VULNERABLE ROAD USERS
TECHNICAL REPORT

FOUNDATION FOR TRAFFIC SAFETY

Safety of Micromobility: Regulations, Data and Stakeholders

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Title

Safety of Micromobility: Regulations, Data and Stakeholders

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Foreword

During the past decade, the AAA Foundation for Traffic Safety has continued to expand our work by devoting efforts and resources to examine emerging topics such as the one presented in this report – the relation between micromobility and traffic safety. Micromobility devices have been reshaping how people travel in the United States, especially in urban settings, but many communities have struggled to ensure their safe use.

This document should be of interest to multiple entities such as practitioners who work for various levels of transportation agencies, policymakers, law enforcement professionals, and researchers. The report includes a synthesis of existing literature on micromobility and current gaps. It also presents micromobility regulations and policies from all 50 states and multiple cities in the United States, results from analysis of several micromobility data sources, and summaries from focus group meetings. This report concludes with actionable recommendations to improve safety of micromobility.

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About the Sponsor

AAA Foundation for Traffic Safety
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List of Abbreviations and Acronyms

AI	Artificial Intelligence
CPSC	U.S. Consumer Product Safety Commission
DOT	Department of Transportation
E-bike	Electric bicycle
EMS	Emergency Medical Services
E-Scooter	Electric scooter
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
GNSS	Global Navigation Satellite Systems
GPS	Global Positioning Systems
HDDS	Hospital Discharge Data System
HIPAA	Health Insurance Portability and Accountability Act
IMU	Inertial Measurement Unit
IoT	Internet of Things
IR	Infrared
KABCO	(K) killed; (A) serious/incapacitated injury; (B) minor/non-incapacitated injury; (C) possible injury; (O) No apparent injury.
LiDAR	Light Detection and Ranging
LLMs	Large Language Models
MDS	Mobility Data Specification
MMUCC	Model Minimum Uniform Crash Criteria
MUTCD	Manual on Uniform Traffic Control Devices
NHTSA	National Highway Traffic Safety Administration
NTSB	National Transportation Safety Board
PSS	Powered standing scooters
SFSP	sequential few-shot prompted
S-pedelec	Speed pedelec
TITAN	Tennessee Integrated Traffic Analysis Network
USDOT	United States Department of Transportation
V2X	Vehicle-to-Everything

Executive Summary

As the deployment of electric bicycles and scooters continues to expand, urban transportation networks frequently encounter evolving safety and infrastructure challenges. This project synthesizes research on micromobility safety to provide an understanding of the current landscape. By examining current regulations, integrating disparate data sources, and synthesizing stakeholder perspectives, this report offers policymakers, municipal planners, and transportation safety researchers strategic guidance to better integrate these emerging modes.

A review of the existing literature reveals knowledge gaps, driven by underreporting and inconsistent device definitions. Traditional police crash logs skew safety perceptions by primarily capturing severe collisions with motor vehicles, missing a substantial number of single-vehicle crashes and non-collision injuries. This project addresses these gaps by triangulating alternative sources, highlighting the specific risks "Out-of-Class" devices pose to youth, and the distinct vulnerabilities of older adults on high-speed e-bikes.

To navigate the complex regulatory environment, the research team developed an interactive map detailing state-level bills and ordinances from 18 representative cities. This tool documents micromobility policies, providing practical applications for local authorities aiming to benchmark their own policies. Stakeholders can use this resource to understand jurisdictional variations and identify friction points, such as the point-of-sale loophole where federal consumer product standards conflict with state road-usage laws.

The analysis of crash data sources highlights systemic quality issues across police department and hospital databases. The report applies the concept of the "safety data iceberg" to conceptualize the current state of micromobility safety data. In this framing, official statistics represent the visible portion above the surface capturing only a fraction of true roadway risk, while a substantial share of incidents, near-misses, and risk factors remain unobserved or underreported. To overcome legacy coding limitations, the research team applied Large Language Models (LLMs) to parse unstructured police crash narratives in Tennessee's TITAN database, successfully recovering and reclassifying hundreds of micromobility incidents. Furthermore, by linking these police records to the Hospital Discharge Data System, the analysis shows that single-vehicle falls, which are largely invisible to law enforcement, account for the vast majority of actual micromobility injuries.

To contextualize these findings, the project incorporated insights from 25 stakeholders across 9 focus groups, including municipal planners, industry operators, and safety and disability advocates. Participants emphasized the urgent need for aligned

regulations and standardized taxonomies. Their input highlighted practical challenges, noting that silent devices and dockless parking create severe physical barriers for visually impaired pedestrians, while outdated federal manuals could delay the implementation of safe street designs.

Building upon these findings, the report offers recommendations spanning policy, infrastructure, and data. Strategic actions include advocating for a unified national taxonomy for data and vehicle types by leveraging tools like the Mobility Data Specification and to resolve classification chaos and align federal product safety standards with laws. Furthermore, the report suggests proactive, self-enforcing infrastructure that naturally manages vehicle speeds, while promoting inclusive streetscapes, such as uniform parking corrals and auditory warning systems, to improve sidewalk accessibility and safety for all users.

Introduction

The rapid expansion of micromobility, particularly electric bicycles (e-bikes) and electric scooters (e-scooters), has transformed traditional travel with more diverse, sustainable alternatives for short-distance travel. According to industry reports, shared micromobility systems generally facilitate tens of millions of trips annually across North America, with a substantial portion of those trips replacing short car trips (Frye et al., 2024). Demographically, while ridership often skews towards younger male populations, users tend to span various income levels and backgrounds, highlighting micromobility's role as a flexible mobility option (Kim et al., 2023; Roig-Costa et al., 2024). However, this expansion has also raised notable safety concerns due to crash injuries, inconsistent regulations, and inadequate infrastructure. This rapid growth has often outpaced urban transportation systems and institutional frameworks designed to manage it, introducing safety, regulatory, and infrastructural challenges (Sanguinetti et al., 2023).

The regulatory landscape governing micromobility in the United States is frequently fragmented across federal, state, and municipal levels. A regulatory loophole often exists in which states have the authority to regulate road use but are preempted by federal consumer product standards from restricting the retail sale of non-compliant, high-speed devices. This can allow unclassified "Out-of-Class" vehicles to enter the market, potentially bypassing established safety governors and complicating local law enforcement efforts. Federal and state agencies could consider aligning product safety standards with road usage laws to help close this point-of-sale loophole. Stakeholders could consider establishing a standardized national taxonomy to help ensure accurate incident classification across all reporting systems.

Crash dynamics generally affect riders differently based on age and speed. Older adults (typically defined in this context as riders aged 50 and above), a designation used to differentiate them from younger, teenage demographics, face elevated risks of severe falls and hospitalization due to the physical and cognitive demands. Concurrently, young riders often exhibit severe, motorcycle-like internal trauma during hospitalization (Hirsch et al., 2024). The alarming rise in severe injuries among young riders may be exacerbated by the "toy myth," wherein parents mistakenly purchase high-powered electric devices for unlicensed minors, potentially unaware of the vehicle's capabilities or the associated risks (Popescu et al., 2024).

Sharing space with motor vehicles dramatically increases the risk of severe collisions and the absence of safe pathways forces riders onto sidewalks, impacting the safety of pedestrians. Ultimately, safety should be treated as a core design requirement through protected infrastructure separating micromobility users from vehicles and pedestrians. Cities that deploy extensive, physically separated micromobility lanes consistently report fewer crashes and lower injury severities (Sanguinetti et al., 2023).

Capturing an accurate safety profile generally requires a unified, data-driven approach. Current micromobility safety analyses often rely heavily on a reactive model driven by police crash logs and hospital trauma records, both of which can exhibit distinct structural biases. Official police statistics tend to capture only the visible tip of the safety iceberg, primarily documenting severe collisions with motor vehicles (Sanjurjo-de-No et al., 2023). This methodology may overlook a substantial number of underreported falls and injuries caused by pavement defects, poor lighting, or instability (Yaqoob et al., 2023).

Maximizing the sustainable benefits of micromobility requires practitioners and operators to transition to a proactive, triangulated safety ecosystem that integrates device standards, reporting systems, and built environments that accommodate micromobility devices.

This report synthesizes existing literature, documents the highly fragmented state and local regulatory landscape, provides a data model to conduct safety analysis, and incorporates extensive stakeholder feedback to provide an overview of micromobility safety in the United States.

The specific objectives of this research are as follows:

1. Identify and document the extent and patterns of risk in micromobility operations by looking into infrastructure, user behavior, shared vs. private ownership, and other contributing safety factors through a review of the current literature.

2. Offer a full perspective on federal, state, and local policy frameworks, including cities with specific definitions and regulations that differ from state regulations.

3. Investigate data management systems that can improve crash reporting and inter-agency communication by examining sources such as police reported crash data, emergency department injury data, and other emerging safety data sources to better understand injuries related to micromobility.

4. Document input from various stakeholder groups regarding the risks, challenges, and opportunities to improve micromobility safety.

5. Provide mitigation strategies and recommendations across three areas: infrastructure improvements, policy improvements, and best practices for device and operational safety.

This report is organized by the research objectives listed above. Each objective is presented as a section with a concise summary highlighting key insights and main findings. Additional supplementary materials, detailed methods, analyses, and supporting evidence are compiled in the Appendices at the end of the report.

Literature Review

The literature review is based on a systematic search across primary academic and transportation-specific databases, including Transport Research International Documentation, the University of Tennessee online library system, Google Scholar, and various organizational websites. The literature scan comprises peer-reviewed articles and high-quality grey literature published primarily between 2010 and 2025 to ensure the findings reflect the most recent regulatory shifts in the industry, key demand drivers, and usage trends.

As detailed in Table 1, the search strategy employed four primary keyword clusters: device modes, safety outcomes, infrastructure, and advanced modeling methodologies. This approach yielded over 120 relevant studies and reports mostly from the United States, Europe, Asia, and Australia. Qualitative analysis software (i.e., NVivo) was utilized to manage and synthesize this documentation. For a compilation of micromobility studies organized by data types, modeling approaches, and international studies, please refer to Appendix A: Literature Review.

Table 1. Literature Review Keyword Categorization

Search Categories	Primary Keywords and Terms
Device Modes	E-bike (Class 1–3), E-Scooter, Shared Micromobility S-Pedelec, LEV
Safety Outcomes	Crash Risk, Injury Severity Score, Head Trauma, Hospitalization
Infrastructure	Protected Bike Lane, Intersection Safety, Lighting, Geofencing
Methodology	Naturalistic Study, V2X, Machine Learning, Bayesian Spatial

The systematic coding of literature identified six key insight categories that capture key initial themes influencing the safety of micromobility:

- Demographics
- Private ownership vs. shared systems
- Infrastructure
- Behavior
- Policy
- Device specifications

These categories provide an overarching framework for understanding the range of conditions and considerations that impact safety outcomes and serve as a reference for presenting the findings from the literature scan and contextualizing evidence from this set.

The following subsections draw on these themes and present findings in two parts, each reflecting a distinct component of micromobility usage:

- **E-Bike Safety Review**—Examines safety trends, crash risk factors, and injury severity associated with e-bike use, focusing on distinctions between personally owned and shared e-bikes, as well as the safety implications of high-speed *Class 3* and *Out-of-Class* models.
- **Safety Review of Other Micromobility Devices**—Investigates broader micromobility safety issues, covering usage patterns, infrastructure impacts, and policy interventions across various micromobility modes beyond e-bikes.

E-Bike Safety Review

E-bikes continue to gain traction in both private ownership and shared mobility programs to reduce car trips but require supportive policies to sustain the benefits of e-bike usage, such as commuting convenience, longer travel distances, faster travel speeds than conventional cyclists, etc. (Popovich et al., 2014; Ling et al., 2017; MacArthur et al., 2018).

MacArthur and Kobel (2014) conducted a comprehensive policy review, identifying regulatory disparities across states. They noted that 30 states do not recognize e-bikes as a distinct vehicle type and highlight that U.S. state-level policies are fragmented. The Consumer Product Safety Commission (CPSC) has designated low-speed e-bikes as bicycles; however, riders are uncertain about speed limits, helmet requirements, and permissible routes.

> Although low-speed e-bikes are federally classified as bicycles, state-level licensing, registration, and helmet laws vary widely. These inconsistencies create confusion for users, law enforcement, and policymakers, sometimes barring e-bikes from bicycle infrastructure or subjecting them to motor vehicle standards.

Large-scale literature reviews have been performed highlighting core themes in e-bike safety, including traffic behavior, environmental benefits, technology, and user patterns (Fishman & Cherry, 2016, Zhou et al., 2023). These reviews detail the evolution of the field from early discussions on travel substitution to urgent concerns regarding crash risk and head trauma as vehicle speeds increase. These studies converge on key policy imperatives: establishing unified e-bike classifications and speed limits, upgrading lane infrastructure, promoting helmet and protective gear use, and addressing risks faced by vulnerable groups, such as delivery couriers and middle-aged adults (categorized in these studies as riders aged 40 to 59, except where noted below).

Research comparing e-bikes and conventional bicycles highlights differences in crash risk, injury severity, and user demographics, as well as distinctions between personally owned and shared systems. E-bike owners, while more familiar with their bikes, tend to ride longer distances and at higher speeds, increasing exposure to crash risks (Schleinitz et al., 2017, Gitelman et al., 2020)

Studies from the Netherlands indicate that e-bike users are not at a higher risk of crashes compared to conventional cyclists when accounting for kilometers traveled, but the severity of injuries remains a concern, particularly among middle-aged adults (Schepers et al., 2014). These studies indicate that e-bike riders, particularly middle-aged adults riding above 25 km/h (approximately 15.5 mph), often have higher emergency department visits but similar injury severity to conventional cyclists (Twisk et al., 2013; Schepers et al., 2014; Verstappen et al., 2021). E-bike riders experience fewer total crashes but exhibit greater injury severity due to their higher operating speeds and greater vehicle mass (DiMaggio et al., 2020; Verstappen et al., 2021). Middle-aged riders, in particular, face elevated risks of severe injuries, including hip and thoracic trauma, when involved in crashes (Lavoie-Gagne et al., 2021). E-bike crashes often involve motor vehicles, contributing to more serious outcomes (Zhang, Nelson & Mulley, 2023).

In the United States, e-bike crashes disproportionately involve adult males (predominantly ranging from 18 to 45 years of age) and motor vehicle collisions, leading to higher hospitalization rates (DiMaggio et al., 2020), with a notable increase in head injuries (Koehne et al., 2024). Studies indicate that e-bikes enable older middle-aged adults (in these cases, ages 50 to 59) to remain active by reducing physical exertion, allowing them to cycle longer distances (Van Cauwenberg et al., 2019; de Haas et al., 2022). However, cognitive load increases at higher speeds, particularly for older riders, making complex traffic maneuvers more challenging while facing near-misses due to misjudged speeds (Haustein & Møller, 2016). Middle-aged e-bike users experience higher hospitalization rates due to balance issues and falls while mounting or dismounting (Schepers et al., 2018). Studies from Switzerland (Papoutsi et al., 2014; Weber et al., 2014; Berk et al., 2022) show that adult e-bike riders over age 40 face higher single-vehicle crash risks, often due to speed and weight factors, though overall injury severity remains comparable to conventional bicycles, suggesting that hospitalization rates are elevated among these middle-aged e-bike users, with thoracic injuries and head trauma being more frequent than in conventional bicycle crashes.

The safety dynamics of e-bikes are heavily influenced by how the vehicles are accessed, operated, and integrated into the built environment. Because rider familiarity, trip purpose, and vehicle ownership models can drastically alter crash exposure, it is crucial to examine these operational factors in detail.

German research highlights that speed differentials between conventional bicycles and e-bikes increase safety risks when both share the same infrastructure (Schleinitz et al., 2017). Studies indicate that riders often overestimate their safety due to quick acceleration and the ability to match vehicular speeds, leading to riskier behaviors on high-traffic roads (Johnson & Rose, 2015). Moreover, inconsistent enforcement and infrastructure deficiencies, particularly on shared paths, amplify crash severity, as higher e-bike speeds increase the likelihood of dangerous collisions (McBain-Rigg et al., 2014).

Overall, the literature suggests that while e-bike injury severity often mirrors that of conventional bicycles, e-bike users' riding behavior and demographics alter crash and injury patterns.

The collective evidence on e-bike safety, described in more detail in the following subsections, identifies the following key findings:

- **Crash likelihood and injury severity:**
    - Elevated operating speeds drastically increase the likelihood of severe crashes and hospitalizations in a mixed-traffic environment (Schleinitz et al., 2017; DiMaggio et al., 2020).
    - While general injury severity may resemble conventional cycling, the combination of increased speed and mass makes e-bikes highly prone to distinct incident types driven by motorist speed misjudgment (Papoutsi et al., 2014; Haustein & Møller, 2016).
    - Middle-aged adults are often more susceptible to hospitalization, particularly from single-vehicle falls, due to the cognitive and physical demands of managing heavier, faster e-bikes (Twisk et al., 2013; DiMaggio et al., 2020).
- **Impact of infrastructure:**
    - Physically separated bike lanes dramatically reduce midblock and intersection crash severity by mitigating speed differentials with motor vehicles (Kondo et al., 2018).

- Bike lane obstructions directly compromise safety by forcing e-bike users into active vehicle traffic, necessitating stricter enforcement (Basch et al., 2019).
- Complex intersections lacking dedicated signaling are among the most frequent sites for severe collisions, largely due to motorists misjudging e-bike acceleration (Lu et al., 2013; Kondo et al., 2018; Chang et al., 2022).
- Obstructions in bike lanes force e-bikes into mixed traffic, severely increasing the risk of sideswipes with heavy motor vehicles (Basch et al., 2019; Hu et al., 2020).
- Current road designs often fail to account for the speed and mass of e-bikes, leaving older riders highly vulnerable, particularly during turning maneuvers (Dozza et al., 2016; Van Cauwenberg et al., 2019; Mayer & Robatsch, 2021).
- Shared systems attract novice and adult riders who face elevated crash risks due to a lack of familiarity with electric assistance and high speeds (Gebhart & Noland, 2014; Weber et al., 2014; Berk et al., 2022).
- Private owners face risks associated with high-speed, long-distance exposure (Almannaa et al., 2020; Bergman et al., 2024).
- Improper parking directly compromises rider safety by blocking dedicated lanes and forcing e-bikes into motor vehicle traffic (Basch et al., 2019).
- Low-income neighborhoods suffer higher crash frequencies due to a systematic lack of protected lanes and adequate street lighting (Younes et al., 2023).

- **Policy and safety regulations:**
  - Fragmented local rules regarding speed, geofencing, and roadway access expose riders to variability in crash exposure (MacArthur & Kobel, 2014).
  - Helmet adoption in shared systems is low (often below 10%) both domestically and globally, increasing severe head injury risks during collision (Graves et al., 2014; Koehne et al., 2024; Chow, 2018; Yahya et al., 2022).
  - The emergence of high-speed e-bikes (Class 3/speed pedelecs) prompts specialized helmet standards capable of absorbing greater impact forces (Wijlhuizen et al., 2014).
  - Helmet laws are most effective when paired with safe infrastructure, and they do not result in risk-compensatory behavior among riders (Schleinitz et al., 2018).
  - A lack of unified parking classifications leads to sidewalk clutter and ADA accessibility issues (MacArthur & Kobel, 2014).

- Geofencing offers a proactive, automated solution to enforce speed limits in high-risk zones where traditional signage fails to alter rider behavior (Langford et al., 2015; Cloud et al., 2023).
- Shared e-bikes require standardized geofencing limits, targeted education, and the rapid deployment of protected cycling infrastructure (Lu et al., 2015; Bergman et al., 2024).
- Inadequate nighttime lighting increases crash severity, an issue requiring infrastructure investment (Chang et al., 2022; Younes et al., 2023).
- Implementing lock-to mechanisms and geofenced parking corrals is a proven strategy to mitigate hazards and organize fleet deployments (Parkes et al., 2013).
- Emerging research increasingly focuses on active safety features, such as Vehicle-to-Everything (V2X) communication systems, which may provide real-time hazard warnings to mitigate risks in complex urban environments (Campolo et al., 2024).

Safety Among Different Classes of E-Bikes

The rising popularity of e-bikes has led to an increased focus on their safety across different classes. In the United States, e-bikes are generally categorized into three main classes: Class 1 (pedal-assist up to 20 mph), Class 2 (throttle-assisted up to 20 mph), and Class 3 (pedal-assist up to 28 mph). However, Out-of-Class e-bikes (i.e., e-motorcycles or e-motos) that exceed these regulatory limits pose additional safety challenges due to their higher speeds and inconsistent classification across jurisdictions. A comparison of safety outcomes across these classes reveals a distinct correlation between higher speeds, crash characteristics, and elevated injury severity.

U.S. studies consistently show that higher-class e-bikes are associated with increased crash risk. Injury data from 2000 to 2017 demonstrate that e-bike–related injuries, particularly among Class 3 and Out-of-Class users, often have a substantially higher likelihood of requiring hospitalization than conventional bicycle injuries, and motor vehicle collisions are notably more common among Class 3 riders (DiMaggio et al., 2020). This trend is accelerating; a notable 432% increase in e-bike–related head injuries occurred between 2020 and 2022, with motor vehicle involvement accounting for 27.6% of these injuries and disproportionately affecting Class 3 and Out-of-Class e-bike users (Koehne et al., 2024).

International studies mirror these findings, emphasizing that the kinetic energy of faster e-bikes generally alters crash dynamics. While Class 1 and Class 2 e-bikes exhibited similar crash rates to traditional bicycles, Class 3 and Out-of-Class models are more frequently involved in high-speed collisions and single-vehicle accidents (Weber et al., 2014). E-bike users were nearly twice as likely to require emergency department treatment compared to traditional cyclists, with Class 3 users demonstrating the highest risk (Schepers et al., 2014). Furthermore, the injury severity was particularly pronounced among middle-aged riders using higher-class and Out-of-Class e-bikes, highlighting demographic vulnerabilities (Verstappen et al., 2021).

Crash Likelihood and Injury Severity

Studies consistently show that elevated e-bike speeds directly increase crash risk, underscoring the need for regulatory measures. E-bikes with higher motor outputs can reach speeds that exceed safe thresholds for mixed-use paths, increasing the risk of severe injuries in collisions (Wang et al., 2019; Alamannaa et al., 2020).

In China, Bai et al. (2017) report that a 1% increase in operating speed in Nanjing leads to a 1.48% rise in rear-end conflicts, supporting calls for formal speed regulations, such as rider licensing and variable speed limits based on lane width and vehicle mix. Yang et al. (2014) further illustrates this issue, with 70.9% of riders exceeding the 20 km/h (approximately 12.4 mph) limit, underscoring the need for stringent oversight and improved rider education to address widespread rule violations at intersections. Similarly, in the city of Kunming, Lin et al. (2008) found that e-bikes travel 47.6% faster than the legal limit of 15 km/h (approximately 9.3 mph), highlighting the prevalence of unauthorized, high-speed e-bikes and the challenges of enforcing speed limits in urban environments around the world.

In Europe, Weber et al. (2014) noted that higher e-bike speeds, whether shared or privately owned, can necessitate additional protective measures, particularly for older adults and novice users who may be unaccustomed to electric assistance. Some municipalities have begun adding protected lanes and imposing lower speed limits in areas with heavy foot or bike traffic (Lu et al., 2015).

Speed differentials among mixed traffic compound crash severity, especially on roads with speed limits exceeding 60 km/h (approximately 37 mph) (Chang et al., 2022). E-bikes traveling faster than conventional bicycles, particularly on mid-block bike lanes contribute to increased collision risks (Langford et al., 2015). European cities face challenges in balancing urban–rural safety needs, particularly in standardizing regulations for faster e-bike classes, such as speed pedelecs (Schepers et al., 2018). Conversely, some e-bike users will deliberately slow down on shared paths, highlighting how rider speed self-regulation varies by context (Johnson & Rose, 2015, Somenahalli et al., 2019).

Research on geofencing and automated systems to restrict speeds in high-risk zones remains limited. Future studies should explore whether such technology can effectively complement traditional speed regulations and help enforce compliance in urban settings. Geofencing could play a crucial role in ensuring that e-bikes adhere to legally defined speed limits, particularly in high-risk areas such as intersections, school zones, and pedestrian-heavy districts.

Impact of Infrastructure

The growing global popularity of e-bikes has intensified scrutiny of the role of infrastructure in crash risk and injury severity. Research frequently shows that e-bike riders sharing lanes with motor vehicles in areas with inadequate facilities can face increased crash risks due to speed differentials and the unique handling dynamics of e-bikes (Bai et al., 2017; Zhong et al., 2022). Policy recommendations frequently highlight physically separated lanes, reconfigured intersections with protected phases (Kondo et al., 2018; Wang et al., 2018), and speed-management efforts (Hu et al., 2020; Yang, Tian et al., 2024).

Roadway design often does not anticipate e-bikes' heavier frames and higher speeds, potentially making riders especially vulnerable at intersections, curves, and merges (Johnson & Rose, 2015; Dozza et al., 2016; Mayer & Robatsch, 2021) and risky behaviors, such as riding under the influence, phone use, and ignoring traffic rules, exacerbate crash risks (Dozza et al., 2016). Mounting and dismounting difficulties, as well as sudden accelerations stress the need for tailored lane widths and traffic rules (Van Cauwenberg et al., 2019).

Well-designed infrastructure can mitigate injury severity (Schepers et al., 2014; Schepers et al., 2018). Existing evidence highlights the safety benefits of physically separated bike lanes, which can reduce crash risks for e-bike riders, particularly for vulnerable groups such as children and middle-aged adults (Embree et al., 2016). Separated infrastructure on roads with speed limits above 35 mph reduces midblock crash severity, while strategic lane placement lowers the odds of intersection crashes by up to 48% (Kondo et al., 2018). Dutch research emphasizes that well-maintained cycling networks, separated lanes, and traffic-calming measures can reduce severe injuries (Wijlhuizen et al., 2014).

Intersections remain high-risk zones due to turning conflicts and complex signal configurations, underscoring the need for design solutions that include dedicated signals and protected intersections. Pejhan (2024) found that intersections pose the highest risk to e-bike riders due to unsafe overtaking maneuvers by motor vehicles. Another study suggests that e-bike riders face increased risks at intersections, where motorists often misjudge their speed, leading to near-miss situations (Haustein & Møller, 2016). Somenahalli et al. (2019) also identified intersections and roads lacking dedicated lanes as key hotspots, with half of micromobility collisions occurring at intersections (Kondo et al., 2018; Shah et al., 2021). Red-light running and stop-sign rolling are common; 70% of riders may coast through low-speed signals (Langford et al., 2015), while motorists often fail to gauge e-bikes' acceleration (Lu et al., 2013; Chang et al., 2022). Crash odds climb further at complex intersections, where collision frequencies spike without dedicated bike lanes (Kondo et al., 2018).

Mid-block crossings also prove perilous: in Taixing City, China, nearly half of fatal e-bike incidents occurred away from signals (Lu et al., 2015), and wrong-way riding rates exceeding 40% intensify risk in lower-volume areas (Langford et al., 2015).

Poor visibility further aggravates location-based vulnerabilities. Poor nighttime visibility hampers both motorists' ability to detect e-bike riders and riders' capacity to navigate obstacles. Nighttime crashes can be mitigated through better street lighting and the widespread use of running lights on e-bikes (Chang et al., 2022; Li et al., 2025). Inadequate lighting in urban centers (Basch et al., 2019), blocked streetlights (Li et al., 2025), or unlit rural roads (Chang et al., 2022) can raise fatal crash probabilities by nearly 200%, which is then magnified by longer emergency response times (Yang, Tian et al., 2024).

Another key issue is obstruction of bike lanes by vehicles, objects, or pedestrians, compromising cyclist safety. Basch et al. (2019) analyzed protected bike lanes in Manhattan, NY, and found that obstructions were present in all study zones, with a total of 233 recorded obstructions at an average rate of 6.6 per mile. Also, obstructed bike lanes and shared lanes increase crash risks by forcing e-bike users into traffic (Basch et al., 2019; Basch et al., 2023; Li et al., 2025), leading to rear-end or sideswipe collisions, especially involving heavy goods vehicles (Lu et al., 2015; Hu et al., 2020). Frequent obstructions in bike lanes, such as parked cars, undermine otherwise effective infrastructure, emphasizing the need for regular maintenance and enforcement (Basch et al., 2019).

Recent work has revealed that important equity dimensions, equitable resource allocation, and enforcement lead to reducing crash frequencies and severity at intersections, mid-block zones, and shared lanes. A lack of funding or political will perpetuates unsafe road conditions, especially among lower-income neighborhoods often lacking protected bike lanes, thereby increasing the likelihood of fatal crashes (Younes et al., 2023). When equitable bike lane networks are neglected, the safety benefits of increased ridership and reduced car dependency may be offset by higher exposure to vehicle conflicts (Bergman et al., 2024). Policy recommendations must emphasize equitable infrastructure investments, enhanced lighting, and speed enforcement in high-risk areas (Wang et al., 2017; Younes et al., 2023; Putra et al., 2024). Dedicated bike lanes, improved lighting, and protected intersections reduce crash risks, while poorly maintained infrastructure and obstructed bike lanes lead to higher injury rates, particularly in low-income areas (Buehler & Pucher, 2021).

Shared e-bikes represent both an opportunity to broaden sustainable transport and a call for proactive, carefully tailored infrastructure and policies. Many cities now feature shared e-bike systems that promise convenient, lower-emission transportation while introducing unique safety implications to the system. Unlike conventional bike shares, shared e-bikes attract individuals seeking faster, less strenuous travel, while requiring specialized regulations and better infrastructure to accommodate their higher speeds.

Shared e-bikes are often used for longer distances or steeper routes, substituting for short car trips, which can alter typical cycling patterns and expose riders to more complex traffic interactions. While these programs offer sustainability benefits, shared e-bike systems introduce additional safety complexities and crash dynamics compared to personally owned e-bikes due to fleet management practices, docking station locations, and rider experience levels.

Comparing personally owned and shared e-bikes, factors such as user familiarity, speed management, and helmet use emerge as safety considerations. Shared e-bike users face lower injury severity but are less likely to wear helmets and often lack riding experience (Frye et al., 2024). Personally owned e-bike riders travel longer distances at higher speeds, increasing crash exposure (MacArthur et al., 2018). Adolescents increasingly use micromobility devices, yet studies on their safety risks remain limited (Goodman et al., 2023).

In Austin, TX, studies found that dockless e-bikes operate at higher speeds than other micromobility devices (e.g., e-scooters) increasing collision risks (Almannaa et al., 2020). In contrast, Chicago's Divvy bike-share program attracted new riders but posed safety challenges for older or inexperienced users (Bergman et al., 2024). Shared e-bike users, who are often less experienced and less likely to wear helmets, may underestimate the electric assistance and misjudge stopping distance (Yang, Baig et al., 2024).

Policy and Safety Regulations

Limited helmet adoption, especially among shared e-bike systems, exacerbates injury risks, with studies highlighting a significant proportion of head injuries among e-bike users compared to conventional cyclists (Graves et al., 2014), resulting in an increasing concern among e-bike riders, particularly adolescents (Koehne et al., 2025; Pejhan, 2024). Almannaa et al. (2020) and Koehne et al. (2025) analyzed e-bike–related concussions and head injuries, revealing an increase in e-bike head injuries, particularly among adolescents. They found that motor vehicle involvement accounted for 27.6% of injuries, with adolescent riders facing the highest risk of such incidents.

