of how robust the highways themselves appear. Our findings suggest that investing in resilient truck stop infrastructure is not just a matter of convenience, it is a matter of national preparedness.

5. Conclusion and Recommendations

This research underscores that truck drivers, while essential to the nation’s freight movement and emergency response, continue to face inconsistent access to safe, functional, and

humane work environments – particularly during crisis conditions when infrastructure vulnerabilities become most visible. Our findings highlight critical gaps in parking infrastructure, spatial disparities in truck stop availability, and regulatory shortcomings that increase risks and operational burdens for drivers. To address these issues, a multifaceted approach is needed.

First, parking capacity must be increased. Increasing the number and size of parking lots, especially in high-risk and high-demand areas, would alleviate routine shortages and provide the surge capacity necessary during disasters. Designing these facilities with flexibility for emergency staging and accommodating larger vehicle flows is essential to disaster preparedness. Additional funding should be allotted towards truck stop or rest area development in high-risk counties to ensure that vulnerable regions do not become truck stop deserts in the event of an emergency. Partnerships with local governments, businesses, or schools should also be pursued to establish surge parking capacity. For example, unused parking lots in local motor vehicle administration offices or shopping malls could be designated truck parking spaces in the event of a crisis. Infrastructure planning should incorporate all available parking locations into official datasets and emergency management planning to better reflect the full range of available capacity and improve responsiveness in times of crisis.

Second, truck stop infrastructure must be modernized nationwide. Parking availability alone does not ensure readiness, and infrastructure may still fail in a crisis if it lacks power or accessibility. A truck stop that experiences flooding, loses power, or sits behind a closed evacuation route is as accessible as one that does not exist. Truck stops should also be equipped with backup power systems to maintain access to essential services (e.g., fuel, showers, restrooms) when disasters disrupt the electrical grid. Pilot programs may be funded to retrofit truck stops in high-risk areas, especially for critical upgrades such as water storage, reinforced construction, and upgraded communication systems. Without such measures, drivers may find themselves stranded without basic necessities.

Third, establishing federal resilience standards for truck stop amenities would provide consistency and predictability to truck drivers' work environment and well-being. Baseline expectations for restrooms, showers, food options, and safety features would ensure that drivers have access to safe and consistent working conditions, regardless of location. A federal designation may also be created and given to truck stops meeting minimum emergency standards (e.g., backup power, communication capabilities) that allows them to serve as a hub for drivers during a state of emergency, supplemented by government incentives. These sites can serve as additional infrastructure and are valuable additions to state and federal emergency planning.

Fourth, expanding equitable access to existing parking infrastructure would help alleviate the already scarce capacity from becoming constrained. Policymakers should encourage the availability of free or low-cost parking, particularly for essential and emergency freight operations. In parallel, regulations should discourage surge pricing during periods of peak demand or crisis conditions to prevent exploitation of vulnerable drivers. Legal protections against predatory towing must also be strengthened. During emergencies, commercial vehicles providing relief or critical supply chain functions should not face excessive fines or unfair towing practices. Clear policies and enforcement mechanisms would protect drivers from financial harm and operational delays.

Finally, robust and real-time communication systems are necessary to ensure drivers have crucial information at their fingertips. Specifically, improving real-time information systems for parking availability and truck stop operational status can significantly enhance efficiency and safety. These systems must be designed to remain functional during power outages and other disruptions, allowing drivers to make informed decisions and avoid unnecessary risks. More government funding may be allotted to companies or university researchers that develop innovations in trucking communications.

Central to all of these recommendations is the principle of involving drivers directly in infrastructure and policy development. Formal mechanisms for driver input would ensure that solutions are grounded in real-world experience and address the actual needs of the workforce. This participatory approach recognizes that those who rely most on the system are also best positioned to identify its strengths and weaknesses. Doing so mitigates the risk of heightened attrition in an already high-turnover industry and would help to create sustainable conditions in which drivers can work long term.

A broader cultural shift is needed to reframe the trucking workplace as a shared responsibility. Treating truck drivers as essential frontline actors in the freight system – not just expendable workers – is critical to a safer, more resilient, and more equitable network. Policymakers, infrastructure providers, shippers, and emergency planners must acknowledge drivers as critical contributors to supply chain resilience and public safety. Ensuring they have the tools, facilities, and protections necessary to perform their work is not just an operational concern but a societal obligation. As one independent owner-operator powerfully stated during our interviews, “We deserve humanity. We are not nameless faces, and that’s all we seek out here — just to be treated with respect.” This simple yet profound appeal captures the human dimension at the heart of these policy and infrastructure challenges.

5.1 Limitations and Future Research

While this study provides a foundation for these recommendations, several limitations constrain its scope. The most significant is the incomplete nature of available parking data. Our analysis captured only a portion of the national parking capacity, primarily focusing on publicly funded rest areas and locations operated by the largest national truck stop chains. Many smaller and independently operated facilities were excluded. Creating a comprehensive national database of truck parking capacity and conducting updated spatial analyses would allow for a more accurate assessment of infrastructure gaps. Our analysis focused on spatial density and parking capacity rather than the availability or quality of other essential amenities (e.g., food, restrooms). These services remain crucial for drivers' welfare and should be further analyzed. Additionally, topic modeling was limited to a specific set of truck stop reviews and time periods, restricting the generalizability of findings. Future research should expand this dataset across a broader range of geographic regions and timeframes. Finally, although interviews with industry experts and former drivers enriched the study, the sample did not fully capture the perspectives of current drivers across all regions. Conducting additional interviews with active drivers and regional stakeholders would deepen understanding and enhance the representativeness of future studies. While limitations exist, the findings still offer a clear path forward. By implementing these recommendations and addressing the gaps identified, stakeholders can significantly improve working conditions for drivers and strengthen the resilience of the nation's freight and emergency logistics system.

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Appendix

Appendix A. Interview Questions

1. Could you describe your background in the trucking industry, regions you cover, and any experience you have with disaster response?
2. What are the features or amenities most important to you or your drivers, and which ones are more critical or less available during disasters?
 - a. Follow up: If you don't have access to the amenities you need, what do you do?
 - b. Follow up: Do you notice variations in truck stop quality or amenities across regions, especially during times of crisis?
3. When HOS regulations are relaxed, how does that change your routine and breaks?
4. What improvements in communication and technologies could help truckers navigate or access truck stops and crisis zones more efficiently?
5. What major improvements can the government or private sector take to improve the value, effectiveness, or usefulness of truck stops in the event of a crisis?