Despite well-established protective effects of helmets, multiple factors hinder their consistent use, including hot or rainy weather, aesthetics, and social norms (Chow

2018, Zhou et al., 2022; Yang, Baig et al., 2024). Helmet use varies widely: about half of Italian riders forgo helmets (Ferraro et al., 2020), while Austria reports higher uptake among e-bike users (Mayer & Robatsch, 2021). In Israel, where severe injuries among e-bike users increased annually, fewer than 10% riders wore helmets (Yahya et al., 2022). In Australia, e-bike safety research reflects a tension between mandatory helmet laws and the practical barriers they impose on spontaneous or short-term bike and e-bike use (Fishman et al., 2013).

Several European nations have introduced mandatory helmet regulations to recognize the heightened risks posed by higher speed e-bikes, particularly speed pedelecs. Research demonstrating the greater impact forces associated with higher-speed crashes prompted the introduction of stricter helmet requirements, such as the NTA 8776 standard in the Netherlands, which applies specifically to e-bikes capable of speeds up to 45 km/h (approximately 28 mph) (Wijlhuizen et al., 2014).

Studies indicate that helmet use does not correlate with riskier riding behavior (Schleinitz et al. 2018), countering concerns that helmets encourage more reckless behavior. Instead, enforcement policies that combine helmet mandates with safer cycling infrastructure have proven more effective at curbing head trauma and enhancing overall e-bike safety. Countries that have implemented incentives for helmet use, educational programs for riders, and high-quality bike lane infrastructure have observed lower injury severity rates among e-bike users (MacArthur & Kobel, 2014).

Parking regulations are a factor in e-bike safety. MacArthur and Kobel (2014) highlight that inconsistent e-bike classifications across federal, state, and local levels create confusion regarding where e-bikes should be parked, whether at bicycle racks, sidewalks, or dedicated e-bike zones. This uncertainty often leads to improper parking behavior, which can increase the risk of tripping hazards for pedestrians and obstructing bike lanes.

To address these challenges, several cities have implemented designated e-bike parking zones, geofencing restrictions, and lock-to mechanisms to prevent haphazard parking. Parkes et al. (2013) illustrate that European cities have successfully mitigated sidewalk clutter by creating clear parking zones and using sponsor-based funding models to support infrastructure development.

Future research should assess the effectiveness of geofencing technologies in restricting e-bike parking to designated areas, particularly in dense urban environments where improper parking can create safety hazards. Additionally, enforcement policies, public awareness campaigns, and improved signage are necessary to ensure that e-bike parking regulations are well understood and consistently followed. Innovations in braking systems, battery management, and rider-assist technologies improve safety but have yet to achieve widespread adoption. Emerging safety technologies, such as V2X communications, may also reduce collision risks.

Key E-Bike Safety Considerations

- **Demographics and Vulnerable Users:**
  - Adults (40+) are more prone to severe e-bike injuries, especially with Class 3 and Out-of-Class models
  - Studies on the safety risks to adolescents remain limited despite their increasing use micromobility devices
- **Shared vs. Personally Owned Devices:**
  - Shared e-bike users face lower injury severity, although they are less likely to wear helmets and often lack riding experience, while personally owned e-bike riders travel longer distances at higher speeds, which increases crash exposure
- **Infrastructure and Environmental Factors:**
  - Dedicated bike lanes, improved lighting, and protected intersections reduce crash risks
  - Poorly maintained infrastructure and obstructed bike lanes lead to higher injury rates, particularly in low-income areas
- **Speed and Behavior:**
  - High speeds correlate with increased crash severity, especially among Class 3 e-bikes
  - Risky behaviors, such as riding under the influence, phone use, and ignoring traffic rules, exacerbate crash risks
- **Policy and Regulatory Challenges:**
  - Inconsistent speed limits, helmet requirements, and e-bike classifications hinder efforts to improve safety
  - Geofencing and speed restrictions show potential, but require broader implementation and enforcement
- **Device Performance Advancements:**
  - Innovations in braking systems, battery management, vehicle-to-everything (V2X) communications, and rider-assist technologies improve safety but have yet to achieve widespread adoption.

Safety Review of Other Micromobility Devices

The purpose of this section is to further explore safety solutions necessary to protect all micromobility users beyond e-bikes. The following section synthesizes safety across these various modes by identifying when, where, and how these devices are used, user's behavioral insights, as well as the role of device features, unsafe roadway environments, and other factors that drive crash risk.

While powered standing scooters (commonly referred to as e-scooters) dominate the current literature and shared-use discussions, other modes, such as electric mopeds and heavier seated scooters, introduce unique risks due to their greater mass, larger wheel size, and higher operating speeds.

Several studies analyzed shared e-scooter ridership across multiple U.S. cities and found peak usage in the evenings and on weekends, particularly around universities and downtown areas, emphasizing their role in recreational and first- and last-mile travel (Mathew et al., 2019; Beck et al., 2020; Abouelela et al., 2023). Studies indicate that e-scooter crashes are more frequent in densely populated urban cores, central business districts, and near transit hubs, where micromobility riders frequently interact with pedestrians, motor vehicles, and other cyclists (Caspi et al., 2020; Zhang, Nelson & Mulley, 2023). Similarly, Bai and Jiao (2020) demonstrated that e-scooter trips in Austin, TX, and Minneapolis, MN, cluster near commercial centers and transit hubs, with ridership influenced by land-use diversity and public transportation accessibility. McKenzie (2019) further distinguished between scooter-share and bike-share usage in Washington, D.C., noting that scooters are predominantly used for leisure and short trips, whereas e-bikes see more consistent commuting use. High pedestrian volumes in shared spaces create conflict points that contribute to falls and collisions, particularly in tourist-heavy zones and entertainment districts (Jiao & Bai, 2020). Unlike larger-wheeled bicycles and mopeds, e-scooters have limited stability in wet or windy conditions, making environmental conditions particularly hazardous (Stigson et al., 2021; Speak et al., 2023).

E-scooter safety and injuries have been extensively studied, revealing high injury rates, particularly head and upper extremity injuries, largely due to falls and collisions with motor vehicles (Mathew et al., 2019; Singh et al., 2022; Tark, 2022; Abouelela et al., 2023). Helmet usage remains low across studies, with rates often below 10% (Haworth et al., 2021; Serra et al., 2021; Karpinski, Bayles, Daigle, & Mantine, 2022), despite the high prevalence of head injuries reported in various regions (National Academies of Science, Engineering, and Medicine [National Academies], 2022; Singh et al., 2022). Factors such as riding under the influence, nighttime usage, speed variations, lack of user experience, and inadequate infrastructure increase crash risks (Zhang et al., 2018; Blomberg et al., 2019; Gössling, 2020; Cloud et al., 2023). Studies comparing cities indicate that those with extensive bike lane networks and better-maintained roads report fewer e-scooter accidents (Stigson et al., 2021; Cloud et al., 2023; Sabbaghian et al., 2024). Additionally, user behavior studies have highlighted that risky maneuvers, lack of compliance with local regulations, and parking issues exacerbate safety challenges (McKenzie, 2019; Tuncer et al., 2020).

Electric mopeds and other low-speed electric devices exhibit distinct crash patterns compared to e-scooters. Unlike standing e-scooters, mopeds are typically used in higher-speed environments, often in mixed-traffic roadways where conflicts with motor vehicles are more frequent (Nikiforiadis et al., 2021). Studies indicate that side-impact collisions and rear-end crashes are particularly severe for moped users due to their higher speeds and limited visibility in traffic (Drimlová et al., 2024). While moped users generally wear helmets more frequently than e-scooter riders, injury severity remains high in crashes involving motor vehicles, with lower-limb fractures and thoracic injuries being more prevalent (International Transport Forum [ITF], 2015).

Higher speed powered standing scooters and larger electric kick scooters share some safety concerns with traditional e-scooters but introduce additional challenges due to heavier frame weights and higher potential speeds. Studies highlight that steering instability at speeds exceeding 25 km/h (approximately 15.5 mph) increases the likelihood of falls, especially in crowded urban settings where reaction times are reduced (Serra et al., 2021). Additionally, quick acceleration and abrupt braking forces have been linked to higher rates of rider ejections and secondary impact injuries (Karpinski et al., 2022). Unlike mopeds, powered standing scooter riders tend to use bike lanes rather than roadways, but inadequate lane width and congestion can increase their risk of sideswipe crashes in mixed-use cycling corridors (Cloud et al., 2023).

The following subsections synthesize key literature reviewed across these varied modes, and the role of behavior, device, crash risk, infrastructure, and policy frameworks on safety. The key findings are listed below:

- **Behavioral hazards:**
  - Safety is undermined by riders exploiting the vehicle’s agility to weave between sidewalks and roads, a behavior that can be exacerbated by nighttime alcohol impairment (Tuncer et al., 2020; Karpinski et al., 2022).
  - Younger demographics drive the frequency of aggressive riding incidents, while older demographics bear the burden of higher injury severity when crashes occur (Blackman & Haworth, 2010; Wang et al., 2019).
  - Standardizing crash data by trips or vehicle kilometers traveled is essential; exposure models prove that while daytime usage is higher, nighttime riding presents a drastically elevated risk for severe trauma (Shah et al., 2021; Abouelela et al., 2023).
  - U.S. e-scooter usage and corresponding crash rates peak during evenings and weekends in commercial and university districts, heavily driven by

recreational use and alcohol impairment (Karpinski, Bayles, Daigle, & Mantine, 2022; Abouelela et al., 2023).

- **Device specifications:**
    - The higher speeds and mixed-traffic usage of mopeds lead to severe side-impact and thoracic injuries, while the acceleration profiles of e-scooters frequently cause rider ejections (ITF, 2015; Karpinski, Bayles, Daigle, & Mantine, 2022).
    - The small wheels and a high center of gravity make e-scooters exceptionally vulnerable to surface irregularities, potholes, and uneven terrain leading to frequent loss-of-control falls and necessitating rigorous pavement maintenance standards (Xu, Shang, Yu et al., 2016; Serra et al., 2021; Karpinski, Bayles, Daigle, & Mantine, 2022).
    - The widespread lack of anti-lock braking systems and consistent lightning drastically increases collision rates, particularly in nighttime or sudden stop scenarios (ITF, 2015; Karpinski, Bayles, Daigle, & Mantine, 2022).
    - Mitigating risks from high motor outputs and thermal battery fires requires urgent industry-wide standardization and manufacturing oversight (Wang et al., 2019; Kazemzadeh et al., 2022).
- **Crash likelihood and injury severity:**
    - Crash rates peak during evening and weekend hours in dense entertainment and transit districts, driven by high user volumes and complex traffic interaction (Abouelela et al., 2023; Blomberg et al., 2019; Caspi et al., 2020).
    - Hospital metrics, specifically the Injury Severity Score and Head Injury Criterion, indicate that head and upper-limb injuries dominate e-scooter crashes, which are exacerbated helmet usage rates that consistently fall below 10% globally, necessitate strict speed and infrastructure interventions to separate riders from motor vehicle (Serra et al., 2021; Sexton et al., 2023; Haworth et al., 2021; Singh et al., 2022).
- **Impact of infrastructure:**
    - Regardless of the specific micromobility mode, cities providing dedicated, smooth-surfaced lanes and enforcing speed restrictions consistently mitigate crash frequencies and overall severities (Stigson et al., 2021; Zhang, Nelson & Mulley, 2023).
    - Potholes, poor lighting, and a lack of protected lanes force riders into active traffic, representing the primary catalyst for severe crashes in North American cities (Almannaa et al., 2021; Cloud et al., 2023).
    - Unsignalized intersections in dense central business districts are among the most frequent sites for micromobility crashes, requiring advanced signal

timing and clear right-of-way markings (Kazemzadeh et al., 2022; Zhang, Nelson & Mulley, 2023)

    - European data confirms that physically separated cycling infrastructure is one of the most effective global strategies for reducing micromobility collisions (Nikiforiadis et al., 2021).
    - Poor surface maintenance and curb transitions are the leading cause of international e-scooter crashes, accounting for over 80% of incidents in studied regions (Haworth et al., 2021; Stigson et al., 2021).

- **Shared vs. private micromobility systems:**
    - Shared users face high crash rates driven by vehicle unfamiliarity, spontaneous risky behaviors, and an almost universal lack of helmets (Haworth et al., 2021; Singh et al., 2022).
    - While shared vehicles suffer from accelerated mechanical wear, their software-limited speeds protect riders from the severe, high-speed impact traumas more commonly seen among private owners (Wang et al., 2019; Kazemzadeh et al., 2022).
- **Policy and safety regulations:**
    - Addressing the U.S. safety challenge requires data-driven policies, including strict geofencing for speed control, specialized helmet standards, and infrastructure upgrades (Bloom et al., 2021; Serra et al., 2021).
    - Europe and Australia lead in utilizing geofencing to strictly enforce variable speed limits based on pedestrian density, offering a blueprint for automated safety compliance (Cloud et al., 2023; Zhang, Du et al., 2023)
    - The shift toward machine learning and video-based surrogate safety measures allows cities to identify conflict hotspots (e.g., poor lighting or complex intersections) before severe injuries occur (Prencipe et al., 2022; Maiti et al., 2024).
    - Mitigating urban hazards requires strict policies for speed reductions and the implementation of lock-to parking corrals to prevent dangerous sidewalk clutter (Gössling, 2020; Stigson et al., 2021).

Behavioral Hazards

Behavioral factors play a crucial role in crash risk. Nighttime riding, often associated with alcohol consumption, contributes disproportionately to severe crashes, particularly among shared e-scooter users (Shah et al., 2021). Studies also emphasize the disproportionate impact on vulnerable groups, with younger riders engaging in more aggressive riding behaviors and older riders facing higher injury severities across micromobility modes due to slower reaction times and balance-related challenges (Blackman & Haworth, 2010, 2013; Wang et al., 2019; Lavoie-Gagne et al., 2021).

Behavioral studies highlight prevalent risky behaviors with direct safety consequences, including sidewalk riding, illegal lane changes, abrupt maneuvers, and low compliance with traffic laws (McKenzie 2019, Tuncer et al., 2020; Sabbaghian et al., 2024). Riders often exploit the dual pedestrian–vehicle status of e-scooters to navigate urban environments, leading to conflicts with pedestrians and increased fall risks. High rates of nighttime riding, frequently associated with alcohol consumption, further elevate injury risks (Blomberg et al., 2019; Karpinski, Bayles, Daigle, & Mantine, 2022; Singh et al., 2022). Speeding and lane violations on curves are common among e-scooter users, especially in areas lacking dedicated infrastructure, heightening crash likelihood (Sabbaghian et al., 2024).

Device Specifications

Micromobility safety is fundamentally shaped by the physical and performance characteristics of the devices and how they are utilized in urban environments. Studies indicate that design features such as small wheel sizes, high centers of gravity, and limited suspension systems in e-scooters contribute to instability and increased crash risks, particularly when encountering road irregularities (Serra et al., 2021). Brake performance is another key safety concern; several studies highlight inconsistent braking capabilities across micromobility devices, with delayed response times increasing collision likelihood (Kazemzadeh et al., 2022; Tark, 2022). In particular, the absence of anti-lock braking systems on many e-scooters and e-bikes has been associated with higher fall and collision rates (ITF, 2015; Serra et al., 2021).

Battery-related issues, including thermal runaway and fire risks, have emerged as hazards, especially for micromobility vehicles with frequent charging cycles (Bascones et al., 2022; Tark, 2022). Studies emphasize the importance of proper battery management systems and enhanced manufacturing standards to mitigate these risks (Gössling, 2020; Kazemzadeh et al., 2022). Furthermore, lighting systems and visibility features vary across devices, with inadequate front and rear lights contributing to nighttime crash risks (Karpinski, Bayles, Daigle, & Mantine, 2022; Zhang, Nelson & Mulley, 2023). Vehicle weight and speed limitations, or lack thereof, also influence safety outcomes.

Innovations in device specifications, such as integrated helmet systems, improved lighting, and shock-absorption systems, have shown potential to enhance user safety (Gössling, 2020; Serra et al., 2021). However, the inconsistent adoption of these features across operators and jurisdictions limits their overall effectiveness. Standardization efforts, particularly for braking systems, battery safety protocols, and structural integrity tests, are essential to ensure a baseline level of safety for all micromobility users (Kazemzadeh et al., 2022; National Academies, 2022).

Crash Likelihood and Injury Severity

Various studies have assessed the safety of micromobility modes by focusing on crash severity, injury patterns, exposure rates, and environmental influences. These metrics provide insights into the factors contributing to micromobility-related crashes and injuries.

Crash rate metrics, including crashes per 10,000 trips, per million vehicle kilometers traveled, and per registered vehicle, are commonly used to standardize safety comparisons across modes and locations (Blackman & Haworth, 2010, 2013; Almannaa et al., 2020). Several studies have leveraged police-reported crash data, hospital records, and insurance claims to calculate these rates, enabling researchers to identify high-risk user groups and environments (Lavoie-Gagne et al., 2021; Stigson et al., 2021). Shah et al. (2021) highlighted that crash risks for shared e-scooters are significantly higher at night, particularly in areas with poor lighting and high pedestrian activity. Exposure-adjusted crash risk studies have shown that nighttime e-scooter incidents are more likely to result in severe injuries due to reduced visibility and increased likelihood of alcohol impairment.

Crash severity analysis often employs Injury Severity Scores, Head Injury Criteria, and other trauma-related metrics to evaluate injury outcomes (Xu, Shang, Qi, et al., 2016; Xu, Shang, Yu, et al., 2016; Serra et al., 2021). Studies utilizing hospital admission data and emergency department visits further assess the severity distribution of injuries by body region and crash circumstances (Bascones et al., 2022; Singh et al., 2022; Tark, 2022). Sexton et al. (2023) reviewed multiple U.S. studies and found that head injuries, fractures, and abrasions are the most commonly reported e-scooter injuries, with severity increasing when motor vehicles are involved. Surrogate safety measures, such as conflict points at intersections and near-miss analysis, have been applied using video motion capture and crowd-sensing technologies (Maiti et al., 2024; Sabbaghian et al., 2024; Neshagaran et al., 2025).

Injury patterns vary across micromobility devices but share common trends. Singh et al. (2022) and Bloom et al. (2021) reported high incidences of head and upper-limb injuries among e-scooter users, and helmet usage rates below 10%. Abouelela et al. (2023) noted that young adult males (ages 18–34) account for most e-scooter-related injuries. Notably, Karpinski, Bayles, Daigle, and Mantine (2022) analyzed e-scooter fatalities and found that 81% occurred at night, frequently involving alcohol impairment and excessive speed. Stigson et al. (2021) found that over 80% of e-scooter crashes in Sweden were single-vehicle incidents, with infrastructure-related factors such as curb-related falls and poor road maintenance playing roles.

Several studies have also integrated environmental variables, such as weather conditions, lighting, and urban form, into safety analyses, using exposure-adjusted models to quantify their effects on crash likelihood and severity (Corcoran et al., 2014; Şengül & Mostofi, 2021; Karpinski, Bayles, & Sanders, 2022). Exposure-based analyses evaluating the effectiveness of infrastructure interventions (e.g., protected bike lanes, traffic calming measures) have shown reductions in crash rates when dedicated micromobility infrastructure is implemented (Cloud et al., 2023; Sabbaghian et al., 2024). Research further suggests that road surface conditions, curb-separated lanes, and improved visibility measures can improve micromobility safety outcomes (Sexton et al., 2023).

Impact of Infrastructure

Infrastructure emerges as a determinant of micromobility safety. Cities with extensive protected lane networks experience lower crash rates and reduced injury severity among micromobility users (Qingyu et al., 2021; Zhang, Nelson & Mulley, 2023). Conversely, areas lacking dedicated lanes or with poor road maintenance exhibit higher crash frequencies. In particular, potholes, abrupt elevation changes, and surface inconsistencies disproportionately impact small-wheeled vehicles like e-scooters, increasing the likelihood of falls and control loss (Sabbaghian et al., 2024).

Intersections pose a particularly high risk for all micromobility users. Studies indicate that crash rates spike in areas with unprotected crossings, unclear traffic control, and poor visibility (Cloud et al., 2023). Additionally, urban design factors such as short block lengths and high intersection density can elevate crash risks by increasing rider exposure to conflicts with motor vehicles (Bai & Jiao, 2020). Research highlights that incorporating traffic calming measures, enhanced intersection treatments, and dedicated micromobility corridors can improve safety outcomes (Kazemzadeh et al., 2022).

Zhang, Nelson, and Mulley (2023) and Qingyu et al. (2021) found that dedicated micromobility lanes can reduce crash risk, particularly at intersections where pedestrian and vehicular conflicts are common. However, e-scooter riders face elevated crash risks in areas lacking protected lanes when forced to share space with vehicles or pedestrians. Cloud et al. (2023) identified inadequate lighting and poor pavement conditions as major contributors to nighttime crashes. Additionally, Almannaa et al. (2021) emphasized the role of road surface quality, noting that potholes and debris disproportionately impact e-scooter stability, increasing single-vehicle falls.

Unlike conventional bicycles or e-bikes, small-wheeled e-scooters are highly sensitive to pavement quality, surface irregularities, and abrupt changes in elevation, making them particularly vulnerable to falls and crashes (Xu, Shang, Qi, et al., 2016; Xu, Shang, Yu, et al., 2016; Serra et al., 2021). Poorly maintained roads, potholes, tram tracks, and sudden surface transitions pose risks, with research indicating that uneven terrain is one of the leading contributors to e-scooter crashes (Karpinski, Bayles, Daigle, & Mantine, 2022; Abouelela et al., 2023). In addition, narrow or obstructed pathways and lack of dedicated micromobility lanes force e-scooter riders into mixed-traffic environments, where speed differentials between micromobility users and motor vehicles heighten collision risks (Sabbaghian et al., 2024).

Intersection design is another key determinant of e-scooter safety. High-traffic intersections, unprotected crossings, and ambiguous right-of-way regulations increase the likelihood of crashes (Stigson et al., 2021; Sabbaghian et al., 2024). Research shows that e-scooter riders experience higher crash rates at uncontrolled intersections, where conflicts with vehicles and pedestrians are more frequent (Kazemzadeh et al., 2022). Cities with protected intersection designs, clear pavement markings, and advanced signal timing strategies report lower e-scooter crash rates compared to areas with ambiguous or outdated traffic control measures (Almannaa et al., 2021).

Shared vs. Private Micromobility Systems

The safety profiles of shared and private micromobility users differ due to variations in user behavior, familiarity with the vehicle, maintenance standards, and operational environments. Shared micromobility vehicles, including dockless e-scooters and shared electric mopeds, are widely accessible and primarily used for short trips by casual users, tourists, or first-time riders. In contrast, private micromobility users are typically more familiar with their vehicles, leading to different crash risks and injury severities (Almannaa et al., 2020; Abouelela et al., 2023).

Studies consistently show higher crash and injury rates among shared micromobility users compared to private users. Shared e-scooter users, in particular, exhibit riskier riding behaviors, including frequent sidewalk riding, abrupt maneuvers, and lower helmet compliance (Haworth et al., 2021; Zhang, Du et al., 2023). Helmet use among shared micromobility riders remains low, often below 10%, whereas private users demonstrate higher compliance rates due to personal ownership responsibility and accessibility to safety gear (Karpinski, Bayles, Daigle, & Mantine, 2022; Singh et al., 2022). Furthermore, shared micromobility trips often occur in high-density urban areas, increasing exposure to vehicular traffic and pedestrian conflicts (Bai & Jiao, 2020; Caspi et al., 2020; Speak et al., 2023).

Differences between shared and privately owned e-scooters also affect safety outcomes. Haworth et al. (2021) found that while private e-scooter users exhibit higher helmet compliance, they engage in riskier behaviors, such as riding in mixed-traffic environments or exceeding speed limits. In contrast, shared e-scooter users have lower helmet compliance but are more likely to ride on sidewalks, increasing the risk of pedestrian conflicts. In that study, illegal behaviors such as sidewalk riding and improper parking decreased among shared e-scooter users over time, likely due to increased rider familiarity and policy enforcement.

Operational differences between shared and private micromobility devices also impact safety. Shared vehicles undergo frequent use by multiple riders, leading to inconsistent maintenance and increased mechanical failures, such as brake malfunctions, loose handlebars, and compromised tires (Kazemzadeh et al., 2022; Tark, 2022). While shared-use operators conduct routine fleet maintenance, the intensity of use contributes to higher rates of equipment degradation compared to privately owned vehicles, where owners are responsible for regular upkeep (Xu, Shang, Qi, et al., 2016; Xu, Shang, Yu, et al., 2016).

Speed regulation further differentiates shared and private micromobility use. Most shared e-scooter systems implement speed limiters, capping speeds between 15 and 25 km/h (approximately 9.3 and 15.5 mph) to enhance safety. However, private micromobility users generally travel at higher speeds, particularly on privately owned e-scooters and mopeds, increasing crash severity when incidents occur (Wang et al., 2019; Almannaa et al., 2020).

Policy and Safety Regulations

Infrastructure improvements remain a focus in reducing the risks associated with these emerging transportation modes. While mixed-use areas promote micromobility adoption, poor integration with existing transportation infrastructure increases the likelihood of crashes (Tuncer et al., 2020). Cities with dedicated lanes, smooth surfaces, and well-enforced speed restrictions experience fewer micromobility crashes, while those with shared road spaces, poor pavement conditions, and weak enforcement report increased injury severity and crash frequency (Tuncer et al., 2020; Zhang, Nelson & Mulley, 2023). Additionally, Karpinski, Bayles, Daigle, & Mantine (2022) highlight the need for visibility enhancements, such as integrated lighting and reflective materials, to reduce nighttime crash risks.

In addition, cities implementing designated parking zones, geofenced no-parking areas, and mandatory lock-to mechanisms have seen measurable improvements in reducing sidewalk clutter and pedestrian complaints (Gössling, 2020). However, enforcement remains a challenge, particularly in areas where dockless vehicles are left in high-pedestrian corridors.

Helmet compliance remains a persistent issue across micromobility modes. While some regions have implemented mandatory helmet laws, compliance rates among shared micromobility users remain low due to convenience factors (Singh et al., 2022; Karpinski, Bayles, Daigle, & Mantine, 2022). Serra et al. (2021) emphasized the need for e-scooter-specific helmet standards, arguing that traditional bicycle helmets do not adequately protect against the unique impact forces associated with e-scooter crashes. Bloom et al. (2021) demonstrated that mandatory helmet laws reduce head trauma severity among e-scooter riders. Studies suggest that regulatory efforts such as integrated helmet rental systems, financial incentives, and public awareness campaigns could enhance compliance rates (Gössling, 2020).

A comparison of regional policies highlights the importance of cohesive regulatory frameworks in mitigating micromobility risks. European cities lead with proactive safety measures, including strict speed limits and geofenced slow zones in pedestrian-heavy areas (Bieliński & Ważna, 2020). These measures have resulted in fewer severe crashes and improved safety outcomes. American cities, while increasingly adopting similar interventions, continue to face regulatory inconsistencies that contribute to higher crash rates (Sexton et al., 2023). The absence of standardized speed limits, inconsistent enforcement of helmet regulations, and gaps in protected infrastructure exacerbate safety concerns in the United States. Longitudinal studies assessing the impact of recent safety regulations, including helmet laws and infrastructure improvements, are needed to guide future policy decisions. Stakeholders can help address regulatory and knowledge gaps integrating telematics and video-based safety measures to capture comprehensive near-miss data beyond traditional crash logs (Prencipe et al., 2022; Maiti et al., 2024).

Australia utilizes a hybrid model, implementing micromobility regulations that combine strict helmet laws and speed restrictions. However, inconsistent enforcement and limited rider awareness have reduced the effectiveness of these policies (Blackman & Haworth, 2013; Cloud et al., 2023).

Emerging technologies offer new opportunities to improve micromobility safety. Advances in braking systems, integrated lighting, and real-time telematics monitoring have shown potential to reduce crash risk (Maiti et al., 2024). Automated emergency braking, collision avoidance systems, and V2X communication could enhance rider safety, particularly in high-risk environments (Sabbaghian et al., 2024). Future research should evaluate the long-term effectiveness of these technologies in real-world applications.

Beyond technological interventions, there is a need for more complete data collection and analysis. Many existing studies rely on police-reported crashes or hospital records, which likely undercount minor incidents and near-misses (Shah et al., 2021). Expanding data sources to include ride-tracking apps, fleet management systems, and crowd-sourced reporting could provide a more complete picture of micromobility risks (Abouelela et al., 2023).

Studies show that municipalities could generally achieve better safety outcomes by shifting from reactive enforcement toward self-enforcing infrastructure, such as physically separated lanes, protected intersections, and tailored pavement maintenance (Stigson et al., 2021; Zhang, Du et al., 2023).

Key Safety Considerations for Other Micromobility Devices

The literature surrounding other micromobility devices, such as e-scooters, electric mopeds, and powered standing scooters, generally reveals distinct safety implications driven by unique device specifications and usage patterns. A synthesis of the current research highlights the following key considerations:

- **Device & Infrastructure Mismatch:** E-scooters' small wheels and high center of gravity increase their vulnerability to surface irregularities, while higher-speed mopeds and standing scooters operating in mixed traffic face elevated risks of severe side-impact collisions
- **Vehicle Standardization:** Mitigating visibility and control issues across these micromobility modes generally requires enhanced vehicle design oversight, including the broader integration of anti-lock braking systems, improved suspension, and standard lighting
- **Behavioral Disparities (Shared vs. Private):** Shared system users frequently exhibit helmet compliance below 10% and may engage in riskier maneuvers due to rider unfamiliarity, where more experienced private owners tend to travel at higher speeds, potentially elevating crash severity
- **Temporal & Environmental Risks:** Nighttime riding, particularly in dense entertainment districts and when associated with alcohol, presents a substantially elevated risk for severe trauma, suggesting a need for targeted temporal interventions
- **Proactive Infrastructure:** Shifting from reactive enforcement toward self-enforcing infrastructure, including physically separated lanes, protected intersections, and tailored pavement maintenance could improve safety outcomes
- **Emerging Technology & Data:** Geofencing can be utilized for speed and parking compliance, and telematics and video-based safety measures can capture comprehensive near-miss data beyond traditional crash logs

Conclusion from Literature Review

The rapid proliferation of micromobility modes, particularly electric-powered vehicles such as e-bikes and e-scooters, has transformed urban transportation by offering sustainable alternatives to traditional motorized travel. However, safety remains a concern due to the increasing incidence of crashes, rising injury severity, and inadequate infrastructure.

The review of e-bike safety presented in this report highlights a complex landscape defined by varying device speeds, diverse riders' demographics, and the role of protected infrastructure. This review emphasizes mode-specific risks such as e-bike mounting difficulties, Class 3 speed differentials, poor roadway lighting, inadequate lane width, and the spillover effects of shared-use infrastructure across the entire micromobility spectrum.

> Overall, integrated regulations, enhanced infrastructure, helmet promotion, and tailored user policies are vital for American cities to maximize e-bike benefits while mitigating safety risks. The increasing prevalence of micromobility devices necessitates proactive urban planning and policy adjustments to ensure their safe and sustainable adoption.