Appendix B. Word Frequency Model Results - Reviews in High-Risk Counties

Region	Pre-COVID-19 Onset Aug 2019 – Mar 2020 (7 mths)	Post-COVID-19 Onset Mar 2020 – Feb 2021 (11 mths)	Pre-Hurricane Ian Sept 2021 – Sept 2022 (12 mths)	Post-Hurricane Ian Sept 2022 – Aug 2023 (11 mths)	Total
WEST	Positive parking 141 lot 108 truck 105 place 87 get 85	Positive parking 176 shower 142 place 139 truck 130 stop 127	Positive parking 252 lot 166 truck 162 clean 157 place 152	Positive parking 194 shower 168 lot 144 clean 141 truck 134	2,495
	Neutral parking 453 spot 335 lot 305 truck 258 get 249	Neutral parking 610 shower 477 get 461 place 431 truck 425	Neutral parking 726 shower 593 place 423 lot 413 get 392	Neutral parking 501 shower 391 lot 295 spot 264 get 261	
	Negative parking 394 spot 314 place 233 truck 231 get 223	Negative parking 400 get 405 truck 383 spot 346 place 342	Negative parking 672 shower 382 get 356 spot 345 place 299 lot 299	Negative parking 566 shower 312 truck 305 place 295 get 288	
MIDWEST	Positive place 8 spot 7 parking 5 door 5 knock 4	Positive fuel 10 place 9 parking 7 stop 8 free 8	Positive food 20 good 13 parking 12 clean 11 truck 8	Positive parking 9 lot 7 place 6 food 6 restroom 4	617
	Neutral parking 56 truck 51 place 41 get 38 stop 38	Neutral parking 118 get 84 truck 75 place 71 lot 69	Neutral parking 124 truck 89 stop 65 lot 62 clean 60	Neutral parking 58 truck 51 place 41 shower 38 lot 37	
	Negative spot 96 parking 90 place 62 truck 59 park 54	Negative parking 137 spot 108 truck 89 place 88 lot 79	Negative parking 195 spot 104 shower 86 truck 83 place 81	Negative parking 150 truck 70 place 70 shower 52 pay 51	
NORTHEAST	Positive spot 4 parking 4 truck 3 allow 2 transflo 1	Positive spot 10 truck 7 parking 4 park 4 leave 4	Positive spot 10 parking 6 food 6 place 3 good 3	Positive parking 10 truck 5 spot 5 place 4 lot 3	19,156
	Neutral parking 29 truck 25 spot 24 park 18 place 16	Neutral truck 54 spot 43 parking 42 open 36 lot 25	Neutral parking 52 spot 41 truck 34 good 26 get 23	Neutral truck 43 parking 42 spot 35 ticket 24 get 22	
	Negative parking 11 stop 6 get 6 restroom 6 place 6	Negative spot 16 parking 14 place 13 good 9 fuel 8	Negative parking 13 spot 12 park 8 truck 8 fuel 7	Negative parking 6 truck 5 trailer 4 good 3 service 3	
SOUTH	Positive parking 109 truck 94 spot 79 stop 72 place 71	Positive parking 144 truck 106 spot 96 shower 91 place 89	Positive parking 234 shower 173 place 157 clean 141 truck 135	Positive parking 196 truck 137 shower 122 lot 113 food 109	14,557
	Neutral parking 444 spot 365 truck 306 lot 267 get 254	Neutral parking 640 truck 410 get 409 lot 405 shower 374	Neutral parking 933 shower 519 clean 470 place 445 lot 440	Neutral parking 829 shower 582 food 490 lot 366 place 365	
	Negative parking 902 spot 520 get 430 truck 403 lot 394	Negative parking 1187 spot 688 truck 586 get 577 place 483	Negative parking 1126 get 603 spot 599 place 559 truck 557	Negative parking 968 spot 441 shower 439 get 420 truck 416	
Σ	7,195	12,116	9,610	7,904	36,832

Appendix C. Word Frequency Model Results - Reviews in Non-High-Risk Counties

Region	Pre-COVID-19 Onset Aug 2019 – Mar 2020 (7 mths)	Post-COVID-19 Onset Mar 2020 – Feb 2021 (11 mths)	Pre-Hurricane Ian Sept 2021 – Sept 2022 (12 mths)	Post-Hurricane Ian Sept 2022 – Aug 2023 (11 mths)	Total	
WEST	Positive parking167 lot150 good135 truck129 stop123 Neutral parking360 shower337 spot316 lot309 get281 Negative shower143 lot139 parking135 place118 truck102	Positive parking335 place304 stop285 lot272 truck249 Neutral parking670 shower589 lot520 get505 place431 Negative shower253 parking206 place184 truck151 lot149	Positive parking538 lot419 clean393 shower346 food331 Neutral parking967 shower809 lot680 clean584 good540 Negative parking381 shower275 place258 lot226 stop199	Positive parking340 clean268 lot267 shower264 food238 Neutral parking638 shower501 lot440 food369 clean367 Negative parking239 lot157 shower152 place131 stop108	34,645	
	MIDWEST	Positive parking599 lot513 place449 spot439 clean412 Neutral parking837 spot620 lot606 shower535 place498 Negative parking425 spot276 lot266 place253 truck251	Positive parking1039 lot908 place840 clean775 stop717 Neutral parking1237 lot950 spot832 place792 shower768 Negative parking695 spot460 truck458 lot433 place402	Positive parking1449 clean1138 lot1028 shower1025 place1004 Neutral parking1792 shower1393 lot1190 clean1107 food962 Negative parking840 lot506 truck488 place465 shower423	Positive parking1091 food732 clean727 good726 lot719 Neutral parking1132 shower935 lot684 clean673 place644 Negative parking501 place304 truck300 shower297 lot275	8,458
		NORTHEAST	Positive parking101 place68 good68 stop67 food60 Neutral parking210 spot185 place137 lot131 get122 Negative parking282 spot202 get168 lot139 place137	Positive parking177 update164 place143 stop121 food118 Neutral parking377 spot274 lot249 shower219 place198 Negative parking421 spot305 pay205 place203 get198	Positive parking260 place157 food156 clean154 shower145 Neutral parking355 shower193 place183 lot172 food165 Negative parking528 spot282 get257 lot212 shower202	Positive parking148 food109 place107 shower103 clean100 Neutral parking288 shower210 food145 lot142 place139 Negative parking342 spot215 get173 shower151 place143
SOUTH			Positive parking943 place701 lot646 clean629 stop604 Neutral parking1994 spot1419 lot1318 place1211 get1163 Negative parking1684 lot1003 spot948 truck902 place900	Positive parking1281 place1080 lot969 stop929 good901 Neutral parking2783 spot1952 lot1930 shower1837 get1745 Negative parking2243 place1397 spot1343 get1284 lot1279	Positive parking2183 food1502 clean1407 good1359 lot1358 Neutral parking4229 shower3051 lot2641 clean2561 food2196 Negative parking2918 shower1543 get1428 place1420 lot1396	Positive parking1544 food1101 clean1083 good1016 shower977 Neutral parking2932 shower2355 lot1758 clean1698 food1507 Negative parking2027 shower1188 place1078 get1055 lot1042
	Σ		24,581	40,766	40,116	28,381