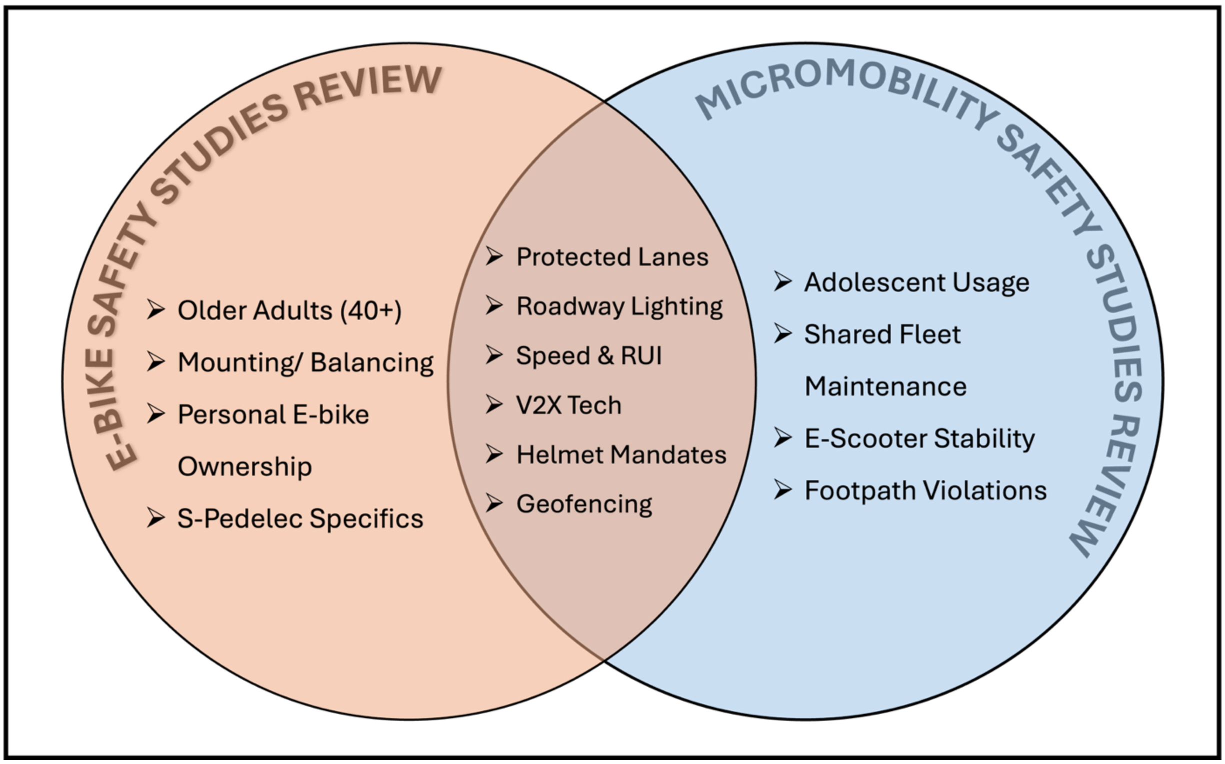
However, e-bikes do not operate in isolation; they are a single component of a rapidly diversifying micromobility ecosystem that includes e-scooters, electric mopeds, and various other lightweight electric vehicles (LEVs). To develop a truly systematic approach to urban safety, it is essential to move beyond e-bikes and examine the broader trends, behavioral insights, and policy interventions associated with these additional modes.

The intersection of e-bike and other micromobility users reveal that distinct user groups face common risks, necessitating a unified approach to urban safety. The E-Bike Safety Review section highlighted a specialized demographic of older, private e-bike owners prone to balance-related injuries, while the

Safety Review of Other Micromobility Devices section identified a younger cohort of shared e-scooter riders characterized by lower helmet usage and high-frequency ridership, and both studies converge on shared safety imperatives.

Figure 1 illustrates this conceptual overlap, demonstrating that while certain risk factors, such as user age, vehicle stability, and ownership familiarity, are highly mode-specific, a significant portion of safety insights apply universally across the micromobility spectrum.

Figure 1: Overlap of Factors between E-Bike and Micromobility Safety Literature



The overlap illustrated in Figure 1 shows that, regardless of vehicle mass or ownership model, infrastructure inadequacies, specifically the lack of protected lanes and poor nighttime lighting, act as the primary determinants of crash severity. Consequently, the story told by this synthesis is one of convergence: while rider behaviors are often mode-specific, the technical and policy solutions, such as V2X communication, geofencing, standardized speed regulations, and riding under influence (RUI), provide a systemic safety net that benefits the entire micromobility ecosystem.

Overall, U.S. micromobility trends require safety measures such as infrastructure upgrades, regulatory clarity, and enhanced enforcement strategies. Addressing these concerns through data-driven policies will be essential for safely integrating micromobility modes into urban transportation networks.

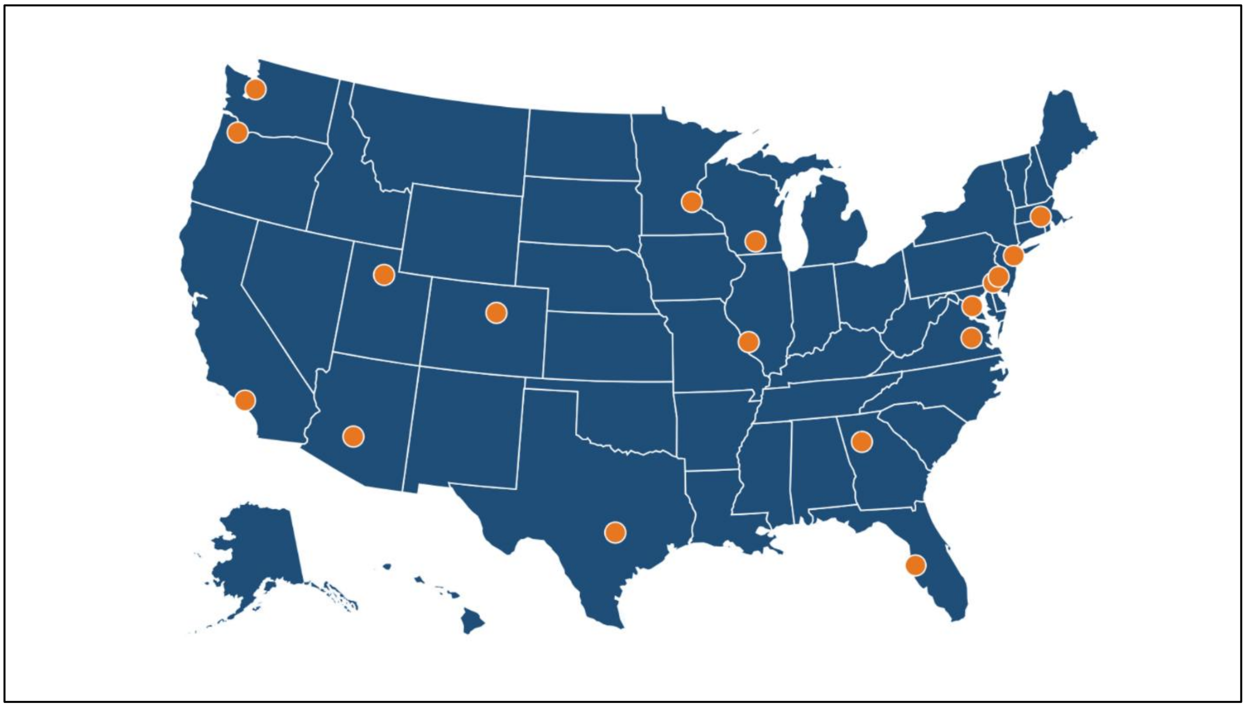
The safety of micromobility users is influenced by a complex interplay of device characteristics, rider behavior, infrastructure design, and policy interventions. While micromobility systems offer sustainable urban mobility solutions, their safety challenges necessitate targeted measures, including improved infrastructure, enhanced enforcement of safety regulations, and technological advancements. Cities must adopt data-driven approaches to micromobility planning, ensuring safety remains central to integrating micromobility into urban transport systems. Addressing these challenges through evidence-based policies will help to maximize the benefits of micromobility while minimizing its risks.

Federal, State, and Local Laws and Regulations

This section summarizes a scan of regulatory information, documented at the federal, state, and municipal level for selected cities. The goal is to provide a concise overview of the evolving regulatory landscape to facilitate a multiscale understanding of micromobility governance, regulatory fragmentation, and alignment across the United States.

The purpose of this effort includes providing safety practitioners with a tool to explore and compare regulatory dimensions across states and selected cities. An interactive web map (https://aaafoundation.org/research/safety-of-micromobility-regulations-data-and-stakeholders/) as shown in Figure 2, was developed by the research team and offers a clear, dynamic view of micromobility policy on various micromobility modes: e-bikes, e-scooters, conventional bicycles, and other micromobility devices. The summary of state- and local-level regulations for the 18 cities displayed can be downloaded as PDF files within the map. These PDFs include recent policies on age limits, helmet-use requirements, licensing, registration, roadway access restrictions, and other relevant information.

Figure 2: Interactive Web-Based Map for Micromobility Regulations in the United States



Federal Regulatory Landscape

At the federal level, e-bikes are regulated as consumer products by the CPSC, which defines them as two- or three-wheeled vehicles with fully operable pedals, a motor of less than 750 watts (1 horsepower), and a top speed under motor power alone of less than 20 mph (House of Representatives, 2011). This governs how e-bikes are manufactured and sold, but not how they are used in the transportation network.

The CPSC also has jurisdiction over other micromobility products that do not meet the definition of a motor vehicle under Federal Motor Vehicle Safety Standards within the National Highway Traffic Safety Administration's authority, including standing scooters without seats and with a top speed under 20 mph, electric skateboards (e-skateboards), and self-balancing devices. These products are categorized by factors such as seating, top speed, and self-propulsion capability and are primarily regulated under general consumer product safety statutes.

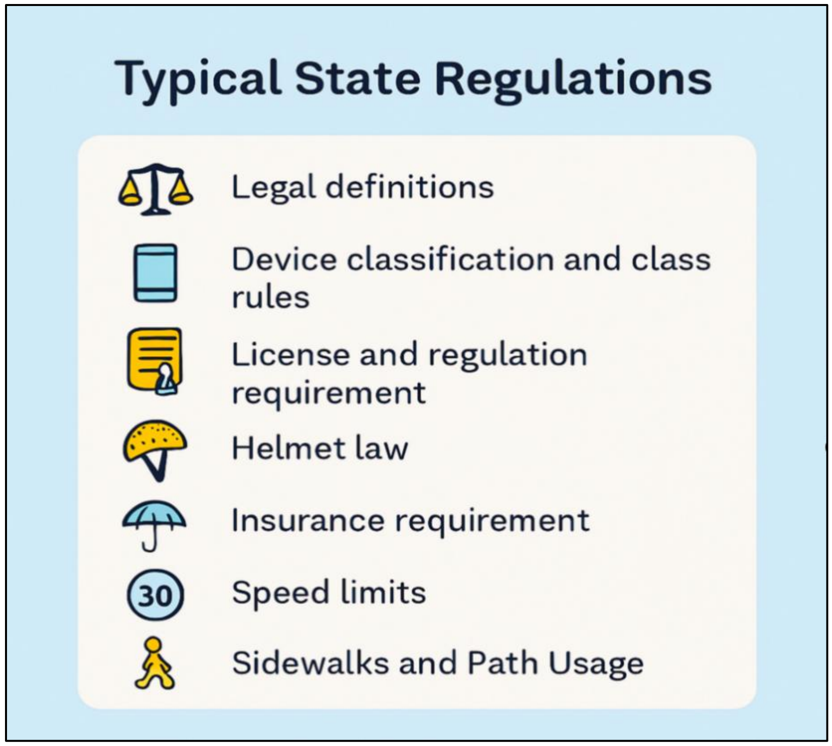
From a transportation policy perspective, the Infrastructure Investment and Jobs Act (H.R.3684), signed into law in 2021, explicitly references e-bikes and adopts the widely used three-class system. It also includes e-bikes, e-scooters, and other small-form vehicles in its broader definitional framework for improving safety and infrastructure for vulnerable road users.

State Regulatory Landscape

In the absence of federal regulation regarding operational rules, states bear the primary responsibility for defining micromobility device categories, use requirements, and safety mandates. This decentralization has produced substantial variability across states, leading to fragmented and sometimes inconsistent frameworks. For instance, most states closely follow a three-class definition of e-bikes, promoted by the advocacy group PeopleForBikes, dividing them into classes based on speed and throttle use. Yet, differences quickly emerge: while states such as California and Colorado have well-established e-bike class definitions and legislation, addressing the use of e-bikes on roads and bike lanes, others, such as Pennsylvania and Delaware, have historically restricted e-scooters and certain e-bike classes due to legislative ambiguity.

States also commonly regulate age restrictions, helmet-use, registration, and insurance requirements. For example, Hawaii mandates a nominal registration fee and imposes age restrictions on e-bike operators, whereas states like Oregon and Washington prioritize infrastructure integration and user education, enabling broader access to micromobility on urban trails and roads.

Mopeds are typically subject to stringent regulations in most states, requiring registration, operator licensing, and insurance because they are classified as motor vehicles. Meanwhile, devices like e-skateboards and privately owned e-scooters are often lightly regulated or ambiguously defined, contributing to regulatory inconsistencies.



Such variability reflects differing state priorities and underscores a key challenge in scaling micromobility nationally. While states control broad regulatory frameworks, they frequently delegate granular operational decisions to local governments, thus amplifying regulatory fragmentation as micromobility proliferates.

In recognition of the substantial regulatory variation among states, the research team documented micromobility regulations for each U.S. state, covering detailed classifications, licensing requirements, helmet requirements, age restrictions, insurance mandates, and usage guidelines. To enhance clarity and facilitate comparisons, these state-specific regulations have been visualized through infographics.

City- and Local-Level Regulatory Landscape

Local governments, particularly cities, often hold the most regulatory authority over micromobility, governing detailed rules for public right-of-way use, parking, and operational standards. Cities primarily regulate shared micromobility services through permitting and licensing processes. Municipalities issue operator permits with clear regulatory requirements, including fleet-size caps, insurance requirements, rider education mandates, data sharing, and specific geofenced operational boundaries.

Local infrastructure-related regulations are also extensive. Cities establish rules for permissible routes, sidewalk riding restrictions, dedicated lanes, and parking corrals, directly influencing the practical use and integration of micromobility within urban transport networks. These localized regulations have a meaningful impact on device adoption, safety outcomes, and public acceptance.

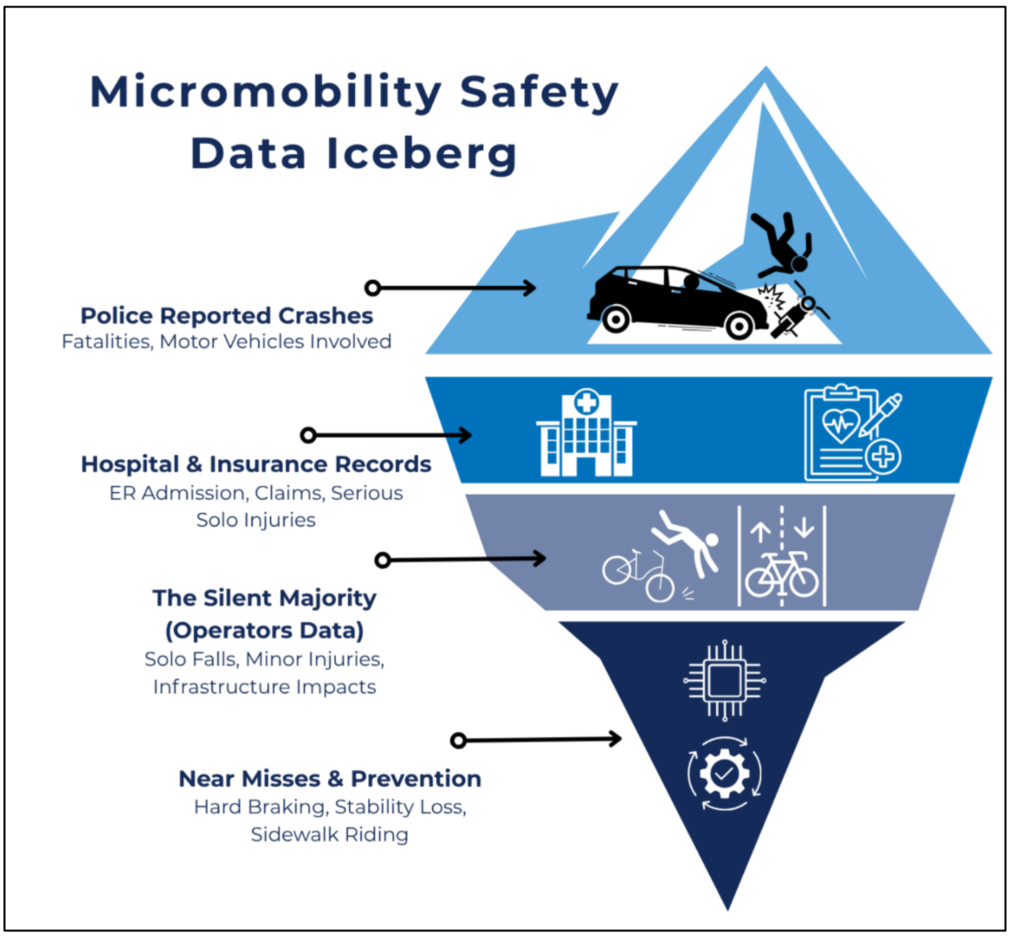
Building on the state-level documentation, 18 representative U.S. cities were selected for a detailed examination of micromobility regulations at the municipal level. City selection was informed by the PeopleForBikes “2025 Best Places to Bike“ rankings, ensuring representation across the full spectrum of bicycle-friendly environments (PeopleForBikes, 2025). Specifically, cities were included from the top, middle, and bottom of the rankings to capture regulatory diversity across urban typologies, ranging from highly bike-supportive municipalities to those with less-developed micromobility infrastructure.

The regulatory variation at the city level is substantial and reflects unique local conditions and policy priorities. For example, Austin, TX, regulates fleet sizes based on usage metrics, requires specific parking practices for devices, and enforces speed limits and geofenced operational zones. Seattle, WA, and Washington, DC, implement regulations mandating equitable access to micromobility, including required deployment in disadvantaged neighborhoods and discounted rates for low-income populations. San Francisco, CA, enforces stringent regulations on micromobility parking and mandates detailed real-time data sharing to maintain operational oversight (National Association of City Transportation Officials, 2019).

Micromobility Safety Data

Current micromobility safety analyses are hampered by privacy regulations, proprietary claims systems, and fragmented data ownership. This limited access creates a “safety data iceberg” for micromobility where the visible tip consists of the most available and commonly used sources while a substantial portion remains hidden in private records that are not yet fully available or unlocked as shown Figure 3. This study sheds light on the scope of micromobility injuries by reviewing two sources available to the team: police crash reports and hospital records. This evaluation intends to highlight limitations and inherent biases by cross-referencing trauma center admissions against police crash logs to reveal a systemic gap in public reporting of crash data.

Figure 3: The Micromobility Safety Data Iceberg



In the United States, the CPSC reported a sharp increase in micromobility-related injuries based on hospital data, while many local police jurisdictions recorded stable or decreasing crash rates (Tark, 2023). Also, research conducted at a Level 1 trauma center found that fewer than 10% of e-scooter-related injuries treated in emergency departments were documented in official police crash reports (Badeau et al., 2019). The nature of the incident drives this gap, while police reports capture nearly 100% of fatalities but miss most of the hospital-admitted injuries that do not involve a motor vehicle. Police data is generally restricted to incidents involving motor vehicles or those exceeding specific monetary damage thresholds. While collisions with automobiles account for approximately 10% to 15% of actual injury outcomes, they constitute over 90% of police crash reports (Cherry et al., 2021). Police reports primarily document the environmental circumstances and the cause of a crash in detail, while frequently omitting the medical outcomes of most casualties.

Conversely, hospital datasets, while capturing a higher volume of injury events, focus exclusively on the nature of the injury for triage and treatment, and often represent injuries that provide little to no data regarding the roadway environment, infrastructure defects, or external crash mechanics. This indicates that the vast majority of micromobility risk that is being reported within medical datasets remains detached from the operational data that city agencies use to justify infrastructure funding.

Furthermore, the operational reality of micromobility is that it is dominated by underreported falls linked to infrastructure deficiencies, necessitating a shift toward more granular and complete datasets. Minimum property damage thresholds and definitions requiring motor vehicle involvement mean that low-speed sidewalk collisions or minor solo falls are routinely excluded from reporting mandates (National Highway Traffic Safety Administration [NHTSA], 2017). Consequently, these events are not included on a city's safety map, unless captured by operator telematics or other internal systems (Cicchino et al., 2021). However, the exact number of incidents is rarely disclosed due to the competing and privacy-sensitive nature of the company's policies.

The goal of this section is to examine primary sources of available data, including Police Reported Crash Data, Emergency Department Injury Data, and Emerging Safety Data Sources.

The objectives of this task are as follows:

- Describe how micromobility definitions have evolved within these data sources
- Demonstrate how sources can complement each other and be linked to reveal a better understanding of micromobility safety
- Develop two case studies using Tennessee's police crash data and hospital records to provide an example of safety insights at the state level.
    - Case Study I: Using artificial intelligence (AI) to analyze crash narratives
    - Case Study II: Insights from hospital records

Historically, micromobility safety analysis among public agencies has been driven by a reactive model that relies on police and injury data. This model has created a fractured data landscape in which minor falls are unrecorded, only car-involved crashes are documented by police, and detailed injury data are reported in hospital records.

The relationship between reported safety incidents and actual occurrences follows an iceberg model. In this conceptual framework, traffic safety professionals often rely on official crash statistics that capture only the visible tip (see Police Reported Crash Data), which typically includes severe, vehicle-involved crashes that trigger a police response. In contrast, most incidents remain submerged in the data, Figure 3 shows these submerged layers represent the silent majority of micromobility safety, comprising hospital admissions (see Emergency Department Injury Data) for solo falls, operator logs of minor injuries, and telematic detection of near-miss events (such as hard braking or stability loss). While invisible to traditional transportation-related reporting methods, these lower layers constitute the bulk of actual risk exposure on the roadway.

The consequences of this underreporting extend beyond simple missing counts; they create a systematic feedback loop that misguides infrastructure investment and safety policy. When datasets exhibit structural biases, such as police logs favoring motor vehicle collisions or hospital records lacking environmental context, jurisdictions face discrepancies in their approach to understanding and treating risk.

Consequently, even if certain types of risk are skewed toward high-visibility corridors, minor arterials, and/or low-income neighborhoods, these areas may remain invisible on safety maps unless they also exhibit more severe risks identified through police data. This fragmentation prevents practitioners from identifying the definitive link between poor infrastructure design and incident rates, ultimately stalling the shift from reactive crash management to proactive, evidence-based safety planning. Infrastructure quality acts as a determinant not only of where crashes occur but also of reported safety events. This dynamic highlights a behavioral bias in which riders tend to assume falls caused by poor pavement are bad luck or user error, often leaving them unreported, while characterizing interactions with cars as external risk that warrants a formal report. When validating the link between infrastructure and safety, a 2025 analysis by Lime and the League of American Bicyclists covering 5 million trips, found that reported incident rates were 34% lower on streets with bike infrastructure than on those without (League of American Bicyclists & Lime 2025). On these roadways, the ratio of unreported falls (detected by sensors) to reported incidents was significantly higher, suggesting that dangerous environments discourage reporting by making riders feel unsafe or at fault.

In addition, without reliable normalization (e.g., standardized crash or injury rates), agencies cannot achieve true cross-jurisdictional comparability. Establishing a reliable safety metric, such as *Crashes per Million Miles,* is challenging because there is currently no standardized definition of what constitutes a crash. Instead, classification depends entirely on the stakeholder who records the event. Police reports are typically triggered only by property damage thresholds (e.g., incidents exceeding several hundred or thousands of dollars) or severe injury. This lack of a unified denominator renders cross-jurisdictional comparisons largely ineffective. Consequently, this fragmentation is the primary driver for the adoption of standards for exchanging micromobility data in which providers notify changes in a vehicle's state (e.g., device is available, or reserved, or in trip) to support regulation, compliance, and analytics. For example, the Mobility Data Specification (MDS), aims to establish a universal digital definition of a *safety event* to ensure consistent reporting across all platforms (see section on Integrated Data Workflow & Analytical Framework).

The industry is currently undergoing a shift from reactive incident logging (waiting for a user report) to proactive safety detection. To achieve this, shared micromobility vehicles are evolving into sophisticated internet of things (IoT) platforms equipped with multimodal sensor fusion, helping to address an underreporting gap by capturing solo falls and near-misses that users rarely report. For a technical review of these emerging technologies, including global navigation satellite systems (GNSS) mapping, kinematic inertial measurement units, AI-powered perception cameras, proximity sensors, and post-incident forensics, please refer to Appendix C: Traffic Crash Narrative Analysis with AI/LLMs.

Police Reported Crash Data

Police reported crash data serves as the foundational source for analyzing micromobility safety, relying on national reporting standards such as the Model Minimum Uniform Crash Criteria (MMUCC) to capture details, including crash characteristics and injury severity. While historical data often grouped emerging modes like e-bikes and e-scooters under generic pedestrian categories, recent updates, including the 2025 MMUCC 6th Edition, have introduced some granular classification. However, challenges remain in utilizing this data source. Police records frequently miss non-collision injuries, such as falls, and the inconsistent adoption of new coding standards across states leads to ongoing misclassification. To build an understanding of micromobility safety, researchers must supplement police data with hospital injury records and leverage advanced AI to retrospectively verify crash details from written narratives.

Data structure and reporting standards

- ▶ Primary structured source from crash characteristics.
- ▶ Working toward standardized reporting nationwide through the MMUCC.
- ▶ Utilizes the KABCO scale for classifying injury severity and captures only a portion of crashes.

Evolution of micromobility classification

- ▶ Historically grouped micromobility users as generic pedestrians, hindering accurate safety monitoring.
- ▶ Recent updates across state and federal databases, including the 2025 MMUCC 6th Edition and ANSI D16 standard, now introduce granular classifications for devices like ebikes and personal conveyances.

Data limitations and analytical hurdles

- ▶ Fails to capture frequent non-collision injuries (such as falls), necessitating supplemental hospital records for a complete picture.
- ▶ Inconsistent state adoption of new coding standards leads to ongoing misclassifications.
- ▶ Historical data requires retrospective verification using advanced AI on crash narratives.

Case Study I: AI Analysis of E-Scooter Narratives in Tennessee Crash Reports

Misclassification of micromobility modes is common in police-reported crash data. This issue largely stems from the relatively recent rise in popularity of micromobility vehicles such as e-bikes and e-scooters. Because these technologies emerged quickly, updates to crash-reporting standards such as MMUCC have not kept pace, making it difficult to accurately classify crashes involving these modes. Without appropriate reporting and coding categories, micromobility modes may be mistakenly classified as pedestrians, bicyclists, or even motor vehicles in police databases.

This case study aims to address coding limitations in structured crash data by analyzing crash narratives involving e-scooters using LLMs to provide a more accurate representation of micromobility-involved crashes. While both e-bikes and e-scooters face reporting challenges, this analysis focuses exclusively on e-scooters because they present unique operational dynamics and suffer from particularly high rates of misclassification compared to e-bikes, which are often simply grouped with standard bicycles. Tennessee was selected as a testbed for detailed analysis because it offers reporting mechanisms such as crash narratives that help differentiate micromobility riders from pedestrians, allowing the team to validate and improve attribution accuracy when parsing crash reports at a state scale.

The objectives of the first case study are as follows:

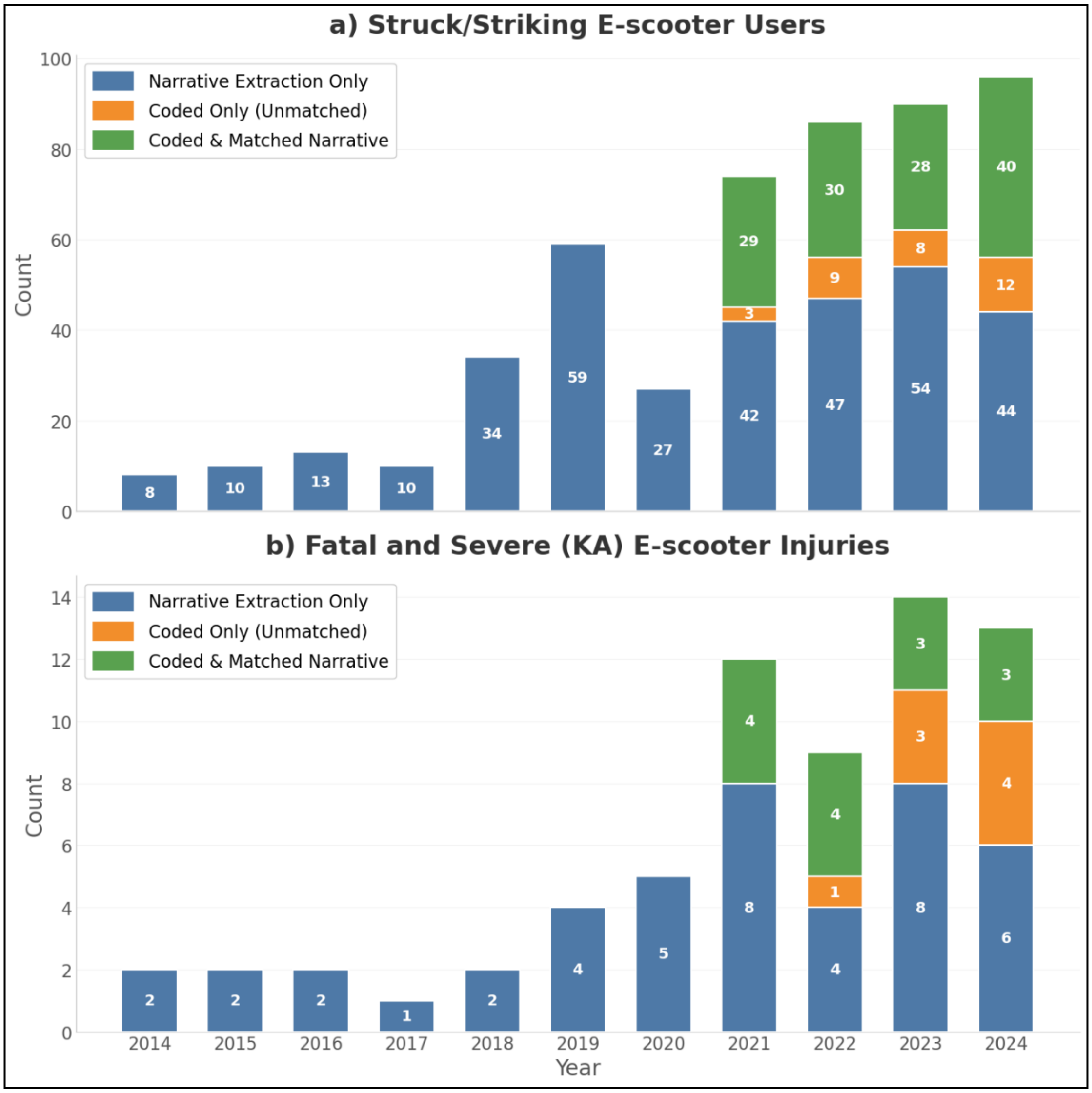
- To leverage AI to extract information from narrative text in police crash reports,
- To uncover subtle but important details mentioned in crash narratives that can shed light on micromobility usage patterns.
    - In particular, data was examined to determine whether users were operating shared or non-shared devices, and whether they were the striking or the struck party in a crash.
- To explore how crash factors relate to user characteristics such as gender, age, and injury severity.
    - These details are rarely captured in structured crash data but can provide valuable insights, especially since micromobility devices travel at higher speeds than pedestrians and can therefore lead to more severe or even fatal outcomes.