Appendix D. Bigram Model Results - Reviews in High-Risk Counties

Region	Pre-COVID-19 Onset Aug 2019 – Mar 2020 (7 mths)	Post-COVID-19 Onset Mar 2020 – Feb 2021 (11 mths)	Pre-Hurricane Ian Sept 2021 – Sept 2022 (12 mths)	Post-Hurricane Ian Sept 2022 – Aug 2023 (11 mths)	Total
WEST	Positive - parking lot: 115 - good food: 96 - truck stop: 98 - truck wash: 61 - fly j: 24 Neutral - truck stop: 394 - parking lot: 257 - fly j: 213 - fuel island: 179 - help save: 68 Negative - reserve spot: 279 - pay parking: 253 - truck stop: 210 - let know: 57 - shower clean: 27	Positive - truck stop: 226 [removed]: 138 - truck driver: 117 - florida north: 54 - fuel desk: 38 Neutral - parking lot: 541 [removed]: 381 - truck stop: 361 [removed]: 246 - health insurance: 222 Negative [removed]: 610 [removed]: 506 - pay parking: 480 [removed]: 380 - old fella: 188	Positive - truck stop: 281 - fuel island: 144 - nice clean: 74 - good food: 67 - fuel pump: 28 Neutral - parking lot: 475 - truck stop: 395 - fly j: 303 - clean shower: 185 - good food: 135 Negative - pay parking: 458 - reserve spot: 220 - truck stop: 219 - shower clean: 155 - drop trailer: 54	Positive - parking lot: 182 - truck stop: 109 - clean shower: 101 - food option: 71 - fly j: 48 Neutral - parking lot: 427 - truck stop: 166 - shower clean: 154 - hot food: 142 - fly j: 119 Negative - pay parking: 463 - truck stop: 272 - shower clean: 102 - good food: 70 - fly j: 67	2,495
MIDWEST	Positive [removed]: 24 [removed]: 16 - driver door: 14 - hour night: 10 - just piece: 9 Neutral - pay parking: 42 - truck stop: 37 - iron skillet: 31 - gmail com: 29 [removed]: 24 Negative - truck stop: 98 - parking spot: 73 - reserve spot: 59 - pay parking: 23 - wait shower: 21	Positive - miller leave: 46 - parking spot: 33 [removed]: 24 - free seat: 22 - refuse let: 11 Neutral [removed]: 141 - truck stop: 118 - wear mask: 69 - nice clean: 55 - gsc transholde: 53 Negative - pay parking: 172 - truck stop: 120 [removed]: 69 - miller leave: 63 - gsc transholde: 19	Positive - good food: 22 - diesel def: 22 - oak grove: 13 - lot parking: 12 - quik trip: 11 Neutral - truck stop: 105 - parking lot: 99 - wendy's: 43 - amazon drop: 41 - truck wash: 29 Negative - truck stop: 194 - reserve spot: 113 - good food: 38 - clean shower: 22 - look like: 19	Positive [removed]: 17 - food restroom: 14 - parking food: 13 - poor quality: 9 - cat scale: 6 Neutral - parking lot: 59 - truck stop: 49 - chrome shop: 40 - shower clean: 23 - wah wah: 13 Negative - parking lot: 125 - truck stop: 63 - hot food: 50 - look like: 21 - clean shower: 14	617
NORTHEAST	Positive - update parking: 6 - open spot: 5 - available truck: 5 - sb take: 3 - dot creep: 1 Neutral - tow truck: 51 - rest area: 27 - particulate filter: 16 - state police: 16 - update parking: 14 Negative - use restroom: 18 - truck stop: 17 - food clean: 14 - good luck: 7 - wish nation: 3	Positive - typical service: 16 - maybe spot: 13 - east coast: 10 - truck stop: 9 [removed]: 6 Neutral - truck stop: 76 - spot open: 55 - new jersey: 32 - open row: 22 - vend machine: 14 Negative - parking spot: 30 - slant blind: 19 - truck stop: 11 - just need: 8 - fuel pilot: 7	Positive - parking spot: 13 - toll road: 13 - spot pm: 13 - beer food: 12 - great sunglass: 4 Neutral - parking lot: 39 - food option: 38 - tow truck: 28 - burger king: 25 - inside clean: 13 Negative - parking lot: 21 - truck stop: 16 - fj steal: 13 - pretty clean: 7 - somebody park: 5	Positive - parking spot: 26 - joe biden: 16 - mon morning: 7 - rarely seemingly: 5 - pm spend: 3 Neutral - parking spot: 46 - truck driver: 33 - take spot: 26 - food option: 19 [removed]: 12 Negative - pilot fly: 15 - truck stop: 11 - need relief: 10 - food shower: 9 - relief road: 8	19,156
SOUTH	Positive - truck stop: 133 - parking lot: 117 - tuning ecm: 86 [removed]: 51 - clean shower: 23 Neutral - parking lot: 449 - truck stop: 306 - tuning ecm: 170 - clean shower: 139 - health insurance: 99 Negative - parking lot: 628 - truck stop: 409 - reserve spot: 348 - look like: 290 - health insurance: 94	Positive - truck stop: 121 - spot leave: 86 - customer service: 72 [removed]: 44 - good food: 35 Neutral - parking lot: 627 - truck stop: 377 - nice place: 179 - health insurance: 138 [removed]: 109 Negative - parking lot: 995 - truck stop: 611 - pay parking: 341 - wear mask: 174 [removed]: 92	Positive - truck stop: 229 - nice place: 109 - fuel island: 99 - clean shower: 59 - nice clean: 28 Neutral - parking lot: 787 - fly j: 270 - drop trailer: 225 - shower clean: 213 - good food: 188 Negative - parking lot: 718 - truck stop: 399 - free spot: 384 - reserve spot: 307 [removed]: 137	Positive - parking lot: 174 - truck stop: 90 - food shower: 80 - friendly staff: 54 - hot food: 40 Neutral - truck stop: 578 - shower service: 368 - fuel island: 367 - good food: 139 - nice clean: 71 Negative - parking lot: 739 - truck stop: 308 - food shower: 303 - look like: 148 - fuel island: 79	14,557
Σ	7,195	12,116	9,610	7,904	36,832