The first case study developed and implemented a methodology using the sequential few-shot prompted (SFSP) model to extract information from Tennessee police-reported crash narratives, utilizing the Tennessee Integrated Traffic Analysis Network (TITAN) database from January 2014 until the end of September 2024. The SFSP model, built on a Llama 3.1 LLM backbone, identifies and classifies micromobility users and devices, determines whether a device is part of a shared system, and distinguishes whether the user was the striking or struck party in a crash. When validated against manually annotated data, the model achieved an accuracy of 94.8% in identifying and classifying non-motorist modes. Temporal analyses of the model's classifications also revealed patterns consistent with the broader rise in micromobility use across U.S. cities, further supporting the reliability of the AI-based classifications. For more information on the application of AI and LLMs to analyze crashes, refer to Appendix C: Traffic Crash Narrative Analysis with AI/LLMs.

Misclassification of Crashes Involving E-Scooters. The TITAN micromobility coding has historically been limited to the "persons on personal conveyances" category, leading officers to frequently classify micromobility users as pedestrians or bicyclists. Figure 4 illustrates the increasing crash counts and injury outcomes across the following three groups:

- TITAN-coded e-scooter riders matched with a crash narrative (shown in green)
- E-scooter crash riders identified solely through the narrative-extraction outputs (shown in blue)
- Remaining TITAN-coded e-scooter riders that were not matched with the crash narratives (shown in orange)

Figure 4: Estimated E-Scooter Striking/Struck a) Counts and b) Injury Trends (2014–September 2024)

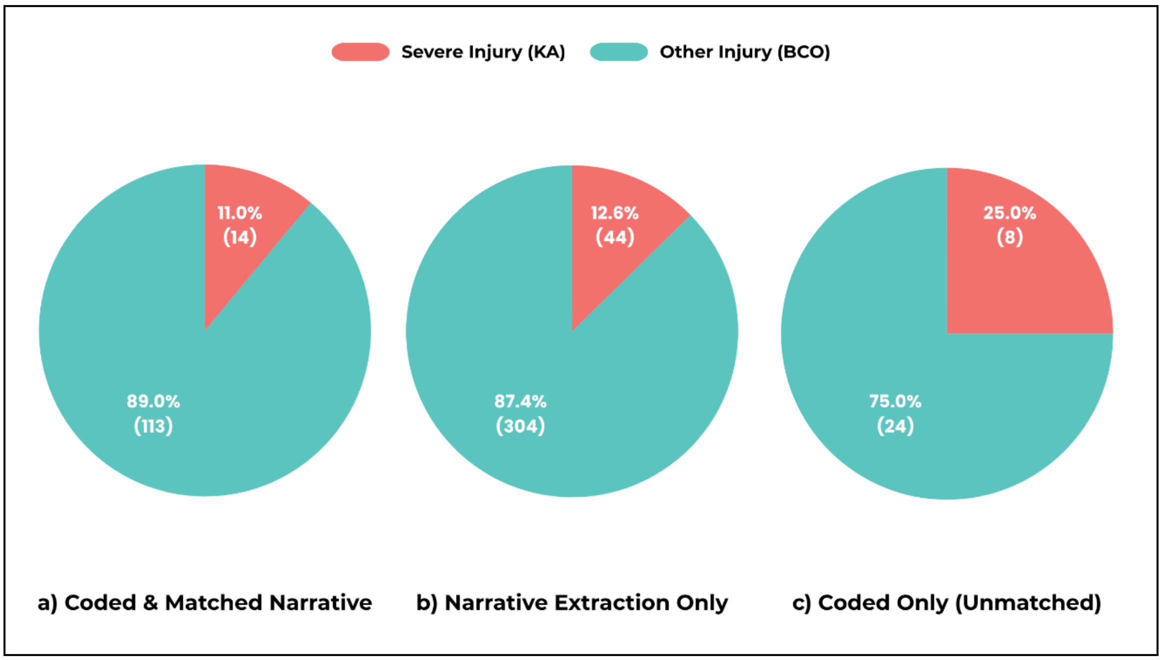


The figure similarly shows a steeper rise in fatal and severe injuries among e-scooter users. In 2020, the number of e-scooter riders involved in traffic crashes dropped, coinciding with the COVID-19 pandemic and lockdowns. However, despite having the fewest crashes, 2020 did not have the lowest severe injury and fatality counts; they were higher than the preceding year. This pattern aligns with general traffic crash trends during the pandemic.

These figures show a notable gap in the dataset, with few cases having e-scooter riders both coded and matched to a narrative (shown in green); given this gap in systematic recording, many e-scooter fatalities and severe outcomes likely remain underrepresented. This mismatch limits completeness, potentially resulting in biased injury severity and frequency estimates, hiding the true scope of e-scooter incidents.

Figure 5 presents a similar pattern for severe injuries among e-scooter riders, with comparable proportions observed in the narrative-extraction-only group (12.6%) and the TITAN-coded cases matched through narrative extraction (11%). In contrast, the number of TITAN-coded e-scooter riders not matched with crash narratives was considerably smaller, severe injuries were disproportionately represented within this group (25%). This pattern may indicate that the crash narratives emphasized injury severity and crash outcomes while omitting references to the micromobility component of the crash.

Figure 5: Comparing Proportion of Severe vs. Non-severe Injuries for E-scooter crashes a) TITAN-coded cases matched with narratives, b) extracted solely from narratives, and c) TITAN-coded and unmatched with the narratives



Discussion and Conclusion. A key finding was the inconsistency in official crash coding practices, which often misclassify micromobility users as pedestrians or bicyclists. Pedestrians, being the most common non-motorist category, account for many of these misclassifications. For instance, e-scooter cases are often coded as pedestrians, while e-bikes are often coded as bicycles. In some instances, micromobility users were even classified as motorists, making identification within those records especially challenging. Although explicit e-scooter coding in TITAN began in 2021, with 152 recorded cases, 121 were correctly classified as e-scooters, yielding a 79.6% matching rate after accounting for the lack of relevant information in the narratives and model classification error. Additionally, the LLM identified 310 e-scooter cases from narratives, reflecting inconsistent definitions and police misclassifications.

This underscores the need for clearer guidelines and training to accurately identify micromobility types. For instance, when a narrative mentions an “electric scooter,” it is often unclear whether it refers to a standing e-scooter or a seated mobility scooter. This ambiguity becomes apparent in the age distributions of shared and non-shared micromobility riders. Only 8% of identified shared e-scooter riders are aged 50 or older, compared to approximately 25% of non-shared e-scooter riders. Such a difference suggests that the SFSP model may be misclassifying electric mobility scooters as e-scooters. Overall, these findings emphasize the need for consistent definitions and improved training to ensure accurate and standardized micromobility classification.

The analysis examined key factors, including whether a micromobility device was motorized, was part of a shared system, or was involved a collision with a motor vehicle. Rather than relying on narrative extraction, these details should be explicitly coded in the crash reporting system to ensure consistent data collection. Capturing such information in a standardized way enables researchers to more effectively analyze user demographics and behavior, injury patterns, and other contributing factors, ultimately supporting policy and infrastructure-based countermeasures to enhance micromobility safety on roadways.

While this study successfully leveraged LLMs to analyze crash narratives and extracted unconventional aspects of micromobility crashes, it also has inherent limitations. Most notably, the extraction process depends entirely on the information contained in the crash narratives. If a narrative lacks details about micromobility devices or includes incorrect information, these errors cannot be detected or corrected, as the narratives themselves serve as the ground truth for AI-based analyses. Secondly, due to the time and processing demands of millions of motorist crash narratives, this methodology relied on keyword searches rather than full-text processing. This approach was practical, as even a 5% error rate would yield tens of thousands of misclassified cases. However, more advanced models, such as GPT-5 or newer large-parameter systems, could reduce errors and better identify micromobility cases currently labeled as motorists. Similarly, a model trained specifically on crash narratives could offer solutions, though developing and integrating such models would require investment in research and infrastructure. State agencies could eventually adopt these tailored models to extract detailed information from crash narratives; however, this would first require more structured narrative reporting with clearer separation between subjective observations and objective crash details.

Despite being an important source of information, crash narratives have rarely been utilized in traditional analyses. Drawing on crash narratives, this study provides valuable insights into the misclassification of micromobility modes and the limitations of police-reported crash coding. This study also offers practical recommendations for state agencies to improve crash coding practices and more accurately represent micromobility crashes in traffic data.

Emergency Department Injury Data

Emergency department visits capture micromobility injuries from falls and fixed-object collisions that are typically not captured in police databases. Hospital emergency department injury data systems records these incidents through standardized medical coding, providing context beyond police-reported crashes.

This data source addresses two gaps in micromobility safety research. First, it reveals systematically underreported non-traffic incidents. Second, in certain jurisdictions, such as Tennessee, hospital records involving traffic crashes can be linked to police databases to enable the corroboration and comparison of injury classifications. This linkage is particularly valuable for assessing how police-assigned KABCO severity ratings align with actual medical diagnoses and treatment outcomes, especially since micromobility users may exhibit injury patterns distinct from motor vehicle occupants.

Hospital injury records use the International Classification of Disease (ICD-10-CM) standard to code micromobility-related injuries. Similar to the recent improvements in police crash coding, the external-cause code set has evolved to include specific micromobility classifications, with e-scooter codes added in 2020 and e-bike codes in 2022.

While hospital records provide detailed information regarding the nature and severity of injuries, a level of underreporting persists. These databases primarily capture victims who receive professional emergency medical care or are transported by emergency services. Therefore, while linking police crash data with hospital records creates a much more complete picture of micromobility safety, inevitable data gaps remain for minor incidents in which users self-treat, visit primary care providers, or otherwise bypass a formal emergency department.

Case Study II: Linking TITAN Micromobility Crashes with Hospital Records

To address the limitations of police-reported crash data, particularly the underreporting of non-traffic incidents like falls and the subjective nature of the KABCO injury scale, this case study expands the scope of micromobility safety analysis. Focusing primarily on e-scooters and e-bikes, this analysis links micromobility crashes identified from TITAN with corresponding hospital admissions and emergency department visits recorded in the Hospital Discharge Data System (HDDS). Furthermore, this study incorporates falls and other non-motor-vehicle collisions recorded exclusively in HDDS to provide a more complete picture of micromobility safety.

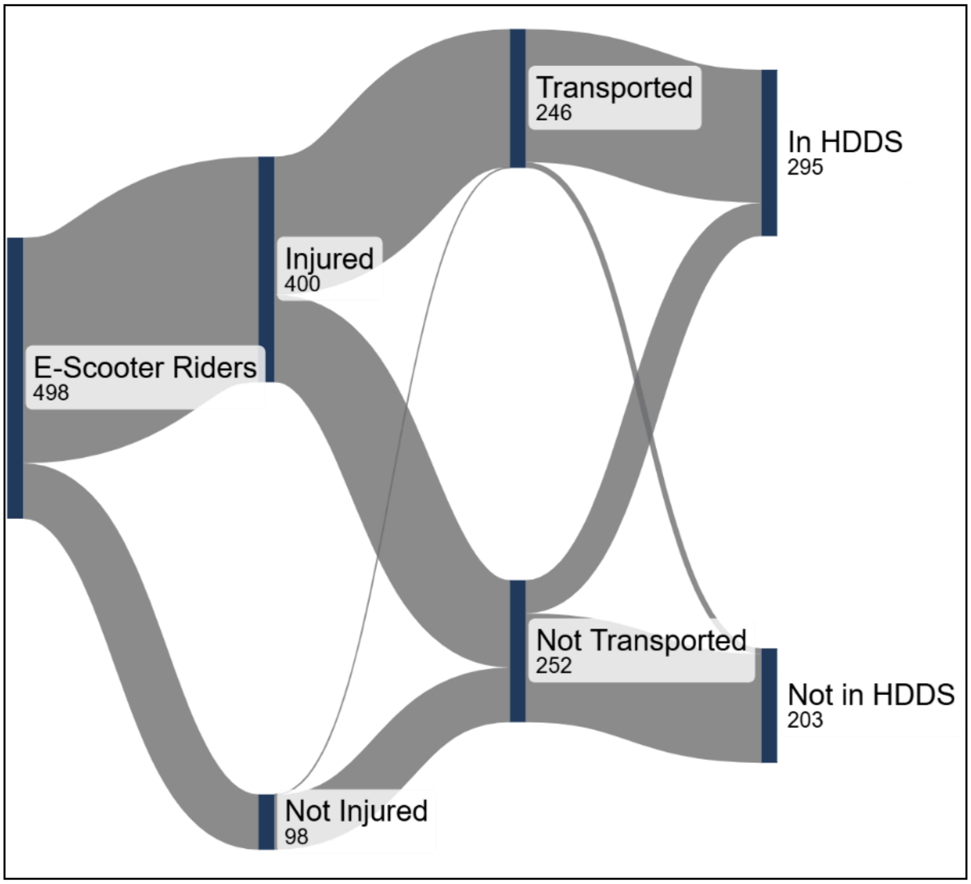
The primary objective of this second case study is to address reporting gaps in traditional police databases by successfully linking TITAN crash records with HDDS medical data. By doing so, this study aims to evaluate the true medical severity of micromobility injuries (bypassing the subjective KABCO scale) and to capture non-traffic incidents that typically go unreported to police. Ultimately, this approach seeks to establish a better understanding of e-scooter and e-bike safety risks.

The SFSP model approach described in Case Study I was applied to tailor the Llama 3.18B model to analyze TITAN crash narratives from 2016 to 2024. When individuals visit an emergency department or are admitted to an acute-care facility in Tennessee, their encounters are recorded in HDDS. Injuries documented in HDDS are grouped into six major body regions: *head and neck, spine and back, torso, extremities, unclassifiable injuries, and injuries lacking sufficient detail for classification*. For this analysis, individuals were included only if they were identified as e-scooter or e-bike riders by the AI model or as explicitly coded by police officers, and if they had an associated HDDS record for a visit or admission occurring within three days of the crash. E-scooter and e-bike analyses are presented separately below.

E-Scooter Analysis

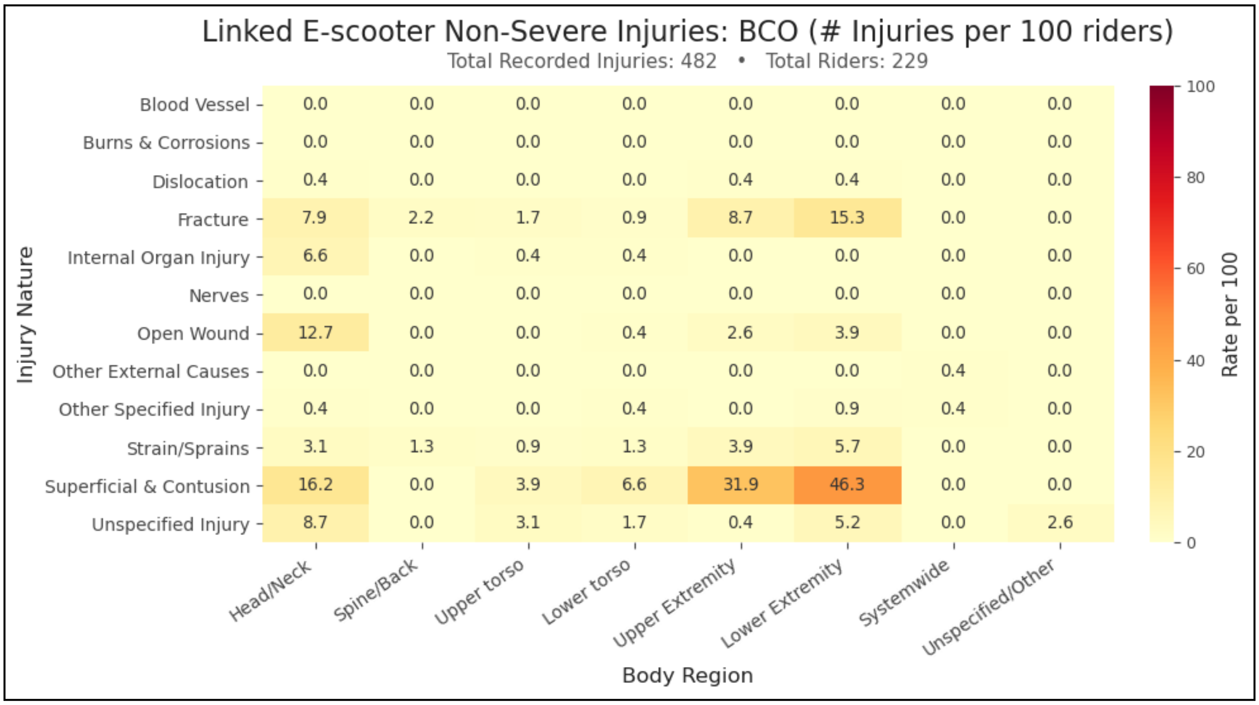
Crash and Hospital Data Linkage. In total, 295 e-scooter riders from 2016 to 2024 appeared in both TITAN crash reports and the HDDS system. This linked cohort emerged from an initial pool of 498 e-scooter riders identified in TITAN crash records (Figure 6). Breaking down this linkage pattern, crash reports listed 98 riders as uninjured or with unknown injury status. One of these riders was identified in HDDS as having been transported by ambulance or medical vehicle to a healthcare facility, and an additional 15 riders were found in HDDS despite crash reports indicating no injuries. Crash reports documented another 155 riders as injured but not transported; 44 of these individuals were located in HDDS, indicating that many sought medical care independently. The remaining 245 riders were reported injured and transported to hospitals, of whom 235 were successfully identified in HDDS.

Figure 6: Sankey Diagram Illustrating Linkage Between E-Scooter Riders in TITAN and HDDS systems



E-Scooter Rider Injury Pattern. Among riders classified with non-severe injuries (B, C, or O on the KABCO scale) in the TITAN data, a total of 482 injuries were recorded across 229 individuals, averaging roughly two injuries per rider. As shown in Figure 7, most of these injuries involved extremities, particularly the lower limbs, and were primarily superficial injuries or contusions. The injury rate for extremity-related injuries was 78 per 100 riders, and the vast majority were minor. Injuries to the head and neck region occurred at a combined rate of 56 per 100 riders; however, only about 15 of these injuries per 100 riders were classified as serious, including fractures, open wounds, and internal organ injuries.

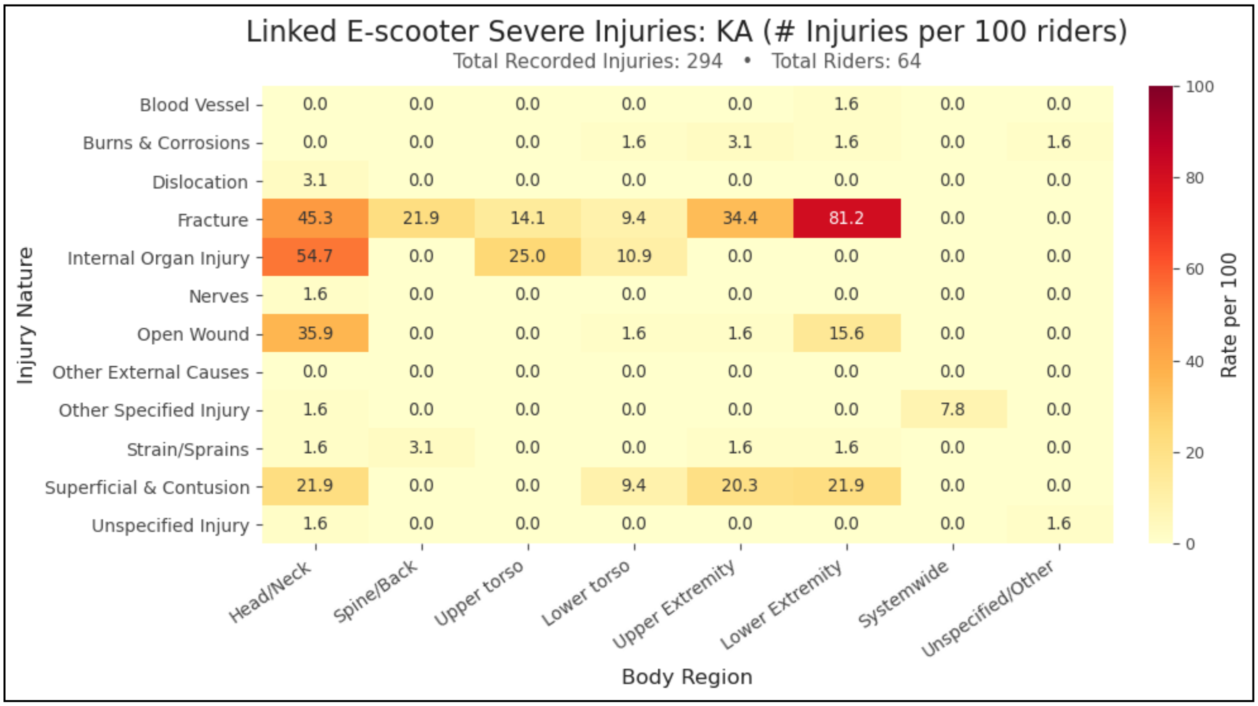
Figure 7: Aggregated Injury Profile for E-Scooter Riders with Non-Severe Injuries Identified in TITAN



Injury Nature	Head/Neck	Spine/Back	Upper torso	Lower torso	Upper Extremity	Lower Extremity	Systemwide	Unspecified/Other
Blood Vessel	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Burns & Corrosions	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dislocation	0.4	0.0	0.0	0.0	0.4	0.4	0.0	0.0
Fracture	7.9	2.2	1.7	0.9	8.7	15.3	0.0	0.0
Internal Organ Injury	6.6	0.0	0.4	0.4	0.0	0.0	0.0	0.0
Nerves	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Open Wound	12.7	0.0	0.0	0.4	2.6	3.9	0.0	0.0
Other External Causes	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0
Other Specified Injury	0.4	0.0	0.0	0.4	0.0	0.9	0.4	0.0
Strain/Sprains	3.1	1.3	0.9	1.3	3.9	5.7	0.0	0.0
Superficial & Contusion	16.2	0.0	3.9	6.6	31.9	46.3	0.0	0.0
Unspecified Injury	8.7	0.0	3.1	1.7	0.4	5.2	0.0	2.6

In contrast, riders classified with severe injuries (K or A) exhibited a substantially higher injury burden. As shown in Figure 8, 294 injuries were recorded among 64 riders, averaging nearly 5 injuries per rider, more than double the rate observed in non-severe cases. These injuries were also concentrated on the lower extremities, but the proportion of severe injuries was much higher. There were more frequent reports of fractures, internal organ injuries, and open wounds in the head and neck region, as well as increased occurrences of spinal and torso fractures.

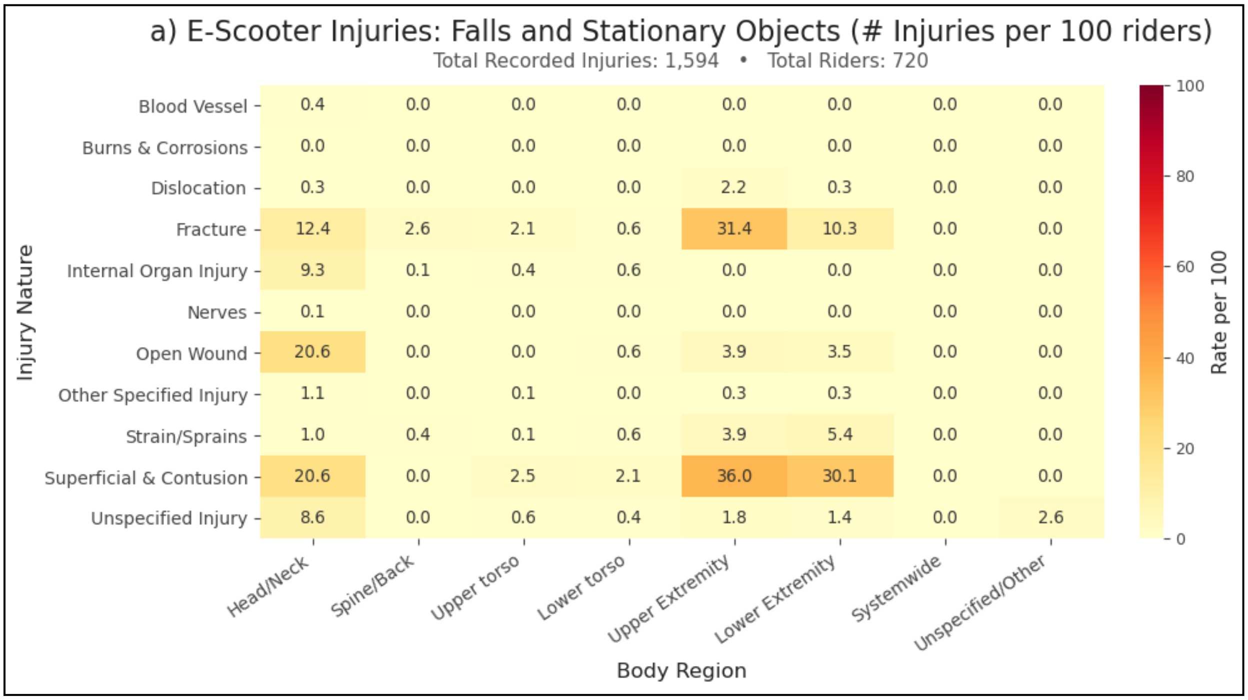
Figure 8: Aggregated Injury Profile for E-Scooter Riders with Severe Injuries Identified in TITAN

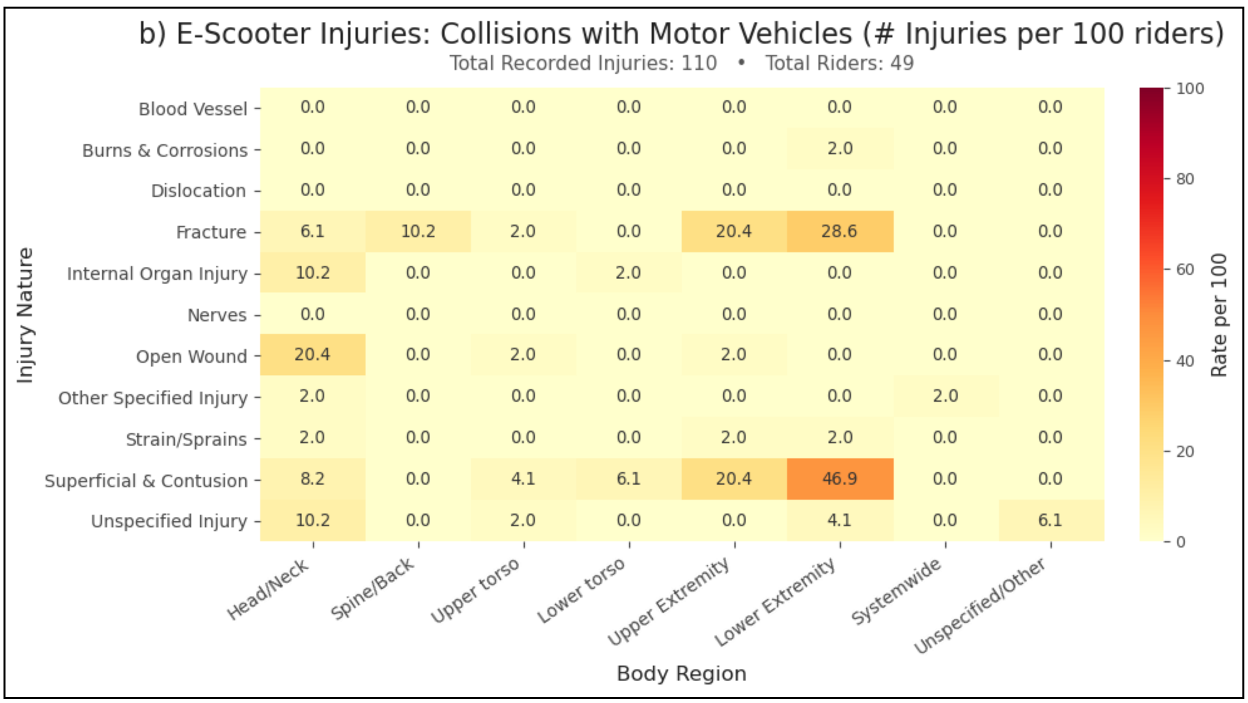


Injury Incidents Excluding Motor Vehicles. An analysis of 776 e-scooter riders with injury incidents recorded solely in HDDS (between October 2020 and December 2024) reveals that most incidents were attributed to falls, accounting for 685 riders (88%), while collisions with motor vehicles accounted for only 49 riders (6%) (Figure 9b). Falls frequently resulted in emergency department visits (95.6%), with very few hospitalizations (4.4%) (Figure 9a). Riders who fell tended to sustain one or two injuries, typically affecting a single body region. In contrast, vehicle collisions showed higher severity indicators, with a larger proportion requiring hospitalization and sustaining multiple injuries across several body regions. (*Note: Full demographic and injury profile for HDDS e-scooter and e-bike incidents are available in Appendix C*).

When comparing injury patterns, non-vehicle incidents showed higher rates of upper-extremity injuries, whereas motor-vehicle collisions showed higher rates of lower-extremity injuries, suggesting distinct biomechanics between falls and impacts (Figure 9b).

Figure 9: E-Scooter Riders Injury Patterns for a) Non-Motor Vehicle and b) Motor-Vehicle Collision Events

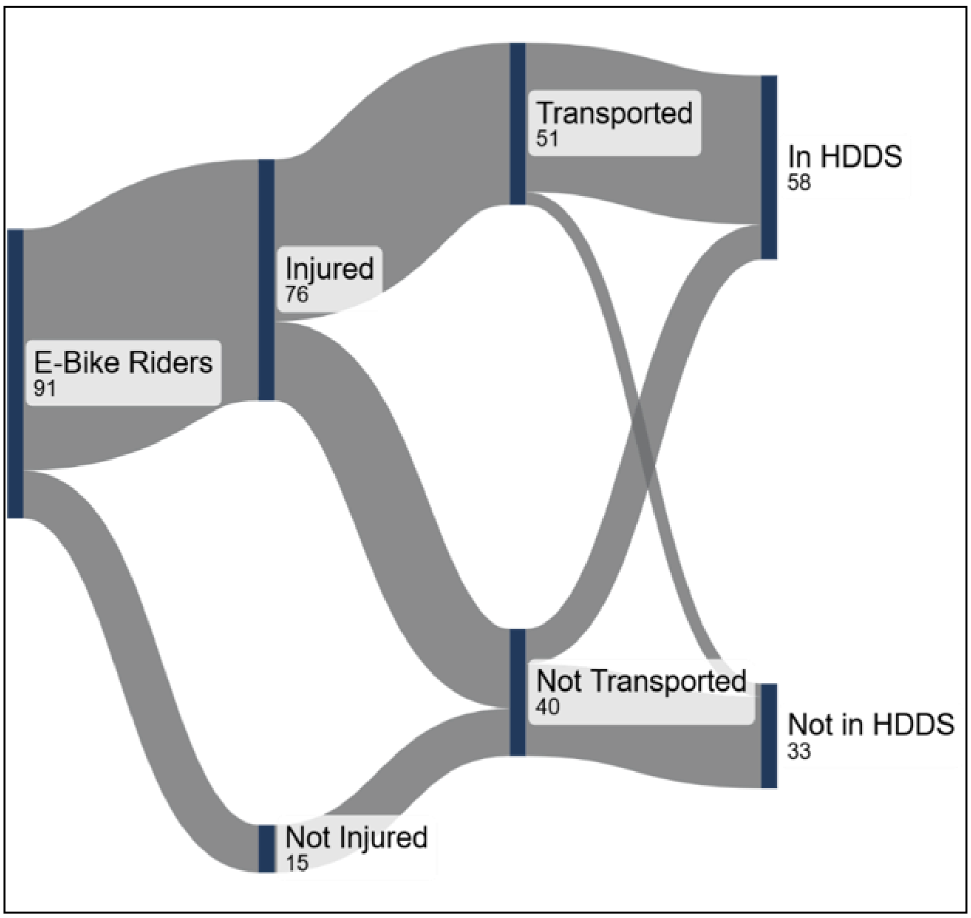




E-Bike Analysis

Crash and Hospital Data Linkage. In total, 58 e-bike riders from 2016 to 2024 appeared in both TITAN crash reports and the HDDS system. This linked cohort emerged from an initial pool of 91 e-bike riders identified in TITAN (Figure 10). Breaking down this linkage pattern, crash reports listed 15 riders as uninjured or with unknown injury status, none of whom were transported; nevertheless, three of these riders were identified in HDDS. Crash reports indicated another 25 riders were injured but not transported, and eight were found in HDDS. The remaining 51 riders were reported as injured and transported to hospitals, with 47 successfully located in the hospital records.