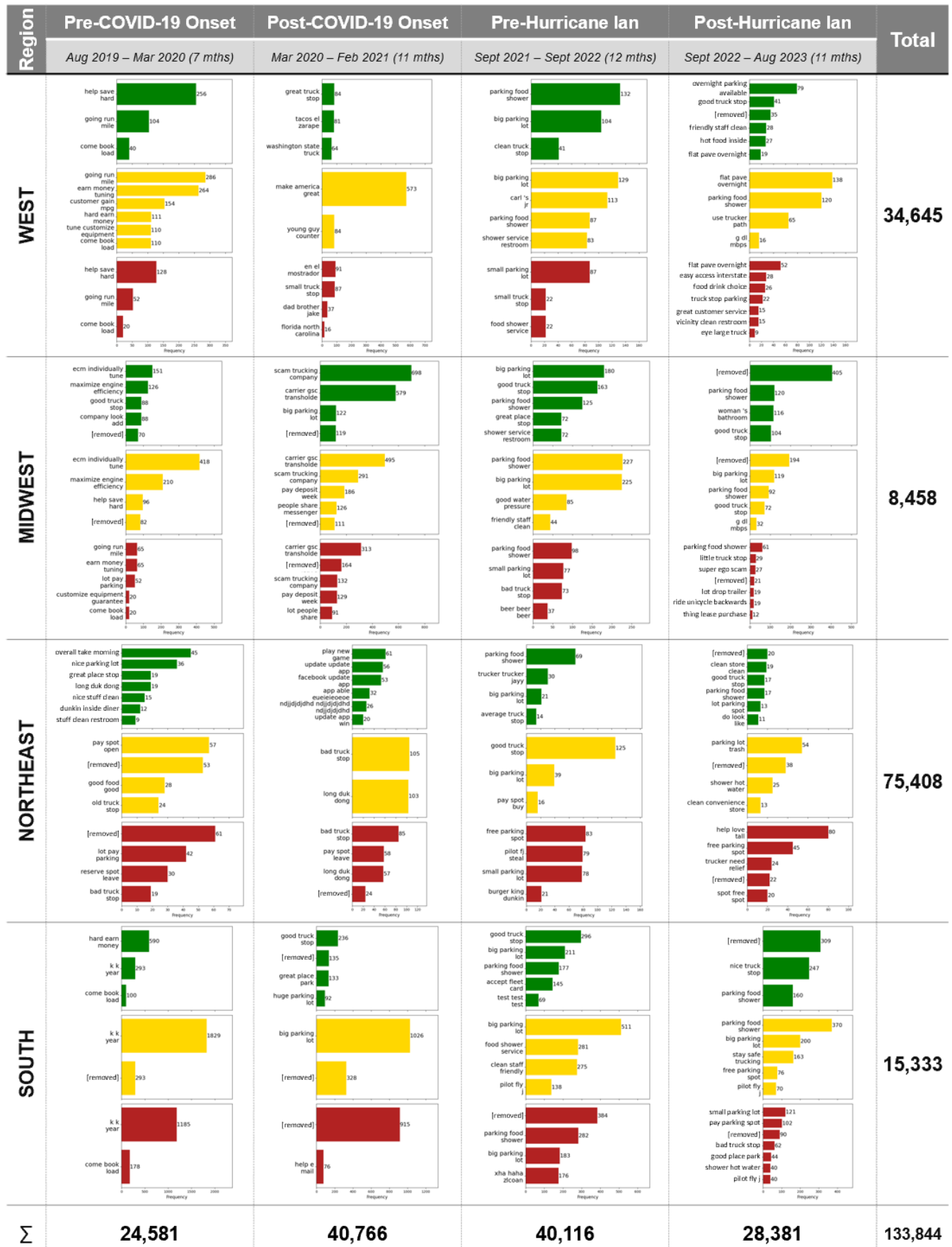
Appendix E. Bigram Model Results - Reviews in Non-High-Risk Counties

Region	Pre-COVID-19 Onset	Post-COVID-19 Onset	Pre-Hurricane Ian	Post-Hurricane Ian	Total
	Aug 2019 – Mar 2020 (7 mths)	Mar 2020 – Feb 2021 (11 mths)	Sept 2021 – Sept 2022 (12 mths)	Sept 2022 – Aug 2023 (11 mths)	
WEST	Positive - truck stop 173 - dirt lot 148 - parking lot 146 - clean shower 41 - tuning ecm 40 Neutral - truck stop 505 - look like 288 - hard earn 180 - tuning ecm 154 - maximize engine 154 Negative - truck stop 205 - lot spot 70 - shower clean 45 - old school 45 - nice place 35	Positive - good food 374 - parking lot 298 - truck stop 212 - hot water 67 - update parking 9 Neutral - truck stop 522 - parking lot 420 - clean shower 286 - fuel island 242 - fly j 235 Negative - truck stop 165 - parking lot 139 - fly j 121 - clean shower 104 - look like 48	Positive - truck stop 344 - parking lot 343 - nice clean 286 - good food 279 - friendly staff 80 Neutral - parking lot 1059 - shower clean 474 - fly j 258 - good food 220 - fuel island 166 Negative - parking lot 347 - fly j 220 - friendly staff 77 - fuel island 73 - shower clean 62	Positive - truck stop 326 - hot food 207 - clean shower 143 - friendly staff 140 - dirt lot 114 Neutral - parking lot 447 - clean shower 363 - truck stop 284 - friendly staff 194 - fly j 165 Negative - parking lot 179 - easy access 103 - truck stop 93 - pave overnight 84 - clean restroom 74	34,645
	Positive - parking lot 448 - truck stop 428 - nice clean 394 - lot spot 214 - good food 146 Neutral - truck stop 756 - parking lot 543 - nice place 331 - fuel island 137 - cat scale 78 Negative - parking lot 316 - truck stop 228 - spot leave 185 - shower clean 70 - fuel island 60	Positive - truck stop 1213 - nice place 850 - gsc transholde 596 [removed] 308 - friendly staff 122 Neutral - parking lot 1098 - truck stop 753 - nice place 606 - clean shower 318 - fuel island 140 Negative - parking lot 583 - truck stop 407 [removed] 358 - look like 131 - fuel island 116	Positive - great place 1046 - parking lot 981 - truck stop 568 - shower clean 598 - food option 361 Neutral - parking lot 1979 - clean shower 509 - hot food 466 - friendly staff 372 - good place 351 Negative - parking lot 974 - look like 205 - clean shower 205 - fly j 147 - friendly staff 84	Positive - truck stop 1087 - clean shower 524 - good food 424 - great place 383 - fuel island 125 Neutral - parking lot 773 - clean shower 527 - truck stop 512 - fuel island 370 - fly j 231 Negative - truck stop 285 - parking lot 283 - good place 223 - hot water 157 - fly j 60	
	Positive - truck stop 117 - parking lot 98 - nice people 37 - old school 31 - clean restroom 21 Neutral - free spot 161 - parking lot 156 - clean shower 98 - truck stop 83 - good food 49 Negative - pay parking 194 - reserve spot 179 - truck stop 133 - lot pay 70 - icandi unj 7	Positive - ndjdjdhd ndjdjdjdhd 170 - truck stop 167 - update app 128 - good food 117 - update facebook 66 Neutral - truck stop 370 - spot open 144 - good food 139 - place park 92 - shower clean 51 Negative - parking spot 344 - reserve spot 302 - truck stop 149 - hot water 64 - fuel island 40	Positive - truck stop 266 - brand new 132 - nice place 91 - clean shower 66 - food shower 27 Neutral - parking lot 364 - great place 108 - pay spot 65 - clean shower 61 - waste time 21 Negative - parking lot 344 - truck stop 159 - pay spot 147 - reserve spot 135 - dunkin donut 57	Positive - truck stop 126 - good food 85 - nice place 57 - good place 47 - clean shower 41 Neutral - parking lot 296 [removed] 86 - hot water 75 - look like 38 - fuel island 36 Negative - parking spot 261 - truck stop 160 - reserve spot 115 - clean shower 74 - look like 14	
SOUTH	Positive - truck stop 601 - parking lot 512 - nice place 494 - spot leave 348 - good food 335 Neutral - parking lot 2639 - gmail com 709 - good food 576 - friendly staff 381 - clean shower 351 Negative - truck stop 1141 - parking lot 1128 - spot leave 492 - friendly staff 403 - shower clean 86	Positive - friendly staff 967 - parking lot 799 - truck stop 711 - great place 539 - good food 380 Neutral - parking lot 2428 - truck stop 1379 - spot leave 1293 [removed] 961 - clean shower 583 Negative - parking lot 1588 - reserve spot 1119 - truck stop 1085 [removed] 536 - fuel island 240	Positive - parking lot 1603 - good food 1330 - clean shower 960 - truck stop 881 - fuel island 62 Neutral - parking lot 4092 - shower clean 2201 - food option 879 - fuel island 812 - friendly staff 733 Negative - parking lot 3377 - shower clean 588 - hot food 381 - look like 370 - customer service 319	Positive - truck stop 1605 - clean restroom 570 - nice place 510 - good food 501 - friendly staff 334 Neutral - parking lot 1803 - clean shower 1254 - truck stop 1026 - food option 1000 - friendly staff 819 Negative - parking lot 1331 - truck stop 829 - place park 599 - hot water 371 - clean shower 318	15,333
Σ	24,581	40,766	40,116	28,381	133,844