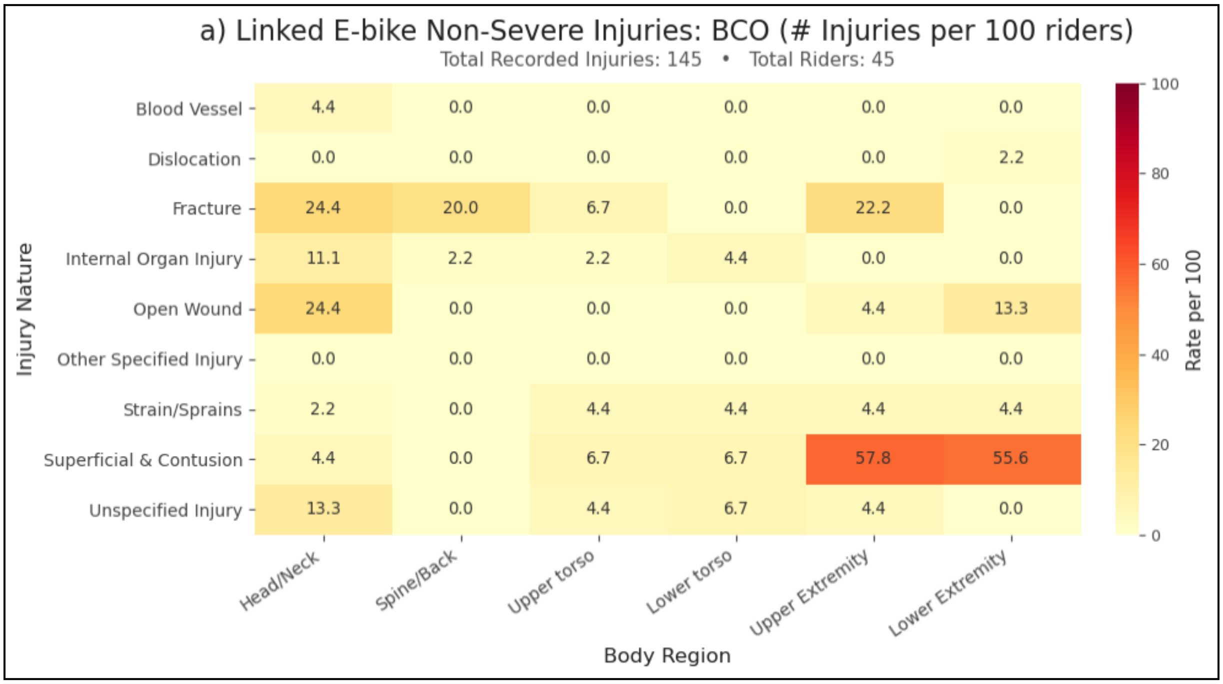
Figure 10: Sankey Diagram Illustrating Linkage Between E-Bike Riders in TITAN and HDDS systems



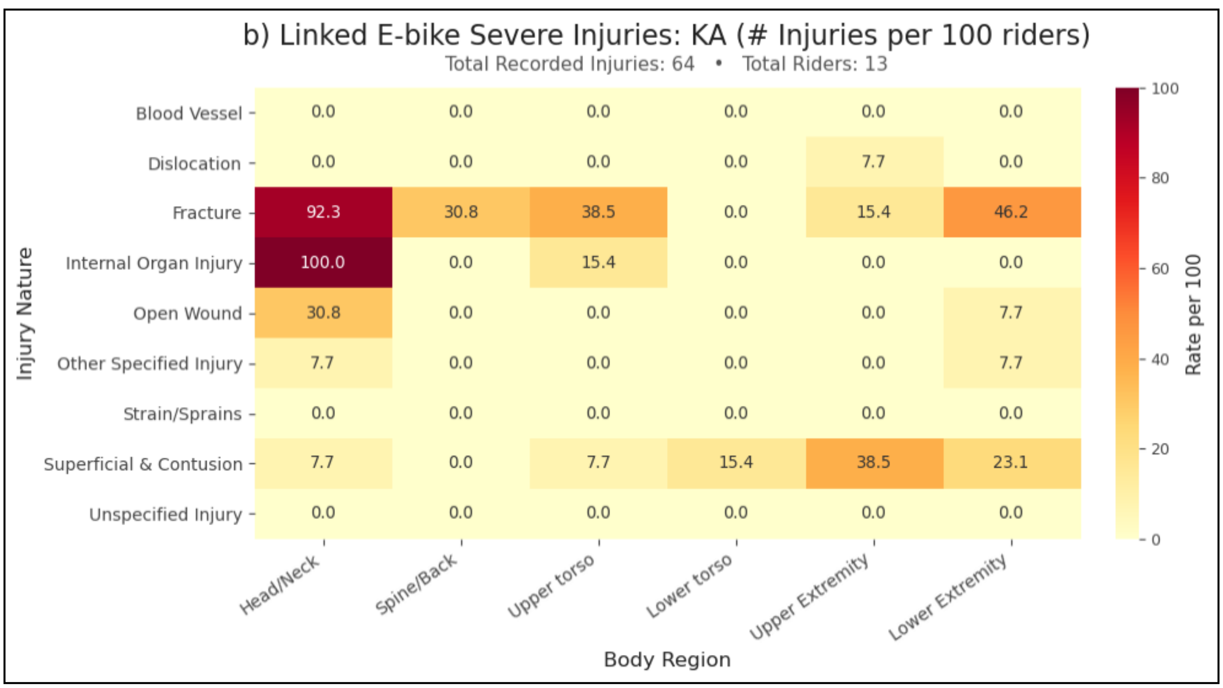
E-Bike Rider Injury Pattern. Among the 58 e-bike riders from TITAN and HDDS matching, 45 were classified as having non-severe injuries and 13 as having severe injuries (*Figure 11*). On average, non-severely injured e-bike riders sustained slightly more than three injuries per person, a somewhat higher injury burden than observed among e-scooter riders. The overall injury patterns were similar to the e-scooter cohort: non-severely injured e-bike riders (Figure 11a) showed injuries primarily concentrated in the extremities (superficial injuries and contusions), whereas severely injured riders

(Figure 11b) exhibited higher proportions of serious injuries such as fractures and internal organ injuries in the head and neck region.

Figure 11: Aggregated Injuries Profile for E-Bike Riders with a) Non-Severe and b) Severe Injuries Identified in TITAN



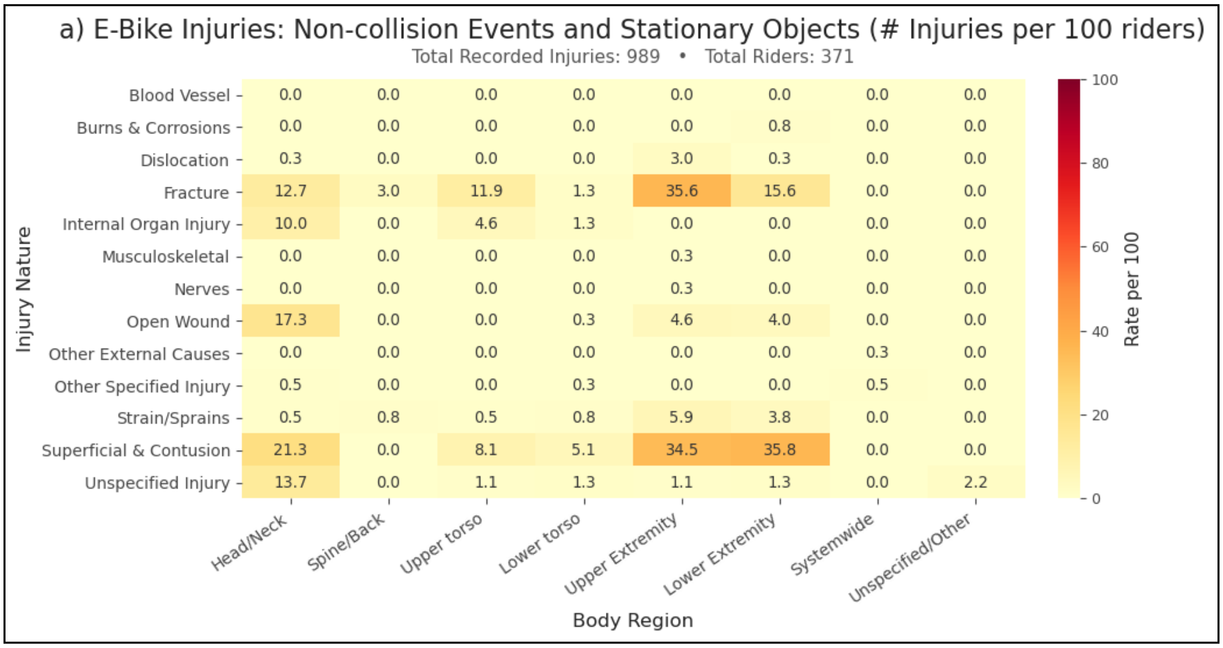
	Head/Neck	Spine/Back	Upper torso	Lower torso	Upper Extremity	Lower Extremity
Blood Vessel	4.4	0.0	0.0	0.0	0.0	0.0
Dislocation	0.0	0.0	0.0	0.0	0.0	2.2
Fracture	24.4	20.0	6.7	0.0	22.2	0.0
Internal Organ Injury	11.1	2.2	2.2	4.4	0.0	0.0
Open Wound	24.4	0.0	0.0	0.0	4.4	13.3
Other Specified Injury	0.0	0.0	0.0	0.0	0.0	0.0
Strain/Sprains	2.2	0.0	4.4	4.4	4.4	4.4
Superficial & Contusion	4.4	0.0	6.7	6.7	57.8	55.6
Unspecified Injury	13.3	0.0	4.4	6.7	4.4	0.0

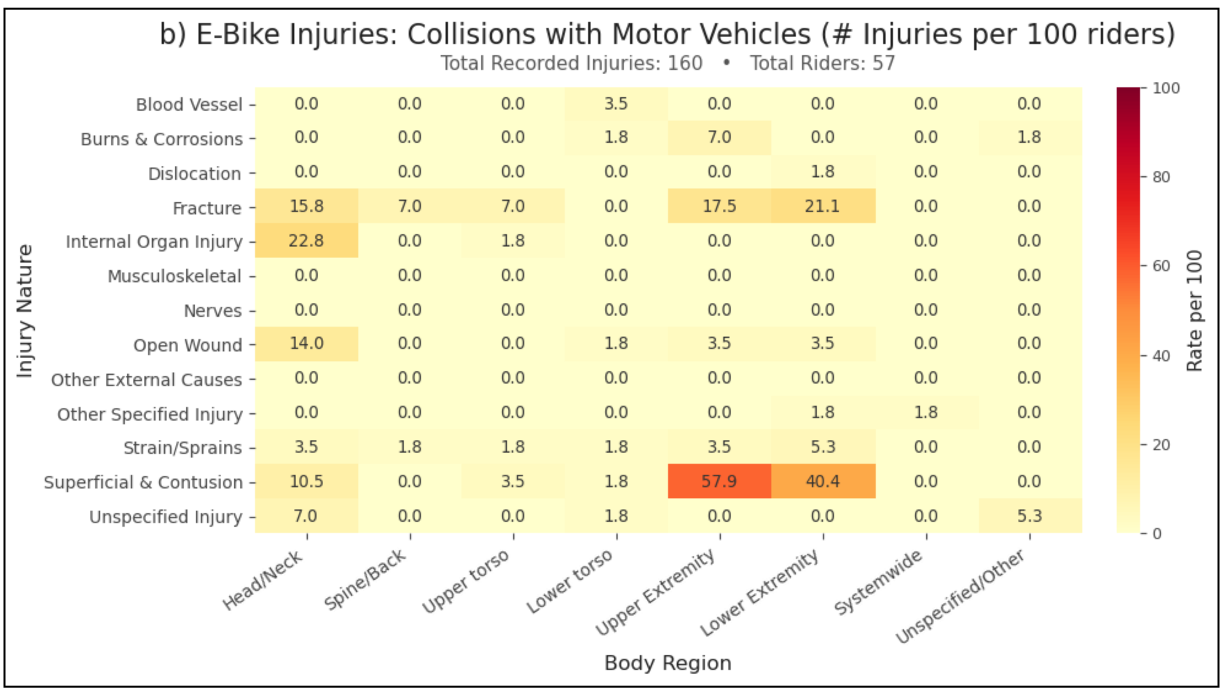


	Head/Neck	Spine/Back	Upper torso	Lower torso	Upper Extremity	Lower Extremity
Blood Vessel	0.0	0.0	0.0	0.0	0.0	0.0
Dislocation	0.0	0.0	0.0	0.0	7.7	0.0
Fracture	92.3	30.8	38.5	0.0	15.4	46.2
Internal Organ Injury	100.0	0.0	15.4	0.0	0.0	0.0
Open Wound	30.8	0.0	0.0	0.0	0.0	7.7
Other Specified Injury	7.7	0.0	0.0	0.0	0.0	7.7
Strain/Sprains	0.0	0.0	0.0	0.0	0.0	0.0
Superficial & Contusion	7.7	0.0	7.7	15.4	38.5	23.1
Unspecified Injury	0.0	0.0	0.0	0.0	0.0	0.0

Independent to the TITAN data, a broader look at the HDDS data for e-bike injury incidents reveals that out of 441 total riders, 371 individuals, were injured in non-collision events or by striking stationary objects. These incidents resulted in 989 total injuries, averaging 2.7 injuries per rider (*Figure 12*a). Another 57 riders were involved in motor-vehicle collisions, sustaining a collective 160 injuries, or an average of 2.8 injuries per rider (*Figure 12*b). Finally, 13 riders struck pedestrians or other non-motorists, resulting in 24 total injuries sustained by the e-bike riders (averaging 1.8 injuries per rider). Injury patterns were broadly comparable across the two groups; however, non-vehicle incidents showed a higher share of extremity fractures, whereas motor-vehicle collisions involved more contusions and superficial injuries. Notably, severe injuries such as head and neck fractures and internal organ injuries were more prominent in motor-vehicle collisions, indicating greater crash severity in those events.

Figure 12: E-bike Rider Injury Patterns for a) Non-Motor Vehicle and b) Motor Vehicle Collision Events

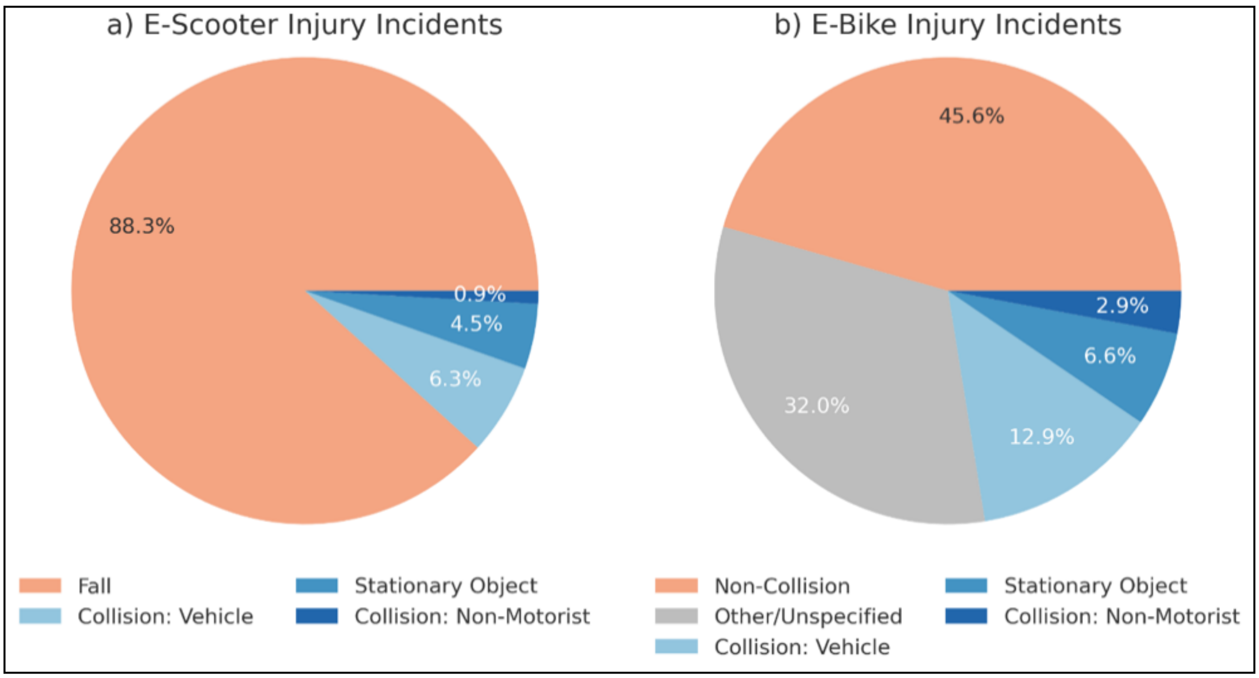




Injury Incidents Excluding Motor Vehicles. Of the 441 e-bike riders with injury incidents recorded in HDDS (between October 2022 and December 2024), non-collision events accounted for 201 riders (46%), while collisions with motor vehicles represented 57 riders (13%) (Figure 13). This represents a substantially higher proportion of motor-vehicle collisions compared with the e-scooter data. Hospitalizations occurred in 12% of cases overall, with a slightly higher rate among stationary-object collisions (21%).

Injury patterns were broadly comparable across the groups; however, non-vehicle incidents showed a higher proportion of extremity fractures, whereas motor-vehicle collisions showed a higher proportion of contusions and superficial injuries. Severe injuries, such as head and neck fractures and internal organ injuries, were more prominent in motor-vehicle collisions, indicating greater crash severity. (*Note: Full demographic breakdowns for HDDS e-bike incidents are available in Appendix C, Table C4*)

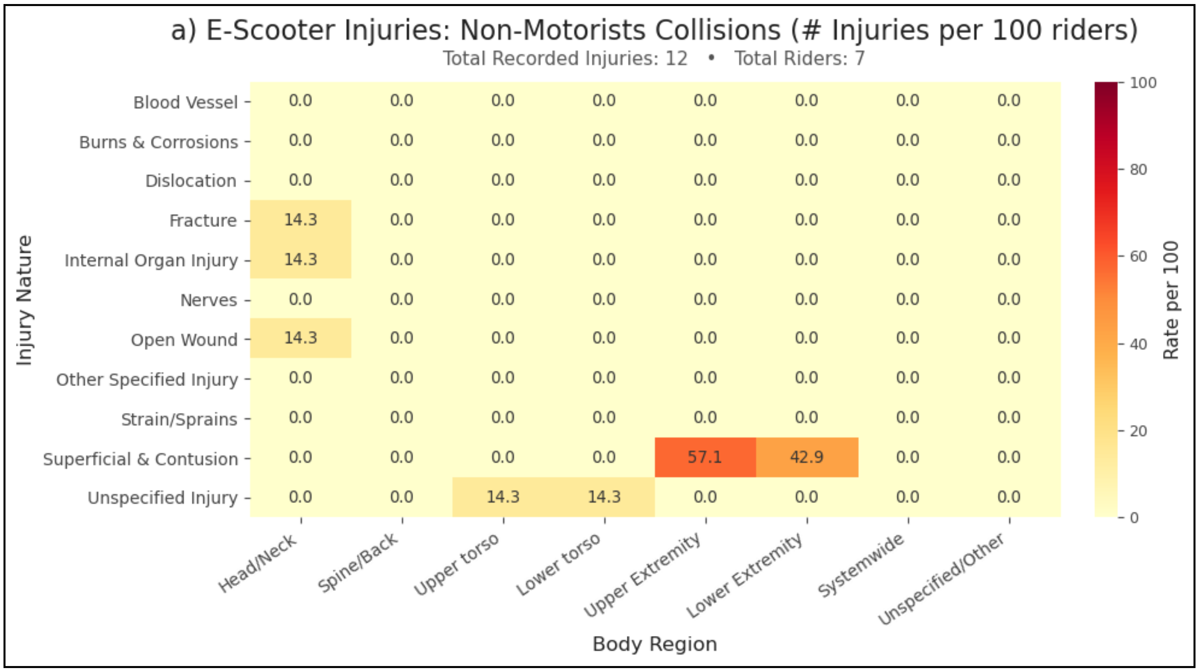
Figure 13. Pie Charts Comparing the Proportion of Injury Caused with HDDS Data Involving a) E-Scooter and b) E-Bike

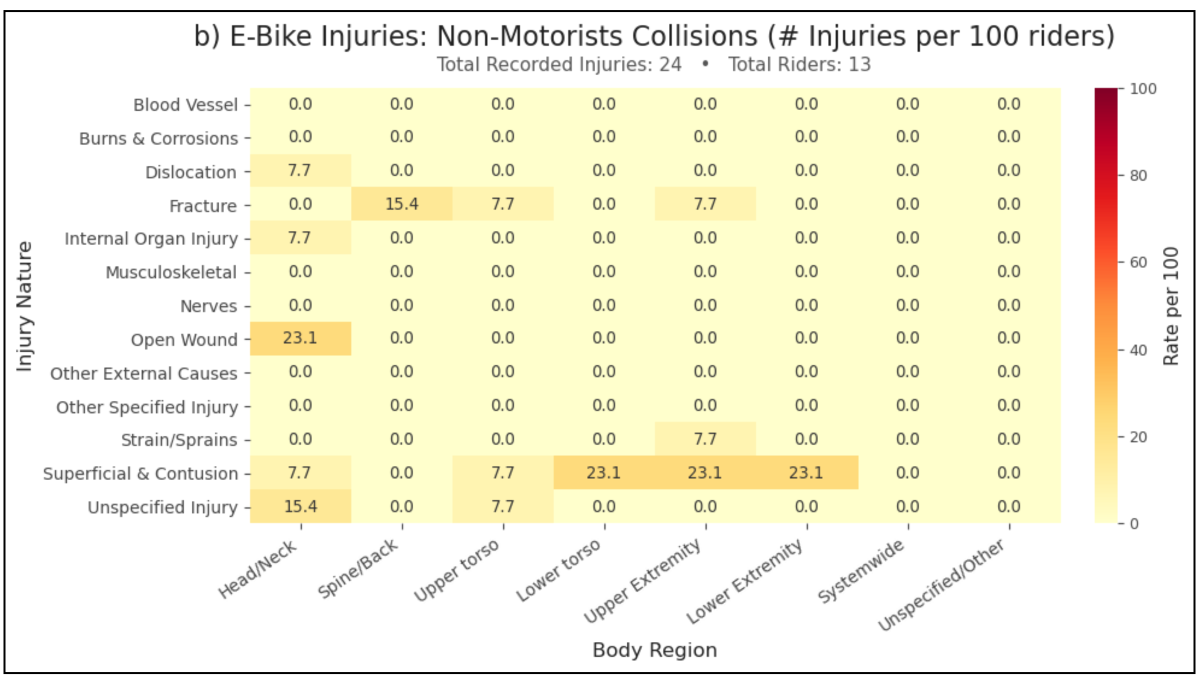


Micromobility Collisions with Non-Motorists. Currently, there is a data gap regarding collisions between micromobility riders and other non-motorists, such as pedestrians or traditional bicyclists. These interactions predominantly occur on sidewalks, multi-use paths, or in bike lanes, and rarely result in severe property damage that would trigger a formal police report. Consequently, they are almost entirely absent from traditional crash databases like TITAN. While hospital records capture some of the resulting injuries, standard medical coding (ICD-10-CM) often classifies these events under broader external-cause categories (such as general falls or blunt force trauma) without explicitly identifying the involvement of a second non-motorized party. Because neither police narratives nor hospital triage codes reliably isolate these specific crash mechanisms, the true frequency and severity of micromobility conflicts with pedestrians and cyclists remain largely unquantified in existing public datasets.

While HDDS does not have a large representation of collisions involving e-scooter or e-bike riders and other non-motorists (pedestrians, cyclists, or animals), the available cases show similar crash biomechanics across both modes. Injuries primarily involve the limbs, with e-scooter riders mostly sustaining contusions and superficial wounds, whereas e-bike riders also experience fractures. Injury counts were comparable, averaging 1.7 injuries per e-scooter rider and 1.8 per e-bike rider (*Figure 14*).

Figure 14: Micromobility Collision with Non-Motorist: representing a) E-Scooter and b) E-bike





Discussion and Conclusion. This case study demonstrated the value of linking police-reported crash data (TITAN) with hospital records (HDDS) to achieve a better understanding of micromobility safety. The analysis revealed that police records frequently miss a substantial portion of the micromobility injury burden, particularly injuries resulting from falls and single-vehicle non-collision events.

By analyzing the HDDS data, the study identified distinct injury profiles between e-scooter and e-bike riders. Notably, while e-scooter riders showed distinctly higher injury rates in the lower extremities, particularly for fractures, superficial injuries, and contusions, while e-bike riders displayed a more even distribution of injuries across both upper and lower extremities. The exception was fractures among severe (KA-coded) riders, which remained more concentrated in the lower extremities. These patterns suggest that crash biomechanics differ between the two modes, potentially reflecting differences in speed, stability, rider posture, or the devices' physical characteristics.

Furthermore, the linkage process highlighted the limitations of the KABCO scale; while it provides a useful initial assessment at the crash scene, the linked hospital data provided the granular clinical detail necessary to understand the true severity and anatomical nature of micromobility injuries. These findings emphasize the need to use multisource data systems to inform infrastructure improvements and safety regulations for vulnerable road users.

Emerging Safety Data Sources

This section of the report explains an evolution in micromobility safety, moving beyond fragmented datasets. Recently, researchers and industry have been shifting towards a triangulated data ecosystem, where operators' telematics, fleet maintenance logs, third-party insurance claims, and self-reported incidents are combined with police and hospital records to create more thorough safety profile. Please refer to Appendix B for more details on device sensors capable of generating telematics data to quantify crash risk and integrate roadway context in future work.

The purpose of this section is to evaluate the breadth and quality of incident reporting channels and propose an integrated workflow that standardizes data collection and aggregates records across multiple sources to produce safety insights and actionable guidance. The resulting outputs will inform infrastructure investments, helmet-use initiatives, and device specifications, while also surfacing opportunities to enhance safety through education to prevent falls.

This integration of emerging data sources aims to transition from a reactive model to a proactive, evidence-based framework allowing stakeholders to transition from simply counting severe crashes to proactively auditing the built environment. By linking these disparate streams, transportation practitioners can address gaps in the existing safety narrative through the following:

- **Providing clear standards, definitions, and classification:** Establishing standardized definitions and schemas across agencies to enable data linkage and reliable safety analysis.
- **Ensuring data provenance:** Implementing completeness and validation checks to ensure the integrity of the data being analyzed.
- **Policy and regulatory alignment:** Tracking evolving standards for device classes and operational rules to keep pace with industry innovation.
- **Improving crash and injury data to close reporting gaps:** Improving consistent coding on police reports while attributing injury severity and body regions to factors like helmet use, protective gear, and speed differentials with other vehicles or pedestrians.
- **Gathering exposure and context data:** Identifying who, where, and when, by analyzing rider age group, trip purpose, time of day, and roadway facility types (e.g., protected lanes, trails, or shared streets).
- **Identifying device and trip attributes:** Utilizing technical data such as vehicle speed, class, and weight to map near-misses and conflicts directly to roadway facility characteristics.

Taxonomy of Incident Reporting Channels

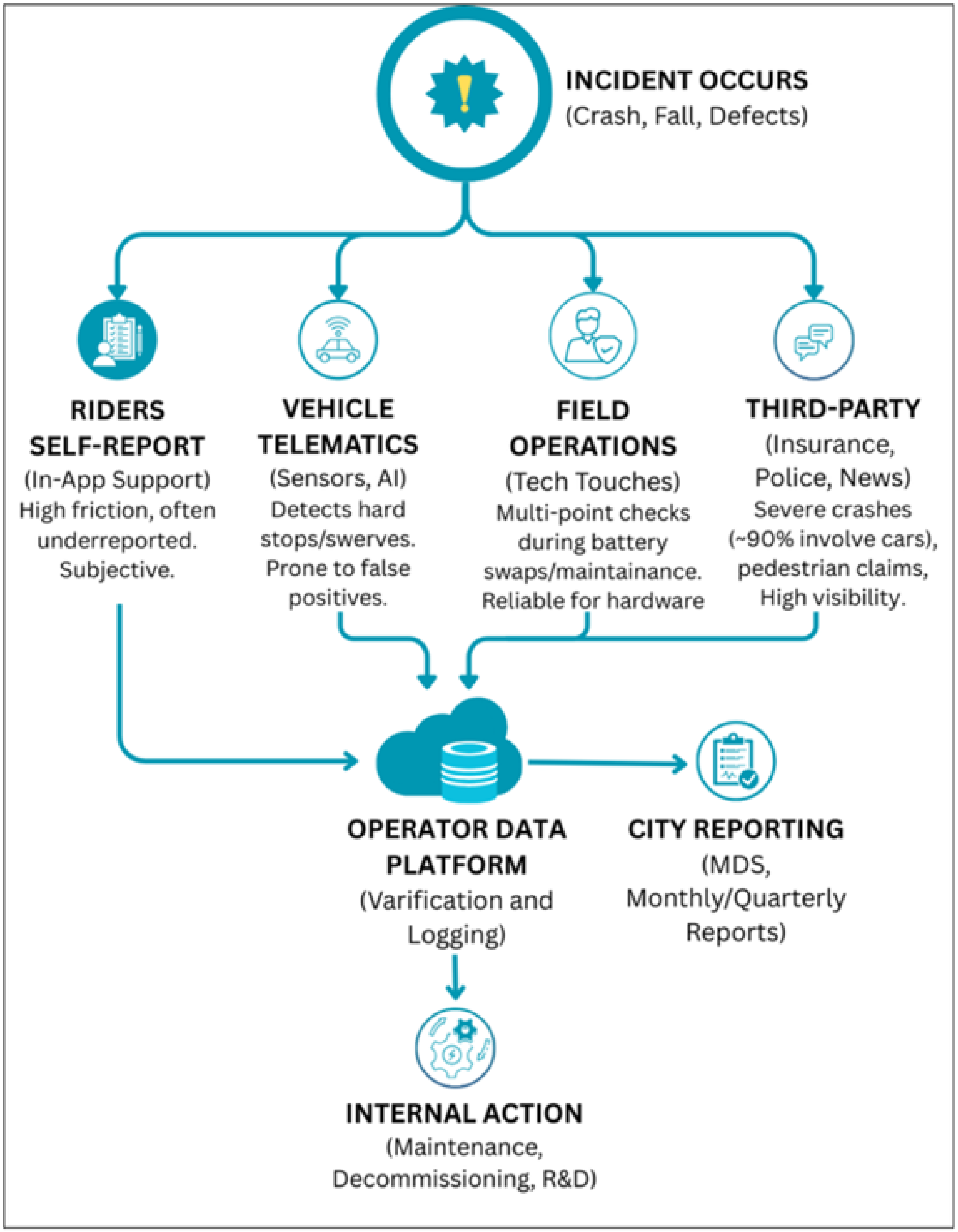
Rather than relying on a singular stream of information, shared micromobility safety data enters the operator's system through four distinct channels, each with unique biases and capture rates.