Appendix F. Trigram Model Results - Reviews in High-Risk Counties

Region	Pre-COVID-19 Onset Aug 2019 – Mar 2020 (7 mths)	Post-COVID-19 Onset Mar 2020 – Feb 2021 (11 mths)	Pre-Hurricane Ian Sept 2021 – Sept 2022 (12 mths)	Post-Hurricane Ian Sept 2022 – Aug 2023 (11 mths)	Total
WEST					2,495
MIDWEST					617
NORTHEAST					19,156
SOUTH					14,557
Σ	7,195	12,116	9,610	7,904	36,832

Appendix G. Trigram Model Results - Reviews in Non-High-Risk Counties



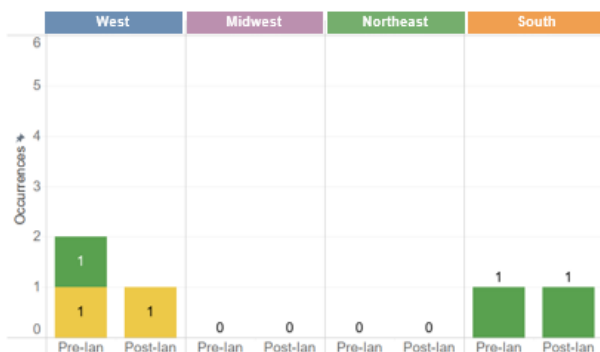
Appendix H. Occurrences of Supplementary Parking Topics Before and After Hurricane Ian, in High-Risk and Non-High-Risk Counties

Hurricane Ian – Occurrences of **Big Parking Lot** as a Topic

Grand Total 16

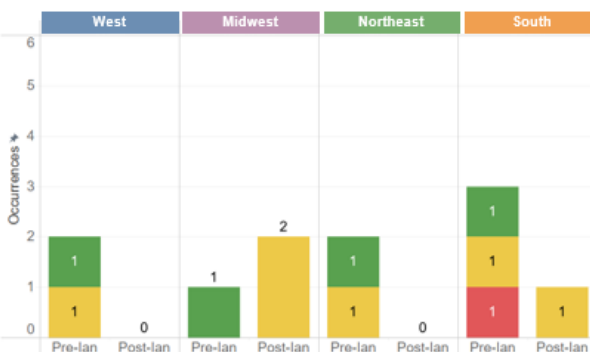
Sentiment	Occurrences
Positive	3
Neutral	2
Negative	0
Total	5

In a High-Risk County



Sentiment	Occurrences
Positive	4
Neutral	6
Negative	1
Total	11

In a Non-High-Risk County

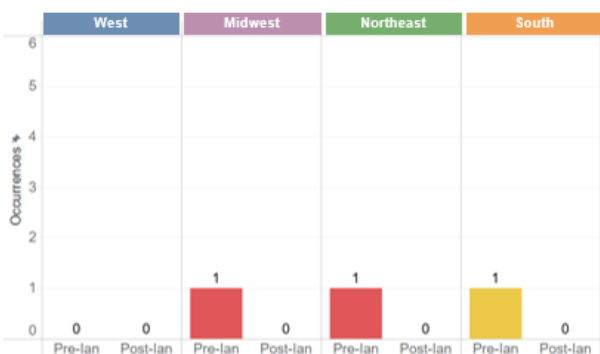


Hurricane Ian – Occurrences of **Small Parking Lot** as a Topic

Grand Total 7

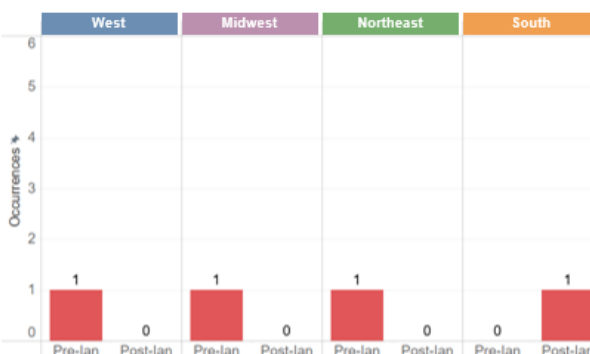
Sentiment	Occurrences
Positive	0
Neutral	1
Negative	2
Total	3