Figure 15 illustrates this complete safety data pipeline. It details the lifecycle of a safety event from detection to actionable data. As shown, a single incident, whether a crash, fall, or hardware defect, is captured through four parallel channels:

- Channel A: Rider-Initiated Reporting
- Channel B: Embedded Device Telematics and IoT
- Channel C: Field Operations
- Channel D: Third-Party Validation

These disparate inputs converge into the operator data platform, where they are verified and logged before informing downstream actions, such as regulatory reporting via the MDS or internal fleet maintenance.

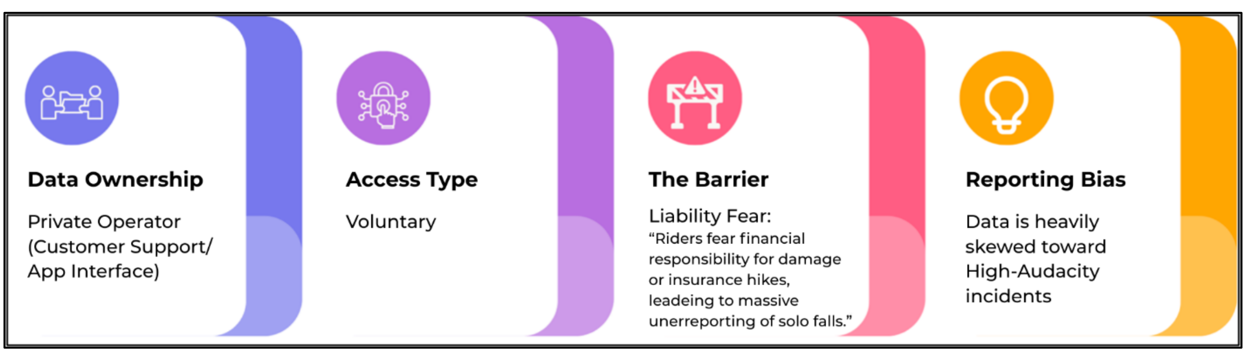
Figure 15: Taxonomy of Micromobility Incident Reporting Channels



Channel A: Rider-Initiated Reporting. Reporting of hazards, conflict points, infrastructure gaps, near-misses, and incidents is captured through the user themselves, which is a common but less reliable source. Figure 16 outlines the structural characteristics of this channel, highlighting that because data access is voluntary and privately owned by the operator, it is heavily influenced by the rider's motivation to report. Users can submit incident reports directly to the micromobility operator in three ways:

- **In-app self-reporting:** Most operators include a feature that allows users to self-report a collision or safety issue at the end of their trips.
- **Customer service and support portals:** A portion of data comes through support tickets and customer-facing teams. During industry focus groups and stakeholder interviews conducted for this study, operators noted that this data is often inconsistent because it relies entirely on user initiative and lacks friction in the reporting interface.
- **Community forums and public safety webforms:** Increasingly, safety data is gathered through municipal "311" systems, community advocacy forums, and dedicated public safety web portals. These external channels provide a non-operator-controlled avenue for both riders and non-riders to document infrastructure hazards or conflicts, though they often lack the technical trip metadata found with in-app reporting.
- This channel suffers from severity bias (National Transportation Safety Board [NTSB], 2022). Studies into rider behavior suggest that reporting rates for minor incidents are low because users often perceive solo falls as "part of the learning curve," or lack a precise, non-punitive mechanism to report them (Sanders et al., 2020). The primary barrier in voluntary reporting is liability concern. Financial responsibility often discourages riders from reporting solo falls, resulting in a dataset skewed toward high-impact incidents (severe crashes) while omitting minor safety events.

Figure 16: Characteristics of Channel A—Rider-Initiated Channel



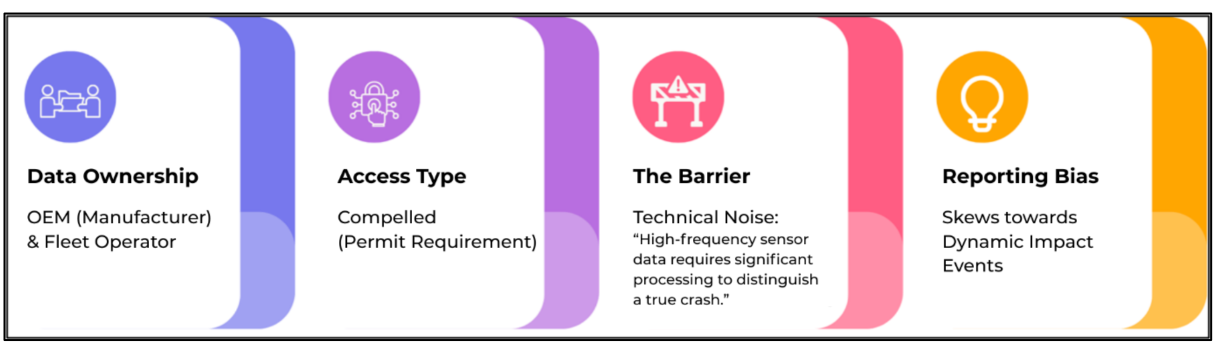
Channel B: Embedded Device Telematics and IoT. The most common variables captured through this channel include the following:

- **On-device event detection:** Detection via accelerometer, harsh braking, falls, tip-overs, GPS geo-references, etc.
- **Device health**: Devices transmit battery status, lock states, speed, and ride duration.

Emerging as the digital black box of micromobility, this channel removes human initiative from the reporting equation. Utilizing the on-board Inertial Measurement Units (IMUs) and accelerometers, the vehicle automatically logs a significant kinematic event when thresholds are breached (e.g., a tip-over combined with high G-force). Unlike Channel A, this channel captures objective vehicle data that can serve as a proxy for the majority of incidents, such as solo falls or harsh breaking events indicative of near misses, which users usually ignore or fail to report (Sanchez-Iborra et al., 2022; Lee et al., 2024).

These automated alerts are increasingly integrated into city oversight via the MDS (MDS 2.1). While MDS does not typically transmit raw high-frequency sensor data, it provides a reporting structure for safety state changes. For instance, when a vehicle's on-board IMU detects an impact, it can trigger a status change to *non-operational* with a specific `event_type_reason` (such as maintenance required) or `dropped_off_fleet` (Los Angeles Department of Transportation, 2018; Open Mobility Foundation, 2023). By tracking these state changes in real time, city regulators can identify high-incident hotspots where vehicles frequently transition out of service due to damage, effectively highlighting dangerous corridors even in the absence of a police report. However, as shown in Figure 17, a major barrier to this channel is technical noise, which requires processing to distinguish actual crash impacts from other handling events.

Figure 17: Characteristics of Channel B—Vehicle Telematics and IoT



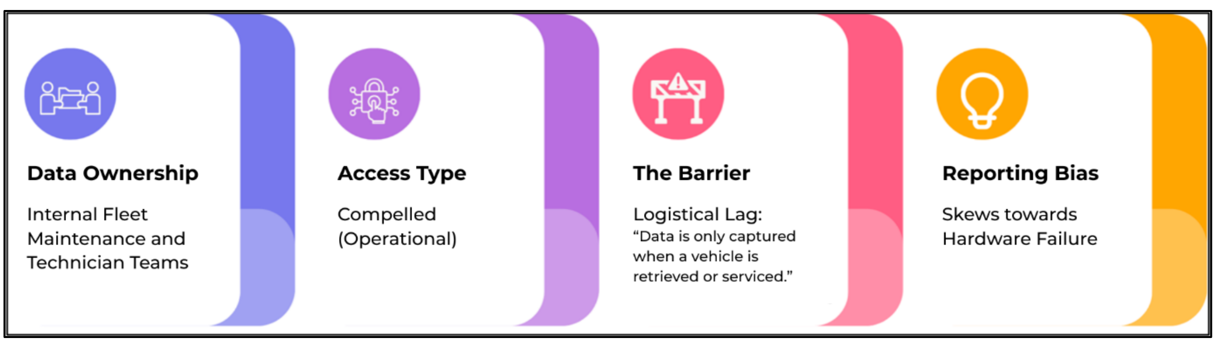
Channel C: Field Operations. The data captured through this channel used to refining training and rider education include the following:

- **Maintenance logs:** Logs of hardware failures, defects, or equipment damage from events rather than user error or sensor noise.

Unlike private ownership, shared fleets benefit from proactive fleet management and maintenance protocols that systematically monitor for defects. Figure 18 details the characteristics of this channel, highlighting that while data access is compelled by operational necessity, it is subject to logistical lag. This means safety insights are often only captured when a device is physically retrieved.

Every battery swap or rebalancing event is a data point. Technicians often perform multipoint inspection during these routine checks. This acts as a proactive, non-user-dependent reporting practice. This channel usually acts as a filter for other channels. If a scooter is flagged by a user (Channel A) or a sensor (Channel B), it is routed to a technician for a field check. Ultimately, because safety data is captured only during physical service intervals, the resulting dataset skews heavily toward hardware defects rather than real-time crash dynamics.

Figure 18: Characteristics of Channel C—Field Operations



Channel D: Third-Party Validation. The data collected through this channel captures the following:

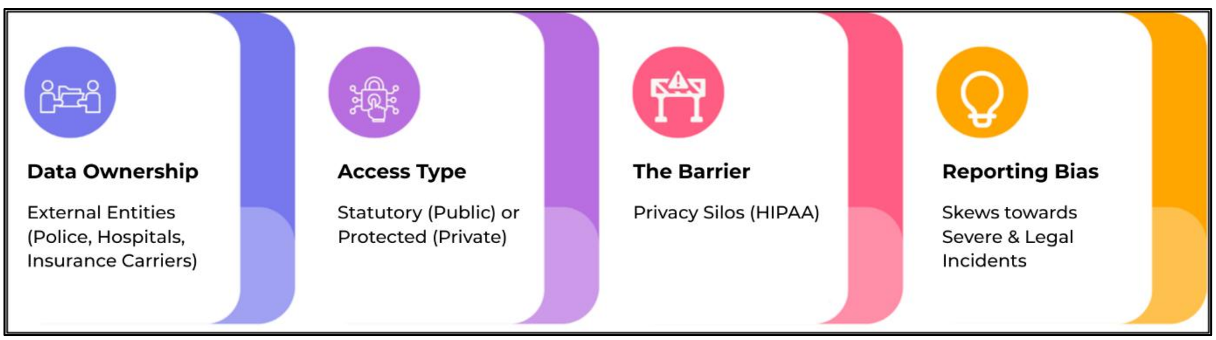
- **Insurance claims:** High volumes of granular collision details of low-impact incidents that never reach official police databases or statewide reporting systems.

Third-party liability insurance claims are increasingly viewed as an essential data set for bridging the reporting gaps inherent in traditional crash records (Canton 2021) and are essential for exposing the underreported data that is otherwise unseen.

Notably, third-party liability claims are often the primary, and sometimes the only, record of pedestrian collisions. Insurance data captures incidents that police reports miss due to statutory reporting requirements. Under MMUCC guidelines, which are followed by most U.S. jurisdictions, law enforcement officers are typically only required to file a formal report if the incident involves a motor vehicle in transport and results in an injury or property damage exceeding a specific monetary threshold, often $1,000 (NHTSA, 2017). Since low-speed sidewalk collisions involving pedestrians, minor solo falls, or small car collisions rarely meet the definition of a motor vehicle crash or exceed the property damage threshold, they are routinely excluded from police records. However, these unsafe events remain valid for third-party liability claims, making this insurance data complementary to traditional crash logs. Furthermore, while the emergency room report also captures these events, it often lacks a specific vehicle code to distinguish e-scooters from other mobility devices, giving insurance data a unique advantage in identifying specific fleet interactions. The dataset is typically biased as it skews toward severe incidents that meet legal or financial liability thresholds.

Figure 19 outlines the structural profile of this channel, showing that while it serves as a validation layer, data access is often restricted by privacy concerns (e.g., HIPAA) and other legal protections.

Figure 19: Characteristics of Channel D—Third-Party Validation

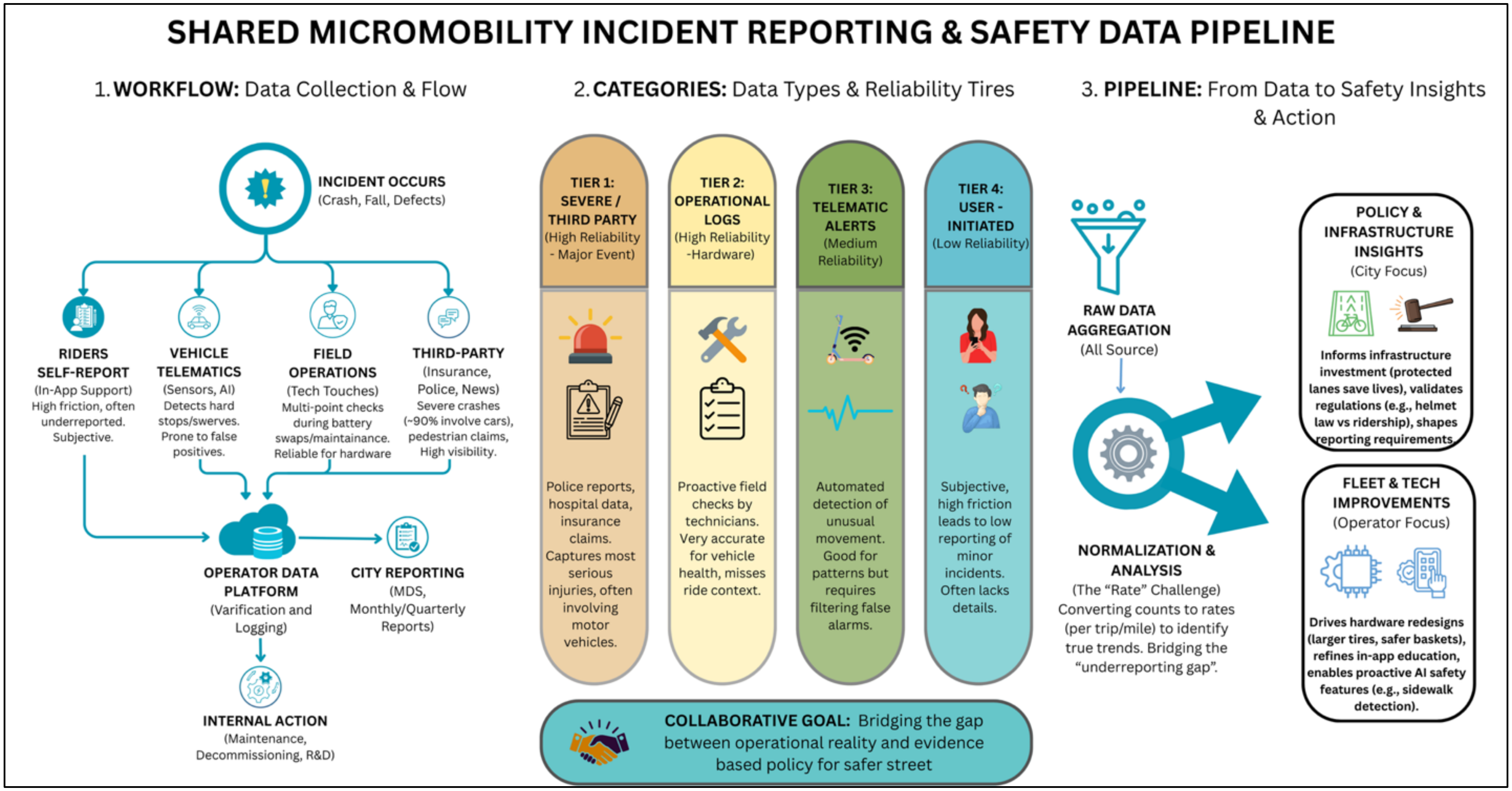


Integrated Data Workflow & Analytical Framework

To understand how safety insights are derived from raw field events, this section presents a safety data roadmap to inform policy and infrastructure, and to drive follow-on safety and operational improvements. As illustrated in Figure 20, this multisource industrial workflow functions as a filtration system, converting data inputs and feeds (e.g., user reports, sensor alerts) into verified safety records, reducing silos through a shared hub and accessible summaries. This process provides standards for enforcing schemas and vocabulary to ensure linkage and comparability. It also serves as a data quality scan, performing validation checks before analysis. This iterative pipeline is vital in converting findings into actions by providing updates and stakeholder feedback.

To bridge the gap between subjective rider reports and objective sensor data, a triangulated workflow is required. The backbone of this integrated flow is MDS. Managed by the Open Mobility Foundation, MDS serves as a standalone digital governance standard that enables standardized, two-way data exchange between municipal agencies and private operators. Operating via dynamic application programming interfaces, this system ensures that safety data is not isolated within private servers but is accessible for public infrastructure planning. By standardizing safety events, such as translating raw telemetry into actionable markers like `maintenance_required`, MDS allows regulators to bypass rider subjectivity and establish precise exposure denominators (e.g., crashes per million miles) for statistically valid cross-jurisdictional comparisons. Furthermore, because every status change is geofenced, this data transforms safety analysis from reactive incident logging to proactive spatial auditing, enabling city engineers to identify and repair infrastructure-induced instability hotspots before severe injuries occur.

Figure 20: Conceptual Framework for the Shared Micromobility Incident Reporting and Safety Data Pipeline



The Data Collection Workflow. The operational lifecycle of an incident, from its occurrence on the street to its final entry in a database, represents the current best practice for capturing safety data. The cycle begins with a physical safety event, ranging from a hardware fault to a collision. Operators currently employ three redundant channels to detect these events: active user-initiated reporting via apps (which is highly subjective and prone to underreporting); passive telematics using vehicle sensors to proactively capture unreported tip-overs or sudden deceleration; and external third-party data ingestion, such as insurance claims or police reports, which serve as a validation layer for severe incidents. Once an alert is detected, it undergoes operator validation to filter out false positives. This involves remote triage to check vehicle logs for sensor errors, and in-field checks where technicians perform safety inspections during routine battery swaps to confirm physical damage. After verification, these incidents are recorded in the operator's internal database and, in advanced markets, pushed to city regulators via the MDS feed. The final step involves operational action, such as decommissioning the vehicle for repair or incorporating the incident into monthly safety reports.

Call to Action

To successfully transition from reactive incident management to proactive, evidence-based urban planning, stakeholders must address the fundamental data ownership barriers and definitional gaps that currently stall progress. The following strategic actions are necessary:

Standardize the Definition of a "Safety Event." Establishing a reliable safety metric requires a unified denominator. Currently, classification depends entirely on the stakeholder recording the event, rendering cross-jurisdictional comparisons largely ineffective. The industry must adopt a universal digital definition of a safety event (such as those outlined in the MDS 2.1 standards) to ensure consistent reporting across all platforms and municipalities.

Establish a Practitioner Resource Hub and Unified Taxonomy. To break down data silos, stakeholders must create an accessible resource hub featuring clear taxonomies that map every incident reporting pathway. Packaging technical outputs and device vocabularies into plain language will make safety data easier to find and utilize for urban planners, policymakers, and advocates, extending its value far beyond technical and operations teams.

Commit to Data Transparency and Reliability. Bridging the gap between operational reality and evidence-based policy requires a commitment to measuring what is currently missing. Institutionalizing an end-to-end pipeline with multistep workflows for the collection, validation, and analysis of safety events will shift safety discussions from anecdotes to empirics, guiding targeted infrastructure interventions.

Implement Standardized Digital Governance. Technical accuracy alone cannot bridge the reporting gap if data ownership barriers persist. While vehicle telematics and field logs are increasingly required by city permits, hospital and rider data remain isolated by privacy laws and liability concerns. Future safety policy must therefore focus on standardized digital governance, creating non-punitive, anonymized channels that incentivize users, medical providers, and private operators to actively contribute to a comprehensive, empirical safety map of the urban streetscape.

Stakeholder Input from Focus Groups

This section of the report presents a synthesis of insights from a series of focus groups and interviews involving diverse stakeholders, including federal and state agencies, policy and design advocates for vulnerable road users, crash data specialists, shared micromobility operators, and disability rights organizations. Through both vertical (within-group) and horizontal (cross-cutting) analyses, several friction points have been identified that currently hinder effective safety management:

- **Data and classification voids:** Inconsistent classification across sectors and geographies prevents consistent identification and coding of devices in crashes, EMS records, and federal reporting systems (such as Fatality Analysis Reporting System [FARS]). This inconsistency renders much of the current national safety data unreliable, preventing a broader understanding of safety trends across places and over time.
- **Regulatory preemption and market loopholes:** Micromobility's rapid, ongoing expansion has created a gap between state traffic laws and federal product standards. While states can regulate road use, they are often preempted by federal law from banning the sale of non-compliant, high-speed "Out-of-Class" vehicles that bypass established safety governors.
- **The youth safety crisis:** Safety officials and medical data highlight a disturbing trend of severe, motorcycle-like trauma among youth riders, often driven by a lack of parental understanding that high-speed electric devices are not bicycles for children, but rather high-risk vehicles.
- **Infrastructure and design limitations:** From the perspective of the visually impaired, silent and ubiquitous devices have become physical barriers on public sidewalks. Simultaneously, planners find that current federal manuals (such as the Manual on Uniform Traffic Control Devices [MUTCD]) can create administrative friction, delaying the implementation of research-driven safety treatments that would provide needed separation between modes on both sidewalks and the roadway.

By bridging these data deficiencies, regulatory challenges, and infrastructure frictions, this report aims to provide a practicable call to action for each stakeholder group. These recommendations focus on modernizing reporting, dispelling public misconceptions, and prioritizing self-enforcing infrastructure to create a safer, more predictable multimodal reality for all roadway users.

Methodology

This section employed a qualitative approach to gather expert perspectives on the safety, regulation, and infrastructure of micromobility. The core methodology consisted of a total of nine sessions (comprising seven semi-structured focus groups and two individual interviews) conducted virtually by the project team between August 2025 and February 2026. A total of 25 stakeholders participated. This design enabled the collection of diverse perspectives from experts across the transportation ecosystem, including representatives from the following nine groups:

- AAA Clubs focus group:
  - Policy and safety advocates
- Bike and Pedestrian Safety and Advocacy Groups focus group:
  - People for Bikes
  - North American Bikeshare and Scooter-Share Association
  - League of American Bicyclists
- Federal Transportation Agencies focus group:
  - NHTSA
  - Federal Highway Administration (FHWA)
  - Volpe National Transportation Systems Center
- State Departments of Transportation and Departments of Safety focus group:
  - Various state DOTs
  - State-level safety officers
- Legislative and Regulatory Bodies focus group:
  - The National Conference of State Legislatures
  - The National Transportation Safety Board
- Industry and Shared Micromobility Providers focus group:
  - Bird
  - Lime

    - Lyft
    - Veo
- Disability and Accessibility Advocacy interview:
    - The American Council of the Blind
- Traffic Safety and Design Experts focus group:
    - Professionals from National Association of City Transportation Officials
    - The Association of Transportation Safety Information Professionals

Each 60-minute session was recorded to ensure transcription accuracy and to faithfully capture stakeholders' specific terminology. Participants were provided with institutional review board–approved consent forms detailing their rights as human subjects and ensuring that their contributions would be analyzed in aggregate to maintain confidentiality. A list of the sample questions and the semi-structured interview script used to guide these focus groups and the individual interviews is provided in Appendix D: Typical Stakeholder Interview/Focus Group Script and Sample Questions.

The research team used a two-tiered analytical framework to synthesize findings. First, a sector-specific vertical analysis was conducted for each group to capture top-level themes and summary points. Second, a cross-cutting horizontal synthesis mapped friction points across all groups to identify where stakeholder interests overlapped or conflicted.

Sector-Specific Analysis (The Vertical Layer)

This section presents unique perspectives and detailed findings from each of the nine focus groups and individual interview sessions. To synthesize the complex, overlapping, and divergent viewpoints across the micromobility ecosystem, Table 2 consolidates each group's top-level themes and detailed sectoral findings into five categories: Definitions and Classifications, Safety and Risk/Exposure, Infrastructure and Design, Regulation and Enforcement, and Education.

Table 2: Stakeholder Perspectives Across Key Micromobility Themes

Stakeholder Group	Definitions & Classifications	Safety & Risk/Exposure	Infrastructure & Design	Regulation & Enforcement	Education & Training
AAA Clubs	Inconsistent coding and a lack of uniform definitions across municipal borders create administrative chaos and complicate inter-jurisdictional reciprocity.	Micromobility collisions not involving cars are rarely recorded in police databases, creating a serious gap in safety data that leaves advocates without actionable evidence.	In the absence of protected lanes, micromobility users default to sidewalks for safety, inadvertently generating public friction that complicates advocacy efforts for dedicated facilities.	Prioritized Challenge: Patchwork regulations and reactionary policies complicate enforcement. Law enforcement struggles to distinguish legal e-bikes from unregulated motorcycles or mopeds.	The term “micromobility” is jargon that confuses the public. There is an urgent need for concise, actionable “one-pagers” to inform legislators, alongside youth-targeted campaigns.
Public Lands Representative	Automated sensors struggle to distinguish e-bikes from conventional bicycles. The 3-class e-bike system is increasingly disconnected from the reality of non-conforming devices.	Experienced riders often pose higher risks to others due to sustained speed differentials, whereas novices generally pose a greater risk to their own safety.	Because active enforcement on trails is practically impossible, pathways require “self-enforcing design”—physical cues and obstacles that naturally force riders to limit their speed.	The federal role should be that of a convener and funder, not a top-down regulator. Impoundment is a potent enforcement tool but risks inequitable impacts on low-income users.	Edge computing offers a privacy-compliant method to monitor near-misses and aggressive behaviors without relying on active enforcement or user education.
Federal Transportation Agencies	A unified national taxonomy is essential. Without standard reporting codes, state-level crash data cannot be reliably aggregated into FARS.	Increasing single-vehicle crashes highlight vulnerability to road conditions. A broad lack of exposure data (miles traveled) prevents accurate risk calculation for private devices.	Federal definitions of micromobility are tied directly to design standards. The operating envelope of these devices makes asset management and pavement maintenance a safety issue.	The traditional “Research-Evaluate-Regulate” cycle is too slow to keep pace with innovation.	First responder toolkits are needed to safely mitigate lithium-ion battery fires. Safety guidance should to be integrated directly onto consumer packaging.

Stakeholder Group	Definitions & Classifications	Safety & Risk/Exposure	Infrastructure & Design	Regulation & Enforcement	Education & Training
Industry & Shared Mobility	Strict, inconsistent speed and classification regulations often penalize compliant shared operators while failing to address non-compliant, private, high-speed mopeds.	Seated scooters provide inherent passive safety benefits over standing models. However, reliance on self-reported crash data is skewed, and telemetry often registers false positives.	e-bikes often show higher incident rates because riders use them for longer commutes that force them onto uncomfortable, high-speed arterial roads.	Strict mandates and contract-driven safety features (like sidewalk detection) can create friction that reduces ridership, inadvertently undermining the "safety in numbers" effect.	Operators express skepticism regarding the efficacy of in-app quizzes, preferring hands-on training via partnerships with local advocacy groups.
Bike & Pedestrian Advocacy	Misclassification of Out-of-Class electric motorcycles and mopeds as compliant e-bikes contaminates crash databases, artificially inflating the apparent danger of active transportation.	A lack of exposure data for private e-bikes prevents accurate crash rate calculations. Systematically missing contextual data (like pavement quality) hinders targeted safety interventions.	Aging infrastructure designed for slower, analog bicycles is creating friction. Facilities should strictly be determined by vehicle speed, weight, and power.	The Toy Myth & Private Fleet Gap: Direct-to-consumer imports bypass standards. High-power devices marketed to youth create severe risks, highlighting a vast safety gap between regulated shared fleets and private ownership.	Consumers urgently need clear education that high-speed electric devices are motor vehicles, not unregulated children's toys.
State DOTs & Departments of Safety	Rigid legacy crash forms force officers to misclassify incidents, severely limiting data accuracy compared to states operating with agile, easily updated electronic reporting systems.	Single-vehicle incidents rarely enter official databases. State databases remain overly car-centric, missing the nuanced infrastructure failures that cause micromobility injuries.	The core safety issue is the lack of safe facilities, forcing riders into vehicular conflict zones. A shortage of trained e-vehicle technicians also leads to dangerous DIY repairs.	Complex legislation often stalls, leaving a regulatory limbo flooded with illegal, "Frankenstein" devices that complicate roadway enforcement.	A massive knowledge gap exists among parents regarding device capabilities. Education must target parents, retailers, and law enforcement simultaneously.

Stakeholder Group	Definitions & Classifications	Safety & Risk/Exposure	Infrastructure & Design	Regulation & Enforcement	Education & Training
Legislative & Regulatory Bodies	Unreliable reporting corrupts the safety dataset. The discrepancy between rich, proprietary shared data and non-existent private data limits comparative analysis.	Regional medical data shows youth e-bike injuries are increasingly internal, resembling severe motorcycle trauma rather than traditional bicycle injuries.	Safe behavior is best regulated through dedicated infrastructure. Without protected lanes, many riders default to sidewalks, altering the risk profile of the device.	States lack the authority to prevent the sale of non-compliant devices due to federal preemption of product standards, creating a massive loophole for online direct-to-consumer sales.	Minors lack licensing and safety training. Broad policies must balance necessary safety education with equitable access for those who benefit most from micromobility.
Disability & Accessibility	The lack of a standardized auditory footprint makes distinguishing between traditional bicycles and motorized micromobility devices nearly impossible for the visually impaired.	Silent devices present a threat to pedestrians relying on auditory cues. Poorly parked dockless devices create unexpected and severe trip hazards.	Floating bus stops and sidewalk riding create intense physical barriers. Uniformity in design, including dedicated parking corrals, is essential for predictable pedestrian navigation.	Broad policy changes are a slow slog at local levels. Advocates desire greater penalties, such as immediate account suspensions, for users who consistently block pathways and curb cuts.	Devices should provide auditory responses or tactile indicators beyond standard Braille so that visually impaired individuals can safely identify abandoned vehicles.
Traffic Safety & Design	Nomenclature confusion and the inability to distinguish device classes corrupt EMS data continuity and hinder national research efforts.	Speed differentials between novice riders and high-speed modified devices create dangerous passing scenarios that necessitate updated width guidance.	Latent demand vastly outpaces street design. The MUTCD creates administrative friction that delays the implementation of research-driven safety treatments.	Policies must align with natural rider behavior (such as allowing rolling stops) to reduce inequitable enforcement across the broader micromobility space.	Proactive video processing can highlight near misses, providing planners with a data-driven rationale for safety improvements before fatalities occur.