In a High-Risk County



Sentiment	Occurrences
Positive	0
Neutral	0
Negative	4
Total	4

In a Non-High-Risk County

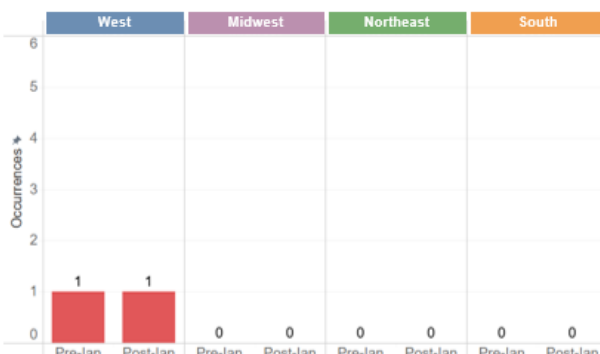


Hurricane Ian – Occurrences of **Paid Parking** as a Topic

Grand Total 4

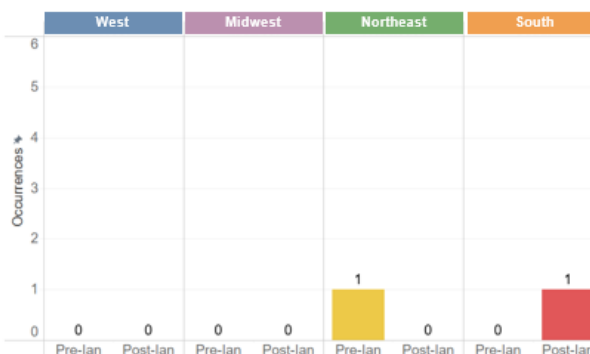
Sentiment	Occurrences
Positive	0
Neutral	0
Negative	2
Total	2

In a High-Risk County



Sentiment	Occurrences
Positive	0
Neutral	1
Negative	1
Total	2

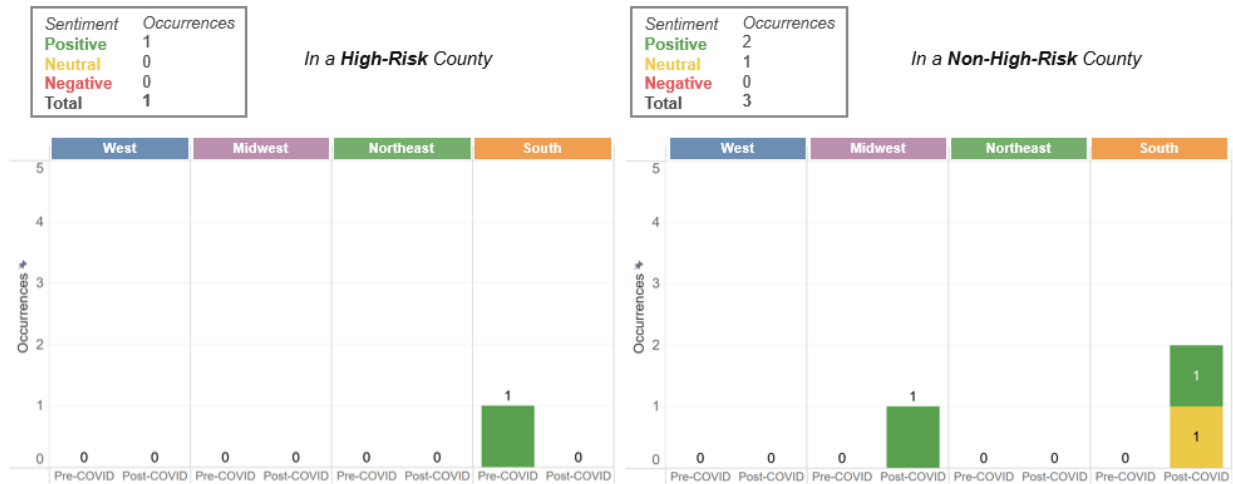
In a Non-High-Risk County



Appendix I. Occurrences of Supplementary Parking Topics Before and After COVID-19, in High-Risk and Non-High-Risk Counties

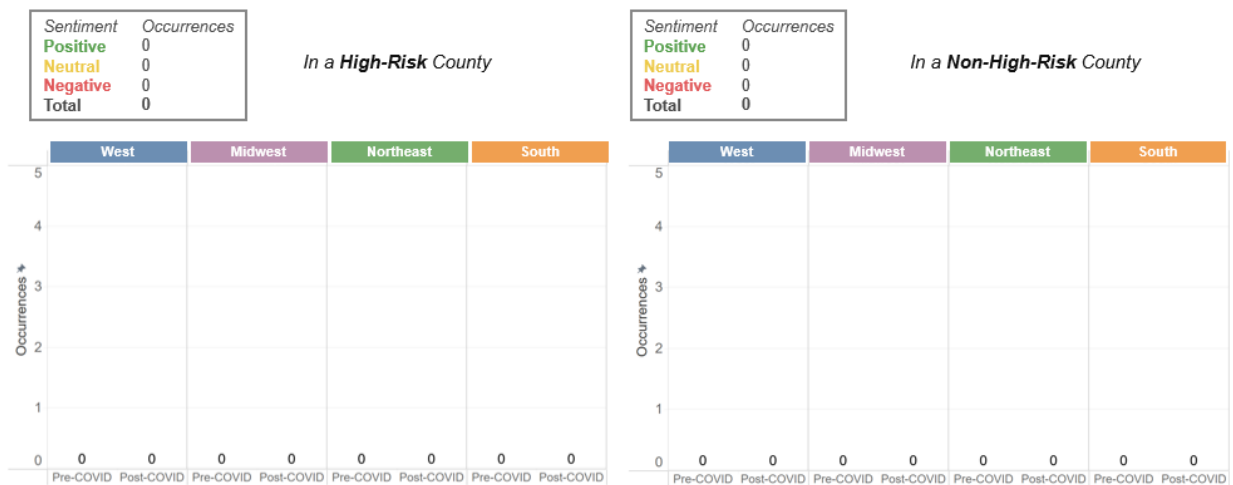
COVID-19 – Occurrences of **Big Parking Lot** as a Topic