The following section presents unique perspectives and detailed findings from each of the nine focus group and interview sessions. Each section begins with a synthesis of the group's primary concerns, followed by their distinct thematic insights.

AAA Clubs Focus Group

AAA representatives view themselves as intermediaries bridging the gap between rapidly changing micromobility technologies and slow-moving legislative bodies. They report that inconsistent data collection is a primary barrier to effective policymaking, as crashes are frequently miscoded as motorcycle incidents or omitted entirely if they occur off-road. This lack of evidence, combined with inconsistent definitions across municipal borders, creates regulatory chaos that complicates both enforcement and public education. Consequently, participants emphasized that succinct (one-pager) educational briefs could help stakeholders establish a common baseline understanding of devices and associated data.

- **Regulatory & legislative challenges:** Patchwork regulations complicate cross-border enforcement. Law enforcement struggles to visually distinguish legal e-bikes from unregulated motorcycles, leading to reactive rather than proactive policy.
- **Absence of "invisible" crash data:** Collisions not involving motor vehicles (e.g., scooter vs. pedestrian) are rarely recorded in official police databases, leaving advocates without actionable evidence.
- **Infrastructure friction:** A lack of protected lanes forces users onto sidewalks, generating public friction (a perceived war on cars) that ironically complicates advocacy efforts for dedicated infrastructure.
- **Messaging gaps:** The term "micromobility" is confusing jargon. Campaigns should target youth through modern channels and promote a unified "Share the Road" model to reduce polarization.

Public Land Representative Interview

Federal stakeholders managing public lands emphasized that the current regulatory focus on the three-class e-bike system is increasingly disconnected from reality due to the flood of non-conforming, direct-to-consumer devices. Because active enforcement on trails and public lands is viewed as practically impossible and potentially inequitable, these stakeholders advocated for self-enforcing infrastructure, designing pathways with physical cues that naturally limit speed rather than relying on police.

- **Safety & risk:** Highly skilled riders have shown some greater risks to others due to sustained high speeds, whereas cautious novices pose risks mostly to themselves.
- **Data & privacy:** Automated sensors struggle to distinguish e-bikes from conventional bicycles (e.g., a rider's body heat obscures the motor in thermal imaging). Edge computing offers a privacy-compliant way to monitor near-misses anonymously.
- **The federal role:** The federal government should act as a convener and funder, facilitating research and data sharing rather than issuing top-down mandates.

Federal Transportation Agencies Focus Group

Federal stakeholders cautioned that the traditional Research-Evaluate-Regulate cycle is too slow to keep pace with micromobility innovation. A primary barrier identified is the lack of a unified national taxonomy: without a standard definition of what constitutes a micromobility device, state-level crash data cannot be aggregated into FARS. Officials also highlighted infrastructure concerns and the risks that battery fires pose to first responders.

- **The exposure paradox:** Estimating total miles traveled for privately owned devices is exponentially harder than for shared fleets, preventing the calculation and comparison of true crash rates.
- **Safety trends & asset management:** A distinct rise in single-vehicle crashes suggests that current pavement maintenance standards and facility designs may be insufficient to safely accommodate small-wheeled devices.
- **First responder risks:** Post-crash lithium-ion battery fires present severe risks to emergency personnel. Agencies propose using toolkits and engaging directly with manufacturers to place safety messaging on device packaging.

Industry and Shared Mobility Providers Focus Group

Shared micromobility operators argued that vehicle form, specifically the shift from standing to seated scooters, offers a greater passive safety benefit than many digital interventions. However, a tension remains between what are viewed as performative safety features requested by cities during the procurement process and the practical realities of fleet operations. Operators cautioned that strict mandates, such as helmet laws or aggressive speed limits, often reduce ridership, undermining the protective safety-in-numbers effect.

- **Data deficiencies:** Automated crash detection via telemetry produces high false-positive rates (e.g., tipped-over parked scooters), forcing operators to rely on skewed self-reported app data or lagging liability insurance claims.
- **Policy & the friction debate:** Speed regulations often unfairly penalize compliant shared fleets while doing nothing to stop the proliferation of non-compliant private e-scooters.
- **Infrastructure & education:** Higher incident rates often stem from long commutes that force riders onto high-speed arterial roads. Operators prefer hands-on training via advocacy partnerships over easily skipped in-app quizzes.

Bike and Pedestrian Safety Advocacy Focus Group

National advocacy groups argue that the primary safety threat to micromobility is not the technology itself, but the rampant misclassification of high-speed Out-of-Class electric vehicles as compliant e-bikes. Stakeholders warned that crash data is currently contaminated by these high-speed incidents, leading to a distorted view of e-bike safety. Consequently, they advocated a strict infrastructure policy based on vehicle speed, weight, and power: devices under 20 mph should be in the bike lane, while faster devices should be regulated in way that they share space with motor vehicles.

- **The toy myth & regulatory gaps:** A dangerous consumer trend involves parents buying high-speed electric motorcycles for children, assuming they are toys. Direct-to-consumer imports bypass safety standards, exacerbating this risk.
- **Shared vs. private safety gap:** Regulated, speed-capped shared fleets boast incredibly low injury rates compared to the unregulated private market.
- **Data misclassification:** Law enforcement frequently miscodes moped crashes as bicyclist fatalities. The systematic lack of contextual data (like pavement quality) hinders targeted safety interventions.

State Department of Transportation and Department of Safety Group

State DOT officials report a widening gap between the rapid evolution of micromobility devices and the rigid infrastructure of state-level crash reporting. While some states have modernized to electronic reporting systems, others remain tethered to legacy paper forms that force officers to misclassify incidents. State safety officers also highlighted a growing crisis involving youth riders on high-speed electric motorcycles, noting that parents often lack the knowledge to distinguish between a compliant Class 1 e-bike and an unregulated motor vehicle.

- **System rigidity & data silos:** State crash databases remain overly car-centric, often missing single-vehicle crashes and forcing safety officials to rely on disconnected hospital and EMS data.
- **Youth & education:** Parents may mistakenly purchase high-speed devices for unlicensed youth who lack basic traffic education. Simultaneously, law enforcement struggles to keep pace with identifying evolving devices.
- **Workforce:** A severe shortage of trained e-vehicle technicians leads to dangerous DIY repairs and fire risks.
- **Infrastructure:** Ultimately, the lack of protected facilities forces riders into vehicular conflict zones.
- **Legislative failure:** Complex legislation often stalls, leaving a regulatory limbo flooded with unclassified devices (gas-powered kits, unclassified mopeds) that defy standard definitions.

Legislative and Regulatory Bodies Focus Group

Stakeholders from the legislative and federal safety sectors identified a regulatory gap in which state traffic laws are undermined by federal preemption of product sales. While states can regulate where devices are ridden, they lack the authority to prevent the sale of non-compliant, high-speed vehicles that blur the line between e-bikes and motorcycles. This regulatory failure, combined with a stark rise in severe, motorcycle-like injuries among youth riders, has created an urgent need for updated federal product definitions and clearer point-of-sale consumer education.

- **Retail gaps & online sales:** The loophole of federal preemption is severely complicated by online direct-to-consumer marketplaces that easily bypass local retail bans.
- **Infrastructure as regulation:** One of the most effective ways to regulate behavior is through protected infrastructure; without it, riders naturally default to sidewalks, altering the risk profile.
- **Proprietary data discrepancies:** Shared fleets possess rich telemetry data, but personal e-bike data is virtually non-existent, preventing policymakers from accurately comparing safety profiles across user types.

Disability and Accessibility Advocacy Representative Interview

A stakeholder representing the blind and low-vision community emphasized that micromobility devices have become ubiquitous physical barriers on public sidewalks. Because these individuals rely on auditory cues to read traffic flow, the quiet nature of e-bikes and e-scooters creates apprehension, particularly when navigating new infrastructure such as floating bus stops (transit islands separated from the main sidewalk by a dedicated bicycle lane). The stakeholder advocated for uniformity and consideration in parking and infrastructure design to ensure that sidewalks remain a predictable and safe environment for all pedestrians.

- **Physical barriers & unexpected obstacles:** Dockless scooters parked over curb cuts leave wheelchair users and blind pedestrians stuck with no safe path forward.
- **Technology & the silent threat:** Devices need auditory responses (e.g., announcing status when touched with a cane) rather than relying on Braille, which is not universally accessible or helpful on unknown vehicles.
- **Predictability & penalties:** Advocates strongly prefer uniform, dedicated parking corrals over dockless systems and call for strict penalties (e.g., immediate account suspensions) for users who block pedestrian rights-of-way.

Traffic Safety & Design Focus Group

Stakeholders from leading traffic safety and design organizations emphasized that the primary safety concern is the absence of dedicated infrastructure to accommodate a latent demand for micromobility trips. Experts highlighted a classification chaos where the inability to consistently identify devices leads to unreliable national crash data. Furthermore, participants identified regulatory friction caused by federal manuals (MUTCD), which complicates the implementation of innovative, research-driven safety treatments.

- **Speed differentials:** The wide range of speeds, from inexperienced riders to 45-mph+ modified devices, creates dangerous passing challenges that require updated width guidance for active transportation lanes.
- **Emerging solutions & policy flexibility:** Proactive video processing can detect near-misses before fatalities occur. Additionally, policies must align with natural rider behavior (e.g., allowing rolling stops) to reduce inequitable enforcement.

Cross-Cutting Synthesis (Inter-Group Analysis)

While the section above focused on individual experts, this section synthesizes those findings into five major national themes.

The Data Void and Classification Chaos

Across all groups, the inability to accurately track micromobility crashes was cited as the primary barrier to evidence-based policymaking.

- **Motorcycle and moped contamination:** Advocacy and industry stakeholders warned that crash data is currently contaminated by high-speed, Out-of-Class electric motorcycles (e.g., Sur-Rons) being misclassified as e-bikes. This artificially inflates the perceived danger of compliant, low-speed e-bikes.
- **State reporting rigidity:** State DOT officials highlighted a severe disparity in data agility. While some states (e.g., Tennessee) have modernized electronic crash reporting, others use legacy paper forms that force officers to miscode micromobility crashes as pedestrian or moped incidents to close a case.
- **The exposure gap:** Federal and industry experts noted that while we can track fatalities—albeit potentially unreliably, given the data challenge described above—they have no reliable way to estimate exposure (total miles traveled) for private ownership. Without this denominator, they cannot calculate an accurate crash rate.

> *"A significant research barrier is that shared fleets have incredible data... but it is proprietary. Meanwhile, personal e-bike data is non-existent. This makes it impossible to compare the safety of a 'regulated shared ride' with that of a 'wild west private ride.'"* > **Federal Transportation Agencies Group**

The Regulatory Gap & Federal Preemption

Differences have emerged between state legislators and federal regulators over the sale of non-compliant devices, including the following:

- **The point-of-sale loopholes:** State legislators expressed frustration that while they can ban non-compliant devices from roads, they are preempted by federal law (CPSC) from prohibiting their sale. This allows devices (high-speed electric motorcycles sold as e-bikes) to flood the market unchecked.
- **Infrastructure as the only real regulation:** Federal public lands and industry experts argued that stricter enforcement (checking device classes) is operationally impossible. Consequently, they advocated for self-enforcing infrastructure, i.e., designing pathways with physical cues (gates, rough pavers, narrow widths) that naturally limit speed regardless of the device's motor power.

> *"Even if local retail bans were possible, they would be easily bypassed by online marketplaces that ship unregulated, high-speed devices directly to consumers, often using 'creative marketing' to label them as compliant bicycles."*
> \> **Legislative and Regulatory Stakeholder**

The Youth & Severity Crisis

A distinct and alarming trend was identified regarding youth riders, particularly by the NTSB and state safety offices.

- **Motorcycle-like trauma:** Trauma registry data indicate that e-bike injuries, particularly among youth, are increasingly resembling motorcycle trauma (internal organ damage) rather than traditional bicycle injuries (road rash/fractures), due to higher kinetic energy.
- **The toy myth and vehicle forms:** The fact that e-motorcycles are heavily in style or in-demand from young riders presents a challenge. E-motorcycles or high-speed e-scooters are often marketed as e-bikes to circumvent regulations or are marketed as toys. Parents often buy them without understanding the technical capabilities or effectively understanding the risks faced by young and inexperienced riders.

> *"Youth are riding these devices without driver's licenses and have never been taught how to navigate traffic, yet they are operating 20+ mph vehicles on public roads."* > **State Departments of Transportation and Departments of Safety Group**

Operational Reality vs. Performative Safety

Industry operators and federal experts pushed back against regulations that lack practical safety benefits.

- **The friction paradox:** Operators argued that strict municipal mandates (e.g., helmet laws, aggressive speed governing) often act as friction that reduces ridership. Paradoxically, this decreases overall safety by undermining the "Safety in Numbers" effect that naturally protects vulnerable road users.
- **Seated vs. Standing:** Operational data strongly suggests a safety dividend from seated scooters (which have larger wheels and a lower center of gravity) compared to standing models, yet regulations often treat them identically. Operators note that features proven to increase safety are frequently sidelined in favor of performative digital technology (such as sidewalk detection) required to win city contracts.

> *"Many safety features, like turn signals or sidewalk detection, are developed primarily to win city contracts (RFPs) rather than because internal data proves they prevent crashes."* > **Industry and Shared Micromobility Provider**

Inclusive Urban Design and Sidewalk Conflicts

When infrastructure fails to accommodate micromobility, the burden falls disproportionately on the most vulnerable pedestrians.

- **The accessibility challenge:** The lack of protected bike lanes forces riders onto sidewalks. For blind and low-vision pedestrians, silent e-vehicles and "*willy-nilly*" dockless scooters parked over curb cuts represent total physical barriers to basic mobility.
- **Design burdens:** Moving users off the sidewalk requires better design, yet planners face regulatory friction from Federal manuals like the MUTCD, delaying the implementation of proven pedestrian protections.

> *"Both traditional bicycles and e-mobility devices are pretty darn quiet... and wheelchair users and blind pedestrians face extreme frustration when scooters are parked directly over curb cuts, leaving them literally stuck with no way to enter or exit the sidewalk."* > **Disability and Accessibility Advocacy Group**

Cross-Sector Call to Action

The following table maps the primary friction points to the stakeholder groups who expressed the most urgent concern.

Table 3: Cross-Cutting Friction Points and Key Stakeholders

Topic	Theme	Key Friction Point / Insights	Primary Concerned Stakeholder
DATA	**Exposure gap**	Fatality data is tracked, but there is a lack of miles-ridden data (exposure), especially for private devices. This prevents calculating true crash rates or comparing shared versus private fleet safety.	USDOT, Industry and Shared Micromobility Providers, Bike and Pedestrian Safety Advocacy Groups, Legislative and Regulatory Bodies, Traffic Safety & Design Experts
	Reporting void	Most crash databases only trigger when a motor vehicle is involved; consequently, single-vehicle falls and non-motorist incidents remain invisible and uncounted.	State DOTs and Departments of Safety, Traffic Safety & Design Experts
	Classification chaos	Inconsistent identification across Crash, EMS, and FARS systems makes national data unreliable. Devices are often miscoded as pedestrians, motorcycles, or mopeds.	AAA Clubs, Public Lands, USDOT, Industry and Shared Micromobility Providers, Bike and Pedestrian Safety Advocacy Groups, State DOTs and Departments of Safety, Legislative and Regulatory Bodies, Traffic Safety & Design Experts
REGULATIONS	**Sales loopholes**	States can regulate road use but are barred by federal law (CPSC) from banning the sale of non-compliant, high-speed devices at the retail counter.	Bike and Pedestrian Safety Advocacy Groups, State DOTs and Departments of Safety, Legislative and Regulatory Bodies
	20 mph threshold	Consensus is emerging that speed and weight should dictate facility access. Devices under 20 mph belong in bike lanes, while faster devices require roadway integration.	Bike and Pedestrian Safety Advocacy Groups, Public Lands, Traffic Safety & Design Experts
SAFETY	**Youth crisis**	Severe, motorcycle-like internal trauma have risen sharply among youth. Parents often purchase high-speed electric devices as “toys,” unaware of performance capabilities or licensing needs.	USDOT, Bike and Pedestrian Safety Advocacy Groups, State DOTs and Departments of Safety, Legislative and Regulatory Bodies
	Battery fire risk	Damaged lithium-ion batteries pose risks in residential settings and create identification and handling confusion for first responders at crash scenes	USDOT, State DOTs and Departments of Safety, Traffic Safety & Design Experts

Topic	Theme	Key Friction Point / Insights	Primary Concerned Stakeholder
INFRA-STRUCTURE	**Self-enforcement**	Active policing of motor wattages or device classes is operationally impossible. Safety must be built into design through physical speed-limiting cues.	Public Lands, Legislative and Regulatory Bodies, Traffic Safety & Design Experts, Industry and Shared Micromobility Providers
OPERATIONS	**Performative safety**	Tension exists between performative city contract requirements (e.g., sidewalk detection) and proven physics-based safety measures (e.g., seated form factors, larger wheels).	Industry and Shared Micromobility Providers, USDOT
ACCESSIBILITY	**Spatial gap**	Lack of dedicated space forces riders into high-speed conflict zones with cars or onto sidewalks, creating unpredictable riding environments.	State DOTs, Traffic Design Experts, Public Lands.
	Sidewalk conflicts	A lack of protected space forces riders onto sidewalks, creating unpredictable parking and silent threats that represent total physical barriers for blind and low-vision pedestrians.	AAA Clubs, State DOTs and Departments of Safety, Disability and Accessibility Advocacy Group, Traffic Safety & Design Experts

Detailed Sector-Specific Calls to Action

Stakeholder Group	Primary Goal	Recommended Actions
AAA Clubs	To bridge the communication gap between technical researchers and legislative bodies.	Develop legislative one-pagers: Create concise, non-academic briefs that define device categories and present safety statistics clearly for policymakers.
		Targeted public campaigns: Move away from micromobility jargon and utilize modern channels to build a long-term safety culture among youth.
		Develop model legislation: Work with communities to develop model legislation that can be adopted statewide to allow predictability for users and consistent understanding for law enforcement.
Public Land Representative	To manage trail safety through design rather than unenforceable policing.	Implement self-enforcing infrastructure: Use physical cues, such as rough-hewn granite pavers or dogleg gates, that naturally limit speeds regardless of motor power.
		Equitable enforcement research: Explore the impact of vehicle impoundment as a deterrent for reckless behavior while ensuring it does not disproportionately harm low-income users.
Federal Transportation Agencies	To create a unified national baseline for safety tracking and first responder safety.	National taxonomy: Establish a standard coding system to allow state-level crash data to be aggregated into FARS.
		First responder toolkits: Distribute resources to help police and EMS safely identify devices and manage lithium-ion battery fire risks at crash scenes.
Industry & Shared Micromobility Providers	To prioritize passive safety through vehicle design and implement balanced operational regulations.	Prioritize vehicle form factor: Use municipal procurement contracts to favor seated e-scooter models and larger wheels, which offer superior stability.
		Promote balanced regulation: Instead of strict mandates, standardize speed governing across operators to prevent dangerous differentials with bicycles, incentivize safety technology (e.g., geofencing), and focus on hands-on education over digital in-app quizzes.
Bike & Pedestrian Advocacy Groups	To protect active transportation safety and data integrity from high-speed, Out-of-Class vehicles.	The 20 MPH rule: Adopt a strict policy that requires devices under 20 mph to use bike lanes, while faster devices are excluded and treated as motor vehicles.
		Audit international sales: Seek access to sales data on illegal or non-conforming devices purchased through international online marketplaces to understand total road risk.

Stakeholder Group	Primary Goal	Recommended Actions
State DOTs & Dept. of Safety	To upgrade legacy reporting systems and address the "Parent Gap."	Digital reporting upgrade: Transition from legacy paper forms to electronic systems to allow for rapid updates to device codes.
		Bridge data silos: Link hospital/EMS data with police reports to ensure "invisible" single-vehicle crashes are captured in safety planning.
		Dispel the "Toy Myth": Target education to parents and bike shops to clarify that high-speed electric motorcycles are motor vehicles requiring training and licensing.
Legislative & Regulatory Bodies	To align federal product safety with state road usage laws.	Close the point-of-sale loophole: Coordinate federal CPSC standards with state bans on the sale of "Frankenstein" devices that bypass safety governors.
Disability & Accessibility Advocacy Group	To protect sidewalk accessibility and navigate the "silent threat" of electric devices.	Mandatory parking uniformity: Replace dockless systems with designated parking corrals to keep sidewalks and curb cuts clear for pedestrians.
		Auditory response features: Mandate that devices emit a company-identifying sound or status update when approached or touched by a pedestrian.
Traffic Safety & Design Experts	To streamline the implementation of research-driven safety treatments.	Streamline MUTCD: The FHWA should reduce the administrative burden on cities seeking "permission to experiment" with bicycle safety treatments such as leading bike intervals.
		Near-miss detection: Utilize emerging video processing tools to identify conflict zones and justify infrastructure investments before fatalities occur.

Highlights from Discussion with Focus Groups

The rapid evolution of the micromobility landscape has outpaced the institutional frameworks designed to manage it. This exploration has illuminated a data-policy issue: while stakeholders across federal, state, and local levels recognize the urgent need for evidence-based safety interventions, current data-collection systems are often too rigid or fragmented to provide the necessary evidence.

To move toward a safer multimodal reality, several fundamental shifts are required:

- **Standardization of information:** The "Classification Chaos" currently obscuring safety trends must be resolved through a unified national taxonomy. Without standardized coding across police, EMS, and hospital systems, the accurate safety profile of compliant e-bikes and scooters will remain contaminated by high-speed Out-of-Class vehicles.
- **Closing the regulatory loophole:** Closing the point-of-sale loophole is essential to addressing the youth safety crisis. If high-speed electric motorcycles can be marketed as toys or e-bikes and bypass state usage bans through federal preemption, vulnerable road users, particularly unlicensed minors, will continue to face motorcycle-level trauma.
- **Prioritizing physics in infrastructure and procurement:** Safety must be treated as a design requirement, not an enforcement challenge. This includes implementing self-enforcing infrastructure to manage speeds naturally and shifting municipal procurement to prioritize vehicle form factors, such as seated e-scooter models and larger wheels, that offer inherent stability over performative digital features.
- **Inclusive urban design:** Finally, the needs of the most vulnerable pedestrians, particularly those with visual impairments, must be integrated into the foundation of street design. Moving away from dockless parking toward uniform and predictable parking corrals is a necessary step in ensuring that the benefits of micromobility do not come at the cost of basic sidewalk accessibility.

By implementing the targeted calls to action identified in this report, stakeholders can begin to bridge the gap between innovation and safety. Creating a predictable environment through modern reporting, clear public education, and dedicated infrastructure is not merely a technical challenge but a vital necessity for continued growth and social acceptance of sustainable urban mobility.

Conclusions and Recommendations

This report has synthesized the complex safety landscape of micromobility through four primary research tasks: a comprehensive literature review, a 50-state regulatory scan, a multisource safety analysis linking hospital and crash data, and extensive stakeholder engagement. The findings consistently indicate that while micromobility offers a sustainable alternative to traditional car travel, its safety benefits are currently compromised by outdated infrastructure, fragmented regulatory definitions, and severe data underreporting.

Key findings and recommendations are presented in this chapter. For additional findings on tasks carried out, please refer to previous chapters presented in this report.

Reconciling Data-Policy Inconsistencies

The Literature Review chapter and Federal, State and Local Laws and Regulations chapter identify a data inconsistency: stakeholders lack the granular evidence required to design a safe environment because existing systems are built for motor vehicles, not lightweight electric devices.

- **Key findings:** The proliferation of high-speed, aftermarket-modified devices has outpaced the existing three-class e-bike classification, creating a grey market of Out-of-Class vehicles.
- **Recommendation:** Agencies should adopt the SAE J3194 Standard, or similar standards for vehicle classification to create a common language across state and local databases, reducing fragmentation and policy enforcement.

Resolving the "Safety Data Iceberg"

As demonstrated by the multisource safety analysis (Micromobility Safety Data chapter), official police crash data captures only the tip of the iceberg, consisting of incidents involving motor vehicles. Our linkage of Tennessee's TITAN database with the HDDS data reveals that the vast majority of micromobility injuries are actually single-vehicle falls or collisions with fixed objects, which remain largely invisible to law enforcement.

- **Key findings:** Demographic analysis (Appendix C: Traffic Crash Narrative Analysis with AI/LLMs) reveals a notable injury skew: while males aged 18 to 34 represent the highest frequency of incidents, older adults (65+) experience a disproportionately higher severity of head, neck, and torso trauma. Across all cohorts, the lack of standardized reporting codes leads to frequent misclassification of devices as bicycles or pedestrians.

- **Recommendation:** Transportation and public health agencies must formalize data-sharing pipelines between hospital emergency departments and police crash records to ensure injury severity and demographic factors are captured, moving beyond the current reliance on police-reported collision narratives.

Addressing the Regulatory Loophole and Youth Safety

The regulatory scan (Federal, State and Local Laws and Regulations) highlights that federal consumer product standards often preempt local efforts to regulate retail sales, creating loopholes where high-powered electric motorcycles are marketed as consumer-grade e-scooters or e-bikes.

- **Key findings:** This regulatory gap is a primary driver of the emerging youth safety crisis, as parents often purchase high-speed devices for minors without understanding the road safety implications.
- **Recommendation:** Policymakers should launch point-of-sale education initiatives that align with local ordinances, while industry operators should deploy in-app safety features, such as geofenced speed limits, to manage device power based on rider age and experience.

The Infrastructure Imperative

Insights from our focus group engagement (Stakeholder Input from Focus Groups), combined with the quantitative results in section Micromobility Safety Data, confirm that the built environment is the primary determinant of crash outcomes.

- **Key findings:** Safety improves drastically when riders are removed from mixed-traffic environments and placed in physically separated lanes. However, a divergence exists between shared-use (rented) and privately owned models; rented devices frequently congest sidewalks, while private high-speed devices lack a designated legal operating space.
- **Recommendation:** The planner should shift from reactive education and signing to self-enforcing infrastructure. This includes the widespread implementation of physically protected bike lanes and uniform “lock-to” parking corrals. These designs are essential not only for rider safety but for ensuring that sidewalk space remains accessible and safe for pedestrians.

Research Limitations

This report represents a snapshot of the micromobility landscape as of June 2026. This is still a very dynamic sector. Policy prescriptions are aiming to keep up with the rapid change in technology and use patterns. Data collection systems lag further behind policy changes. While the application of LLMs to crash narratives and the linkage of hospital datasets represent methodological advancements, these results are anchored in regional case studies and may not represent the full spectrum of national geographic trends. Still, AI supported systemic crash investigation may overcome many of the challenges with siloed data systems and assist in device categorization and data linkages between datasets. This is an important area of future research. Lacking data collection frameworks, many of the policy problems (e.g., electric motorcycles and youth) are drawn from experiences of advocates and practitioners and often based on trends seen on the street or in the media if not distinguished in crash datasets. As such, our recommendations are based on those perceptions and could be updated if better data can support better decision making.

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Appendix A: Literature Review

U.S.-Based Studies

Table A1 provides a summary of the United States-based (and broader North American) studies evaluating micromobility safety extracted from the provided literature review. The research is categorized by six primary themes: demographics, private ownership versus shared systems, infrastructure, behavior, policy, and device specifications. Findings highlight the unique crash risks, injury patterns, and infrastructure needs within the North American context, alongside the limitations inherent to the diverse data collection methods employed.

Table A1: Summary of United States-Based Studies on Micromobility Safety

Theme	Study	Mode	Key Findings	Limitations
Policy	MacArthur & Kobel (2014)	E-bikes	Fragmented state-level policies create confusion, often barring e-bikes from bike infrastructure or subjecting them to motor vehicle standards.	Survey methods lack direct crash or near-miss measures and are subject to recall bias.
	Lusk et al. (2015)	Bicycles	Existing police crash templates miss details like impact points and facility types, showing a need for expanded reporting.	Relies on police-reported data which misses micro-level details and near-misses.
	Bloom et al. (2021)	E-scooters	Mandatory helmet laws significantly reduce head trauma severity among e-scooter riders.	Relies on hospital and trauma records which miss less severe injuries and non-ED crashes.

Theme	Study	Mode	Key Findings	Limitations
Behavior	MacArthur et al. (2018)	E-bikes	Visibility, speed differentials, and inconsistent cycling infrastructure remain persistent safety concerns for riders.	Surveys lack direct crash measures and rely on subjective retrospective reporting.
	Popovich et al. (2014)	E-bikes	Users frequently feel unsafe sharing roads with motor vehicles in Sacramento due to a lack of bike lanes and driver aggression.	Qualitative interviews capture user perceptions but lack objective crash metrics.
	Ling et al. (2017)	E-bikes, conventional bicycles	Improved health and time savings are key motivators; younger cohorts value environmental benefits more.	Self-selection bias and reliance on self-reported behaviors.
	Karpinski, Bayles, Daigle, & Mantine (2022)	E-scooters	81% of e-scooter fatalities occur at night, frequently involving alcohol impairment and excessive speed.	Excludes near-miss events, minor crashes, and limits findings to fatal incidents.
Infrastructure	Schneider et al. (2022)	Bicycles	Protected bike lanes increase perceived safety, but poor winter maintenance in Minneapolis discourages year-round ridership.	Relies on commuter survey perceptions rather than direct crash exposure tracking.
	Basch et al. (2019, 2023)	Bicycles, Micromobility	Bike lane obstructions in NYC force cyclists into traffic, increasing dynamic safety challenges and crash risks.	Field observations are time-consuming, location-specific, and susceptible to observer bias.
	Kondo et al. (2018)	Bicycles	Bike lanes reduce crash odds at specific intersection types (e.g., 4-exit intersections: 48%).	Lack of direct bicycle flow data and inability to analyze temporal changes.
	Bai & Jiao (2020)	E-scooters	E-scooter trips in Austin and Minneapolis cluster near commercial centers and transit hubs, heavily influenced by land-use diversity.	System-level usage data lacks rider-specific demographics and detailed crash contexts.

Theme	Study	Mode	Key Findings	Limitations
Demographics	Shah et al. (2021)	E-scooters, bicycles	E-scooter crashes in Nashville involve younger demographics, more out-of-town visitors, and a higher share of females compared to bicycles.	Police crash databases suffer from reporting inaccuracies and micromobility classification issues.
	Koehne et al. (2025)	E-bikes	A 432% increase in e-bike-related head injuries (2020-2022) disproportionately affected adolescents and older adults.	Emergency department data omits crashes that do not result in a hospital visit.
	Abouelela et al. (2023)	Shared e-scooters	Ridership peaks during evenings and weekends; young adult males (18–34) account for the majority of injuries.	Fleet management datasets provide broad coverage but lack specific crash contexts.
Device Specs	DiMaggio et al. (2020)	E-bikes, E-scooters	E-bike injuries involve older males, have higher hospitalization rates, and involve more motor vehicle collisions than traditional bikes.	Hospitalization and consumer data omit less severe crashes and near-misses.
Private vs. Shared	Almannaa et al. (2020)	E-scooters, E-bikes	Dockless e-bikes operate at higher speeds than e-scooters in Austin, TX, increasing collision risks; road surface quality impacts scooter stability.	System usage data lacks qualitative rider attributes and granular crash details.
	McKenzie (2019)	E-scooters, shared bikes	In Washington, D.C., scooters are predominantly used for leisure and short trips, whereas e-bikes see more consistent commuting use.	Relies on broad usage statistics without detailed safety or crash analyses.
	Bergman et al. (2024)	Shared e-bikes	Chicago's Divvy bike-share attracts new riders but poses elevated safety challenges for older or inexperienced users.	Shared system data is often localized and may not generalize to privately owned devices.