Grand Total 4



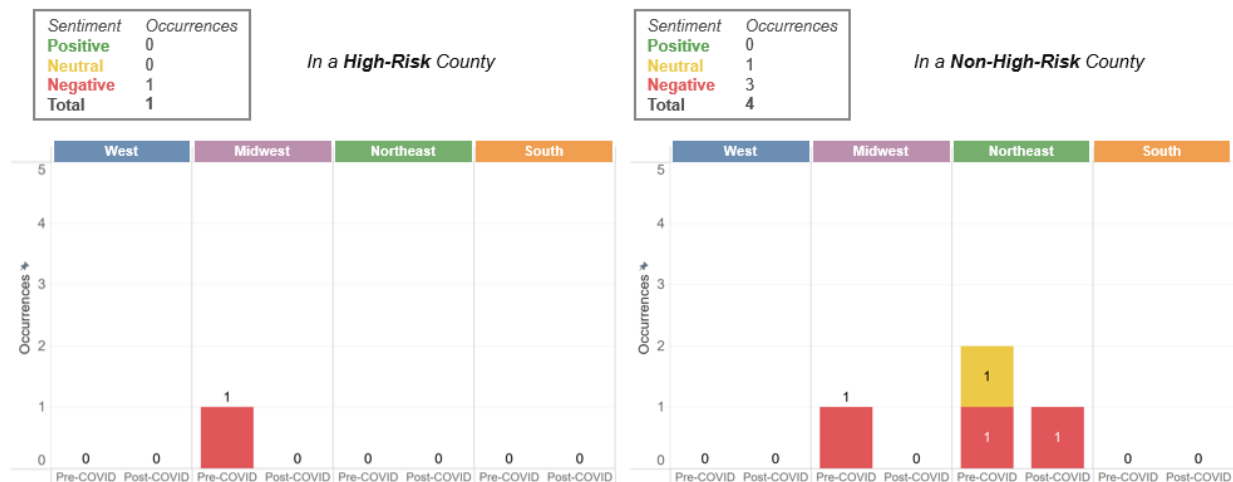
COVID-19 – Occurrences of **Small Parking Lot** as a Topic

Grand Total 0



COVID-19 – Occurrences of **Paid Parking** as a Topic

Grand Total 5



Appendix J. Occurrences of Cleanliness as a Topic Before and After Hurricane Ian, in High-Risk and Non-High-Risk Counties

Hurricane Ian – Occurrences of **Cleanliness** as a Topic

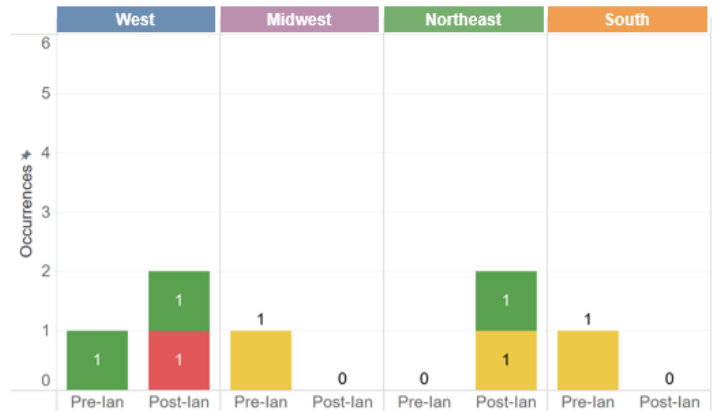
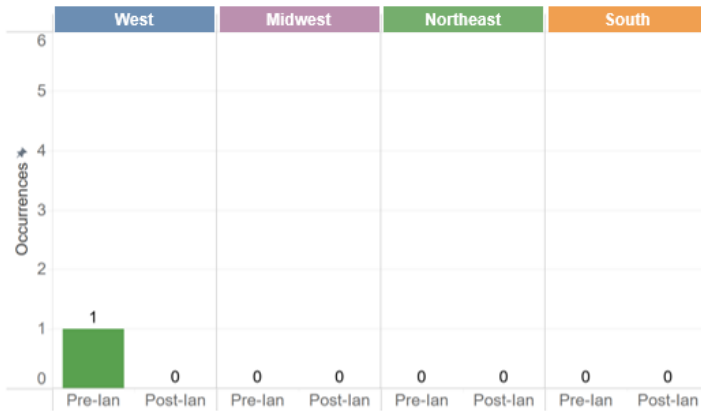
Grand Total 8

Sentiment	Occurrences
Positive	1
Neutral	0
Negative	0
Total	1

In a **High-Risk** County

Sentiment	Occurrences
Positive	3
Neutral	3
Negative	1
Total	7

In a **Non-High-Risk** County



Appendix K. Occurrences of Cleanliness as a Topic Before and After COVID-19, in High-Risk and Non-High-Risk Counties

COVID-19 – Occurrences of **Cleanliness** as a Topic

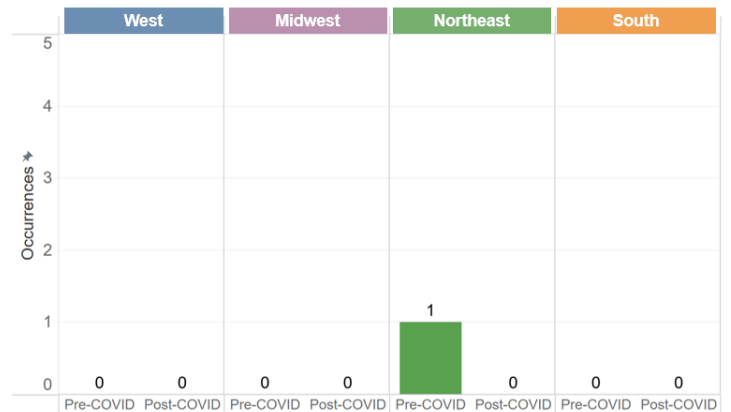
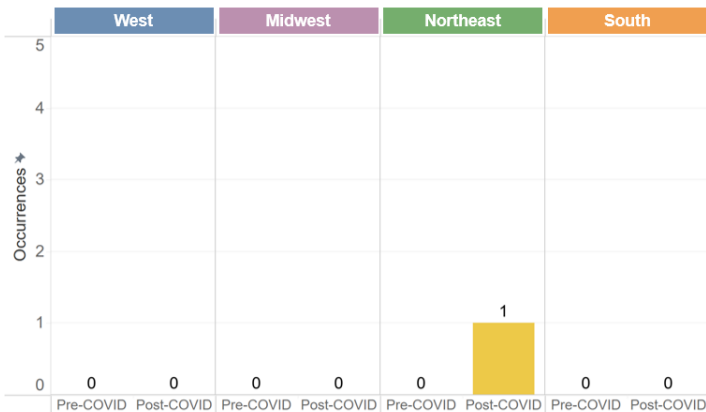
Grand Total 2

Sentiment	Occurrences
Positive	0
Neutral	1
Negative	0
Total	1

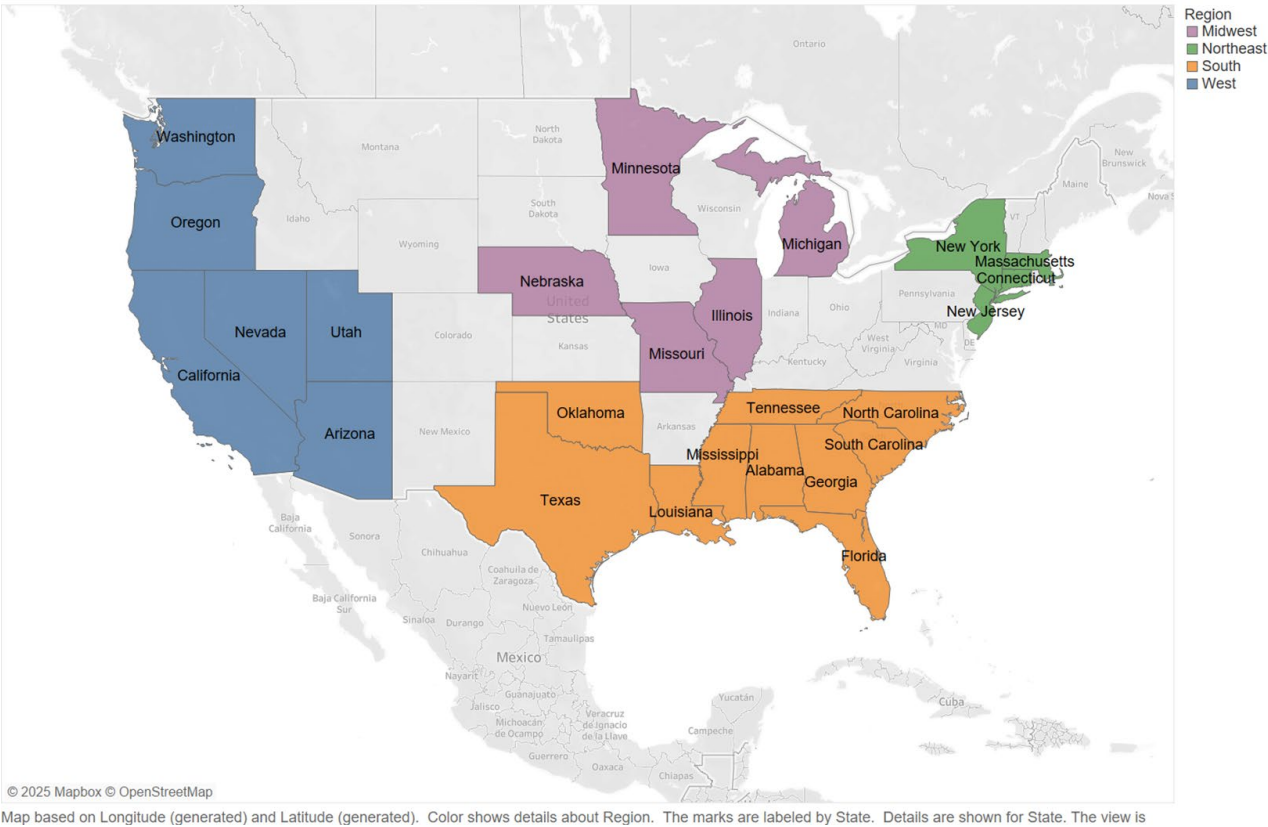
In a **High-Risk** County

Sentiment	Occurrences
Positive	1
Neutral	0
Negative	0
Total	1

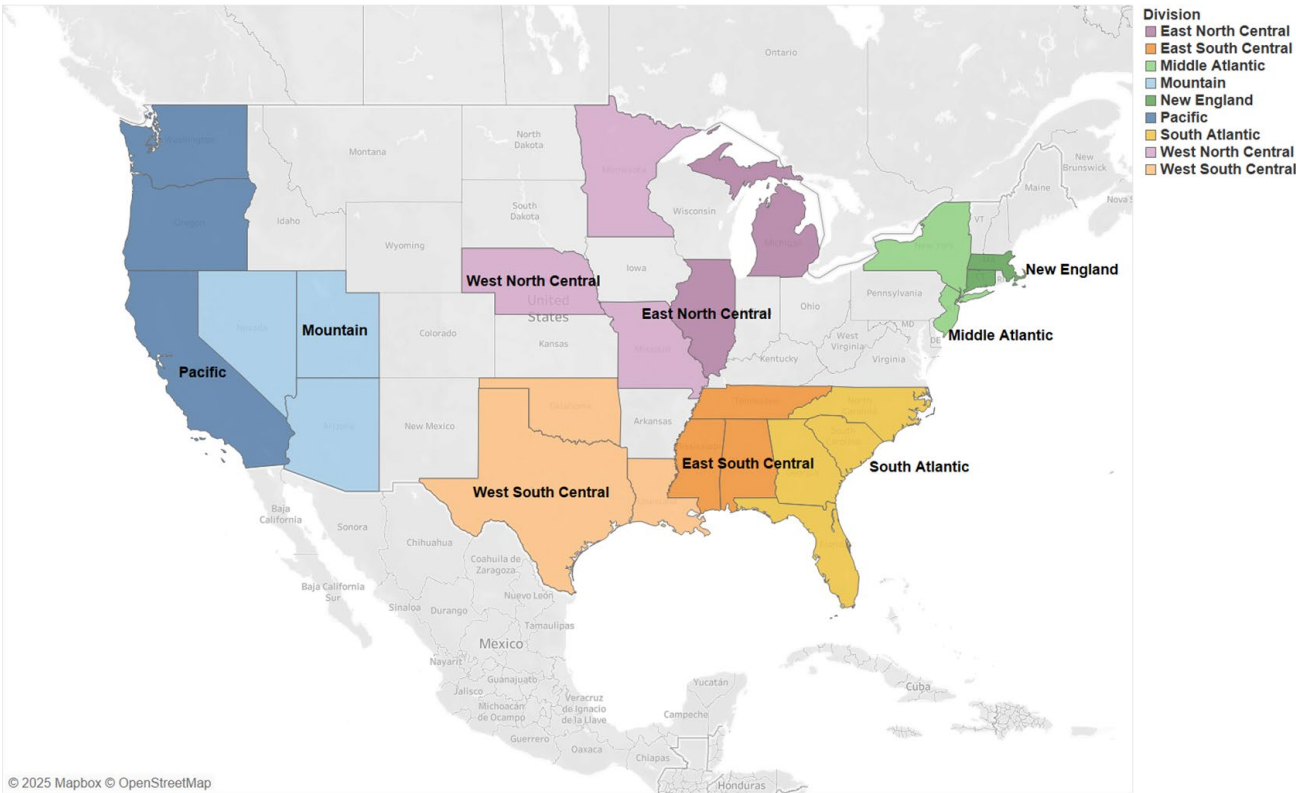
In a **Non-High-Risk** County



Appendix L. States with High-Risk Counties by Region



Appendix M. States with High-Risk Counties by Division



Appendix N. FEMA National Risk Index (NRI)