International Studies

Table A2 provides a comprehensive summary of the international studies evaluating micromobility safety extracted from the provided literature review. The research is categorized by six primary themes: demographics, private ownership versus shared systems, infrastructure, behavior, policy, and device specifications. Findings highlight the unique crash risks, injury patterns, and infrastructure needs within the international context, alongside the limitations inherent to the diverse data collection methods employed.

Table A2: Summary of International Studies on Micromobility Safety

Theme	Study	Mode	Key Findings	Limitations
Demographics	de Haas et al. (2022)	E-bikes	Commuting e-bikers increasingly use less car trips	High panel attrition
	Haustein & Møller (2016)	E-bikes	Older riders report balance issues	Lacks actual crash records
	Ferraro et al. (2020)	Bicycles	Older urban riders use safety gear more frequently	Uses non-random sampling
	Prati et al. (2020)	E-bikes	Younger riders face higher crash severity	Relies on self-reported data
	Hu, Lv et al. (2014)	E-bikes	Older age drastically increases injury severity	Excludes fatal crashes prior to hospital
	Wang et al. (2021)	E-bikes	Riders over 55 show a 31% higher severity risk	Missing traffic flow data
Private vs. Shared	Xiaolong et al. (2024)	Shared e-bikes	Speeding increases on wider lanes with low density	Excludes individual rider traits
	Zhang, Du et al. (2023)	Shared e-bikes	Safety attitudes heavily impact accident rates	Lacks observational validation
Infrastructure	Chang et al. (2022)	E-bikes	Horizontal curves and high speeds worsen crashes	Excludes near-miss incidents
	Wang et al. (2018)	E-bicycles	Barrier-separated roads reduce severity	Missing traffic volume variables
	Bai et al. (2017)	E-bikes	Wider bike lanes reduce rear-end conflicts	Uses surrogate safety measures

Theme	Study	Mode	Key Findings	Limitations
Behavior	Ma et al. (2023)	Scooter-style electric bicycles	Running red lights and phone use increase severity	Subject to potential model bias
	Wang et al. (2022)	E-bikes	Route familiarity and seating height alter severity	Discretization biases data
	Putra et al. (2024)	Multi-modal	Drunk driving and red-light running spike crashes	Missing temporal trends
	Schleinitz et al. (2018)	E-bikes	E-bike users ride faster regardless of helmet use	High self-selection bias
	Yang et al. (2024)	E-bikes	Delivery workers and males take more risks	Relies on single-city data
	Yang et al. (2014)	E-bikes	Most riders exceed speed limits and skip helmets	Limited generalizability
	Wang et al. (2024)	E-bikes	Driver speeding and sunshades worsen crashes	Misses exact vehicle speeds
	Ran et al. (2021)	E-bikes	Overconfidence strongly drives risky riding	Limited to college populations
	Wang et al. (2020)	E-bikes	Herd mentality increases traffic rule violations	Missing real-time behavior tracking
	Tang et al. (2020)	E-bikes	Social reactivity drives red-light running willingness	Lacks objective measurements
	Yang, Tian et al. (2024)	E-bikes	E-bikers show 67% higher risk behavior than cyclists	Potential underreporting of near-misses
	Zhong et al. (2022)	E-bikes	Phone use multiplies injury risk tenfold	High potential for recall bias
	Huang et al. (2023)	E-bikes	Wrong-way riding is the leading behavioral risk	Potential observation errors
	Wang et al. (2024)	E-bikes	Avoidance maneuvers and helmets lessen severity	Classification biases present
	Qian et al. (2020)	E-bikes	Drunk riding and carrying passengers spike risk	Cannot prove direct causality
	Venmani & Rajendran (2025)	E-bikes	Speed increases risk while helmets reduce severity	No real-time riding data

Theme	Study	Mode	Key Findings	Limitations
Policy	Feng et al. (2010)	E-bikes	Weak enforcement led to a sixfold mortality increase	Misses minor crash data
	Zhou et al. (2022)	E-bikes	Mandatory helmet policies lower crash involvement	Only short-term post-policy assessment
	Guo et al. (2017)	E-bikes	License plate registration correlates with safer riding	Limited infrastructure variables
Device Specs	Matkovic et al. (2020)	E-scooter	Neural networks successfully classify micromobility	High sampling-rate dependence
	Schepers et al. (2014)	E-bikes	Heavy weight and front traction cause balance issues	Only applies to Dutch cycling contexts

Appendix B: Emerging Safety Data Sources

Telematics Data Collection from Embedded Vehicle Sensors

The industry is currently undergoing a shift from reactive incident logging (waiting for a user report) to proactive safety detection. To achieve this, shared micromobility vehicles are evolving into sophisticated IoT platforms equipped with multimodal sensor fusion. This shift addresses an underreporting gap by capturing solo falls and near-misses that users rarely report.

Geospatial Exposure: The "Map" (GNSS & GPS)

While GNSSs are often categorized as operational tools, they serve as the fundamental ground truth for safety exposure data. By recording precise timestamps and coordinates, GPS provides the denominator, such as Total Vehicle Miles Traveled and Trip Duration, which are required to normalize raw crash counts into meaningful risk metrics, such as incidents per million miles.

However, standard GPS faces limitations in dense urban environments leading to accuracy that can drift by several meters. This lack of precision makes it difficult to reliably distinguish between a street and a parallel sidewalk, a distinction vital to safety enforcement. To mitigate this, modern fleets are transitioning to Dual-Band GNSS (Navixy, 2024) and Dead Reckoning, which integrates high-frequency IMU data with GPS to maintain submeter positioning accuracy during satellite signal outage (ubox, 2023). This combined approach allows for more reliable geofencing and lane-level safety analysis.

Kinematics: The "Inner Ear" (IMU & Accelerometers)

The foundation of vehicle safety data is the 6-axis IMU, which monitors vehicle stability in real time. Acting as the vehicle's vestibular system, high-fidelity IMUs are now standard equipment on nearly all modern shared e-scooters and e-bikes. While historically associated with e-scooters for fall detection, IMUs are now integrated into e-bike mid-drive motors and battery management systems to facilitate torque sensing, anti-theft alerts, and advanced motor assistance (Open Mobility Foundation, 2023). The hardware typically comprises a 3-Axis Accelerometer, which measures linear acceleration (G-force) to detect sudden impacts or hard braking, and a 3-Axis Gyroscope, which measures angular velocity (roll, pitch) to detect tip-overs or swerving maneuvers. Modern fleet vehicles utilize high-frequency IMUs operating at 50 to 100 Hz; this resolution captures jerk (the rate of change of acceleration), providing the granular data needed to distinguish a crash from a benign event such as a pothole impact.

Algorithmic processing has evolved alongside this hardware. Early systems relied on simple threshold logic (e.g., *Tilt* > 60º + *Force* > 3g = *Crash*), which often suffered from high false-negative rates during low-speed falls. In contrast, current systems employ machine learning models, such as convolutional neural networks and support vector machines to analyze the temporal signature of a fall. Recent research has demonstrated that these models, when trained on larger-scale fleet telemetry, achieve fall detection accuracies ranging from 97.1% to 99.3% (Lee et al., 2024). This processing is increasingly supported by on-device "TinyML" capabilities, enabling incident detection in under 250 milliseconds and, in theory, triggering active safety measures or immediate emergency response alerts (Sanchez-Iborra et al., 2022).

Perception: The "Eyes" (AI-Powered Cameras)

To address the inherent limitations of GPS (specifically its inability to reliably distinguish between a street and a parallel sidewalk due to signal multipath), operators are increasingly deploying computer vision modules that process video streams locally on the vehicle edge. Technologies often utilize forward-facing cameras to perform real-time semantic segmentation of the riding surface. These systems have demonstrated high fidelity, achieving greater than 95% accuracy in classifying distinct environments, including sidewalks, bike lanes, and roadways (Navixy, 2024; STV, 2025).

This perception layer enables immediate intervention, such as real-time speed throttling upon sidewalk entry and pedestrian density detection, which alerts riders to slow down in crowded areas. Furthermore, in the context of safety analytics, these vision-based sensors offer an advantage over reactive kinematic sensors: the ability to identify near-miss conflicts. By detecting hazardous interactions with vehicles or pedestrians that do not result in a crash, these systems generate a rich dataset of potential safety hotspots, providing insights for urban planners and policymakers.

Proximity: The "Reflexes" (Ultrasonic and Infrared)

Adopting mature technologies from the automotive industry's advanced driver assistance systems sector, premium micromobility vehicles are integrating short-range active sensors that function as the vehicle's reflexes for obstacle avoidance and operational integrity. Primary among these is an ultrasonic sensor (i.e., sonar). It emits high-frequency sound waves to measure time-of-flight reflections from nearby objects. This technology could be particularly useful for larger cargo e-bikes and three-wheeled scooters, where it provides blind-spot detection and provides haptic and acoustic warnings to alert riders to obscured hazards such as bollards or pedestrians in proximity (STV, 2025).

Complementing this acoustics layer, infrared and optical time-of-flight sensors provide precise, short-range depth mapping. These are increasingly deployed in kickstands or wheel housings to detect vandalism (sensing if a vehicle has been tipped or dragged into a non-compliant area, even when camera views are obstructed) and in seat or deck modules to verify rider presence, effectively preventing ghost riding (accidental acceleration without a passenger).

Forensics: The "Nerves" (Hall Effect Sensors)

While less visible than cameras, Hall effect sensors can be useful for post-incident forensics. These magnetic sensors provide non-contact feedback on the state of mechanical components. By measuring the magnetic field variance within the brake and throttle assemblies, these sensors record the exact percentage of applications (0%–100%) with millisecond precision, while multiple integrated Hall effect sensors simultaneously track precise rotational position and acceleration (Barnes & Brennan, 2012). This creates an immutable data log capable of verifying or refuting users' claims, such as brake failure, by revealing exactly when and how forcefully the brakes were engaged relative to the impact site.

Furthermore, Hall effect sensors integrated into the brushless DC hub motor track precise RPM and wheel rotation. This telemetry validates dynamic stability, enabling analysis to distinguish between a locked-wheel skid and loss of traction during a crash event. Finally, binary Hall switches monitor kickstand status, acting as a safety interlock that prevents motor engagement while the vehicle is parked, thereby mitigating common injury risks for new users.

Infrastructure-Based Remote Sensing (Video and LiDAR)

While embedded vehicle sensors provide a rider-centric view of safety, roadside remote sensing may help to capture the environmental and behavioral context of the street. These data opportunities are often deployed by public sector agencies for ad hoc analysis, or are part of larger traffic surveillance activities. Technologies such as pole-mounted AI cameras and light detection and ranging (LiDAR) at intersections offer a stationary, high-vantage perspective that the vehicle itself cannot achieve.

- Measuring on-road behavior: Unlike vehicle telematics, which record the outcome of a maneuver, roadside sensing measures the behavior itself. Research conducted on 26 streets in Nashville, TN, and Portland, OR, utilized video-based platforms to examine riding patterns relative to infrastructure, finding that the presence of dedicated bike lanes dramatically reduced sidewalk riding and conflict rates (Cherry et al., 2021).

- Conflict and near-miss analysis: Roadside sensors use surrogate safety measures, such as post-encroachment time and time-to-collision, to identify near-misses that do not result in a crash report. In Nashville, LiDAR deployments have revealed crossing patterns, allowing officials to understand where pedestrians and micromobility users spill into traffic or narrowly avoid collisions with motor vehicles (STV, 2025).
- Capturing non-connected entities: A primary advantage of roadside sensing is the ability to track interactions with non-connected entities (e.g., pedestrians or private vehicles) that lack telematics hardware. By assigning safety scores to intersections based on these interactions, planners can prioritize infrastructure interventions, such as adaptive signal control or mid-block crosswalks, proactively rather than reactively.

Appendix C: Traffic Crash Narrative Analysis with AI/LLMs

The application of LLMs to traffic crash narrative analysis is gaining popularity with the advent of advanced AI models like ChatGPT. Researchers have demonstrated that LLMs can overcome the limitations of conventional statistical models by processing unstructured crash narratives to capture contextual nuances (Zhao et al., 2025; Zhen & Yang, 2025). For instance, SafeTraffic Copilot is a Llama 3.1-based LLM fine-tuned on 6,205 real-world crash cases totaling 14.5 million words from five U.S. states, customized for traffic-crash prediction and interpretation. The model demonstrated 33.3% to 45.8% improvements in average F1-Scores over existing approaches for crash type, severity, and injury prediction tasks (Zhao et al., 2025). Likewise, CrashSage is another supervised, fine-tuned Llama-3 8B model for crash severity inference, and its performance was compared against baseline tabular models (CatBoost, TabTransformer, FT-Transformer) as well as general LLMs using zero-shot, few-shot, and chain-of-thought prompting strategies. While CrashSage was able to outperform baseline models, the comparison metrics were only marginally better than a few-shot learning model based on LLaMA3-8B and LLaMA3-70B (Zhen & Yang, 2025). That said, CrashSage models have outperformed the zero-shot-chain of thought models, which relied more on prompt engineering (Zhen et al., 2024).

Another such example is the CrashLLM framework, which reformulates crash event feature learning as a text reasoning problem, boosting F1 scores from 34.9% to 53.8% over traditional methods and enabling “what-if” situational-awareness analyses using structured and unstructured crash data (Fan et al., 2024). Additionally, research from Chalmers University shows that open-source LLMs fine-tuned with low-rank adaptation could outperform GPT-4o in extracting crash details, such as travel direction, collision manner, and crash type, while requiring minimal training resources (Zhao et al., 2024). Researchers have also explored the capabilities of very light LLMs (1 billion parameters) using fine-tuned Llama 3.2 to automatically infer adverse driver actions from crash narratives and demonstrated a superior performance against conventional machine learning classifiers including Random Forest, XGBoost, and CatBoost. This model could also provide probabilistic reasoning capabilities for counterfactual scenario analysis (Chen et al., 2025).

Analyses Involving Vulnerable Road Users

The application of AI to vulnerable road-user crashes faces unique challenges due to data heterogeneity and the underrepresentation of these users compared to vehicle–vehicle collisions. Das et al. (2020) were among the first to analyze narrative data regarding pedestrian crashes, concluding that machine learning could identify crash types from text narratives. They applied machine learning tools, including XGBoost, to classify pedestrian crash types from police crash narratives, achieving accuracy rates of up to 77% for training data and 72% for test data when automating the labor-intensive Pedestrian and Bicycle Crash Analysis Tool classification process (Das et al., 2020).

For emerging micromobility modes, AI applications have focused primarily on injury detection rather than crash classification. A natural language processing study using random multimodal deep learning searched 36 million clinical notes to identify e-scooter injuries, achieving 92% accuracy in correctly classifying notes with the keyword “scooter” as predictive of e-scooter injury or not, identifying 1,354 injured individuals across 180 clinics and 2 hospitals in greater Los Angeles (Ioannides et al., 2022).

Despite these advances, gaps remain in applying LLMs to micromobility crash classification. Most AI applications focus on general traffic crashes, with limited work specifically addressing e-scooters, e-bikes, and other micromobility devices. The challenge of distinguishing micromobility crashes from pedestrian or bicycle crashes in police narratives, particularly for historical data predating improved coding standards, remains largely unaddressed in the literature.

Case Study I | Extended Result

Model Validation

The candidate narratives were processed using the SFSP model. To validate accuracy, 96 hand-picked crash narratives were manually labeled into five categories: bicycle, e-bike, e-scooter, pedestrian, and other. The manual labels were then compared with the SFSP model–generated classifications. The analysis revealed approximately 94.8% accuracy for the SFSP model when validated against human annotations, as shown in Figure C1.

Figure C1: Confusion Matrix Comparing Actual Labels (row) vs. SFSP-Generated Labels (columns)

		LLM Classifications (Predicted)				
		Bicycle	E-Bike	E-Scooter	Other	Pedestrian
Manual Labels (Actual)	Bicycle	64	1	0	1	0
	E-Bike	0	2	0	0	0
	E-Scooter	0	0	15	1	0
	Other	0	0	1	4	1
	Pedestrian	0	0	0	0	6

Accuracy: 94.8% (91/96)

Non-Motorist Classification

After validating the SFSP model's accuracy, potential miscoding in TITAN data labels was assessed. Of 27,604 narratives involving at least one non-motorist, 1,431 unique crashes (3,260 individuals) involved multiple non-motorists. Among these, 1,335 crashes involved individuals with identical non-motorist coding (3,040 individuals). For the remaining 96 crashes (0.3% of all narratives) involving multiple distinct non-motorist types (220 individuals), the crash narrative was linked to the modes most relevant to micromobility (specifically e-scooters, personal conveyances, bicyclists, and other cyclists). For example, crashes involving both a pedestrian and a personal conveyance user were classified as "person on personal conveyance."

After running the SFSP model on 27,604 narratives, it identified four major categories: pedestrians, bicycles, e-scooters, and e-bikes. The model also assigned "unable to classify" labels to ambiguous cases and "out of scope" labels to modes beyond the study's focus (e.g., horse-drawn carriages). Remaining modes, such as skateboards, kick scooters, one-wheel vehicles, seated medical mobility devices, and roller blades, were grouped as "other unmotorized micromobility (UMM)" or "other motorized micromobility (MMM)" devices, depending on whether they were motorized.

TITAN coding was compared with SFSP classifications in Table C1 and Figure C2. TITAN labels indicated pedestrians in 72.7% of narratives, bicyclists in 17.5%, and e-scooters in 0.6%. The SFSP model correctly identified 17,639 pedestrian narratives, 4,583 bicyclist narratives, and 121 e-scooter narratives, collectively representing 81% of all narratives, as shown in Figure C2(a), reinforcing model accuracy for these dominant categories. The remaining 19% involved cross-category classifications, which are detailed in Figure C2(b), which provides a “zoomed-in” view of the data that excludes the massive pedestrian and bicyclist totals to make the smaller micromobility categories visible. Among pedestrian-coded narratives, the model could not classify 3.2% and identified 10.1% as out of scope. Notably, the model identified 224 pedestrian-coded narratives as bicyclists, 177 as e-scooters, 162 as other MMM, and 200 as other UMM, representing a small share of total pedestrians but a considerable portion of potential micromobility misclassifications.

Table C1: Cross-Tabulation Analysis of SFSP Model Classifications vs. TITAN Coding

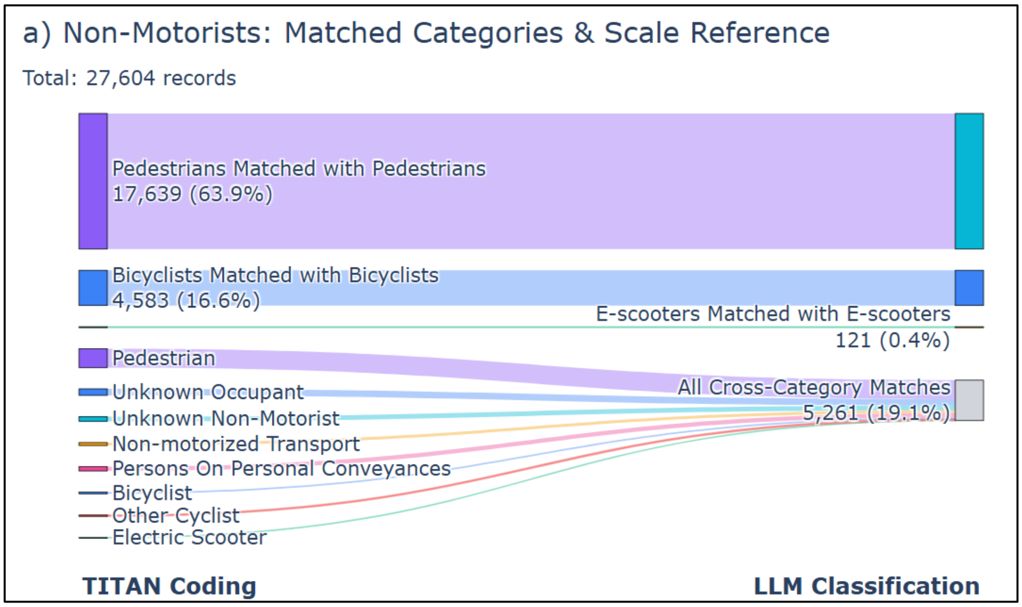
	SFSP Model Classifications									
TITAN Non-Motorist Codes	**Bicycle**	**Pedestrian**	**E-scooter**	**E-bike**	**Other MMM**	**Other UMM**	**Out of Scope**	**Unable to Classify**	**Total**	**Missing**
Bicyclist	4,583 *(95.6)*	98 *(2.0)*	7 *(0.1)*	50 *(1.0)*	1 *(0.0)*	5 *(0.1)*	25 *(0.5)*	27 *(0.6)*	**4,796 *(100.0)***	50
Pedestrian	224 (1.1)	17,640 *(87.8)*	178 *(0.9)*	2 *(0.0)*	162 *(0.8)*	201 *(1.0)*	1,045 *(5.2)*	632 *(3.1)*	**20,084 *(100.0)***	285
Persons on Personal Conveyances	21 *(3.8)*	72 *(13.1)*	86 *(15.7)*	6 *(1.1)*	58 *(10.6)*	33 *(6.0)*	221 *(40.3)*	52 *(9.5)*	**549 *(100.0)***	10
Non-Motor Vehicle Transport Device	3 *(0.8)*	19 *(4.9)*	6 *(1.6)*	0 *(0.0)*	7 *(1.8)*	7 *(1.8)*	295 *(76.8)*	47 *(12.2)*	**384 *(100.0)***	0
Other Cyclist	99 *(56.6)*	10 *(5.7)*	31 *(17.7)*	13 *(7.4)*	3 *(1.7)*	9 *(5.1)*	7 *(4.0)*	3 *(1.7)*	**175 *(100.0)***	2
Unknown Non-Motorist	2 *(0.3)*	110 *(17.8)*	3 *(0.5)*	0 *(0.0)*	3 *(0.5)*	6 (1.0)	426 *(68.9)*	68 *(11.0)*	**618 *(100.0)***	4
Unknown occupant	4 *(0.5)*	26 *(3.1)*	1 *(0.1)*	0 *(0.0)*	0 *(0.0)*	5 *(0.6)*	771 *(90.7)*	43 *(5.1)*	**850 *(100.0)***	1
Total	**4,936 *(18.0)***	**17,975 *(65.5)***	**312 *(1.1)***	**71 *(0.3)***	**234 *(0.9)***	**266 *(1.0)***	**2,790 *(10.2)***	**872 *(3.2)***	27,456 *(100)*	352

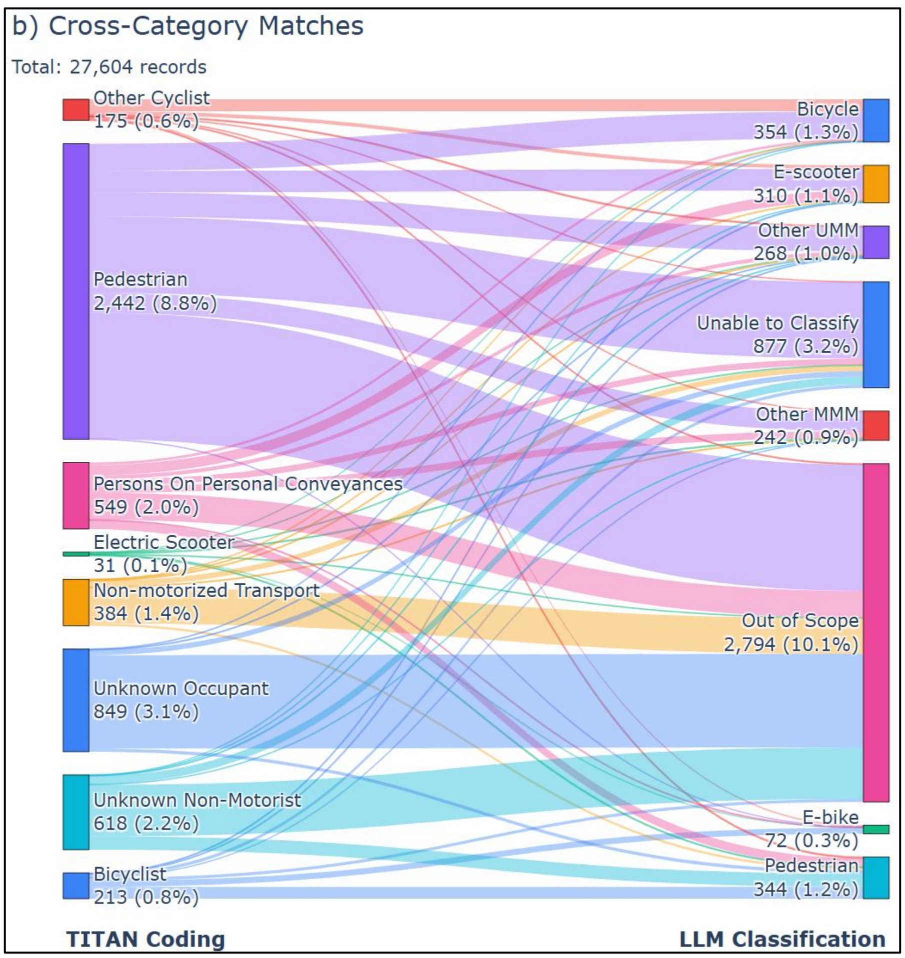
Another important TITAN code likely to contain micromobility misclassifications is “persons on personal conveyances.” While only 549 narratives (2%) carried this coding, the model classified 221 as out of scope, 86 as e-scooters, 58 as other MMM, and 33 as other UMM devices, making it an important contributor to misidentified micromobility modes. Conversely, bicyclist coding was highly consistent in TITAN, with the model correctly classifying 96% of TITAN-coded bicyclists as bicyclists. The model rarely classified e-bikes, potentially because officers may not mention or identify e-bikes during crash investigations.

It was also observed that unknown occupants were unlikely to be non-motorists: the model classified only 35 of 849 unknown-occupant narratives as non-motorists, while classifying the majority as out of scope, likely indicating motor vehicle occupants. Similarly, the model identified most “occupants of non-motor vehicle transportation devices” as horse-drawn carriages and similar vehicles outside the study scope, classifying over 77% of this coding as out of scope.

Ultimately, 431 e-scooters, 72 e-bikes, 242 other MMM, and 268 other UMM devices were identified from the 27,604 non-motorist crash narratives. Among e-scooter cases, 41% were originally coded as pedestrians, 20% as “persons on personal conveyances,” and 7% as “other cyclists.” In contrast, 69% of e-bike cases were coded as bicyclists and 18% as “other cyclists.” Other MMM devices (such as Segways, hoverboards, one-wheel scooters, motorized skateboards, and seated medical mobility devices) were primarily found in pedestrian and personal-conveyance coding categories. Similarly, other UMM devices (including skateboards, roller skates, kick scooters, and other unmotorized micromobility modes) also appeared most frequently in pedestrian and personal-conveyance classifications.

Figure C2: Non-Motorist Matching: a) Matched Categories (Pedestrian-to-Pedestrian, Bicyclist-to-Bicyclist) and Scale Reference, b) Cross-Category Matches Zoomed In





Shared E-scooter Identification

The SFSP model was customized to extract information on whether a mentioned micromobility device was part of a shared system. The model was specifically prompted to recognize major shared e-scooter and e-bike companies. As a result, the model identified 142 shared e-scooter users, one shared e-bike rider, and 12 users of other shared micromobility devices. Given the limited representation of shared e-bikes, the analysis focused exclusively on shared versus non-shared e-scooters.

A distribution analysis across user characteristics (such as gender, age group, suspected alcohol or drug presence, and injury severity) was conducted to assess whether these characteristics differed based on shared status. Male users constituted the majority of e-scooter riders in both categories. Alcohol and drug involvement did not differ between the two groups. However, age group exhibited the strongest difference: shared e-scooter users were disproportionately concentrated among individuals aged 16–34, whereas younger riders (0–15) and older riders (50 and above) were more heavily represented among non-shared e-scooter users. This pattern likely reflects broader inconsistencies in crash reporting, as some devices involving older adults may correspond to seated medical mobility scooters generically described as “electric scooters.”

Table C2: Descriptive Statistics Comparing Shared vs. Non-Shared E-Scooters

Panel	Category	Non-Shared *(%)*	Shared *(%)*	Group Comparisons	Total
Overall	Average Age	31.3	29.3	1.097 *(0.273)* [a]	-
	Counts	302	143	-	445 *(28 unspecified)*
Gender	Female	86 *(28.5)*	47 *(32.9)*	0.955 *(0.621)* [b]	133
	Male	213 *(70.5)*	95 *(66.4)*		308
	Others	3 *(1.0)*	1 *(0.7)*		4
	Subtotal	302 *(100.0)*	143 *(100.0)*		445
Age Group	0–15	63 *(21.1)*	13 *(9.1)*	26.310 *(<0.001)* [b]	76
	16–24	83 *(27.8)*	54 *(37.8)*		137
	25–34	58 *(19.4)*	44 *(30.8)*		102
	35–49	30 *(10.0)*	19 *(13.3)*		49
	50 and above	65 *(21.7)*	13 *(9.1)*		78
	Subtotal	299 *(100.0)*	143 *(100.0)*		442
Race	Black	76 *(25.2)*	49 *(34.3)*	5.652 *(0.059)* [b]	125
	White	167 *(55.3)*	76 *(53.1)*		243
	Other/unknown	59 *(19.5)*	18 *(12.6)*		77
	Subtotal	302 *(100.0)*	143 *(100.0)*		445
Alcohol Presence	Absent/unknown	298 *(98.7)*	139 *(97.2)*	2.144 *(0.277)* [c]	437
	Present	4 *(1.3)*	4 *(2.8)*		8
	Subtotal	302 *(100.0)*	143 *(100.0)*		445
Drug Presence	Absent/unknown	299 *(99.0)*	143 *(100.0)*	0.000 *(0.555)* [c]	442
	Present	3 *(1.0)*	0 *(0.0)*		3
	Subtotal	302 *(100.0)*	143 *(100.0)*		445
Injury Severity	Minor Injury	201 *(66.6)*	103 *(72.0)*	1.351 *(0.509)* [b]	304
	No Injury	64 *(21.2)*	25 *(17.5)*		89
	Severe Injury	37 *(12.3)*	15 *(10.5)*		52
	Subtotal	302 *(100.0)*	143 *(100.0)*		445

Note: [a] Welch t-test statistic, [b] Chi-square test statistic, [c] Fisher's exact test statistic; p-value in parenthesis

Micromobility User as a Motorist Classification

The SFSP model was applied to examine 118 crash narratives associated with vehicle–vehicle coded collisions. The model classified these incidents as follows: 49 e-scooters, 30 e-bikes, 26 other micromobility devices, 6 bicycles, and the remainder as out-of-scope entries.

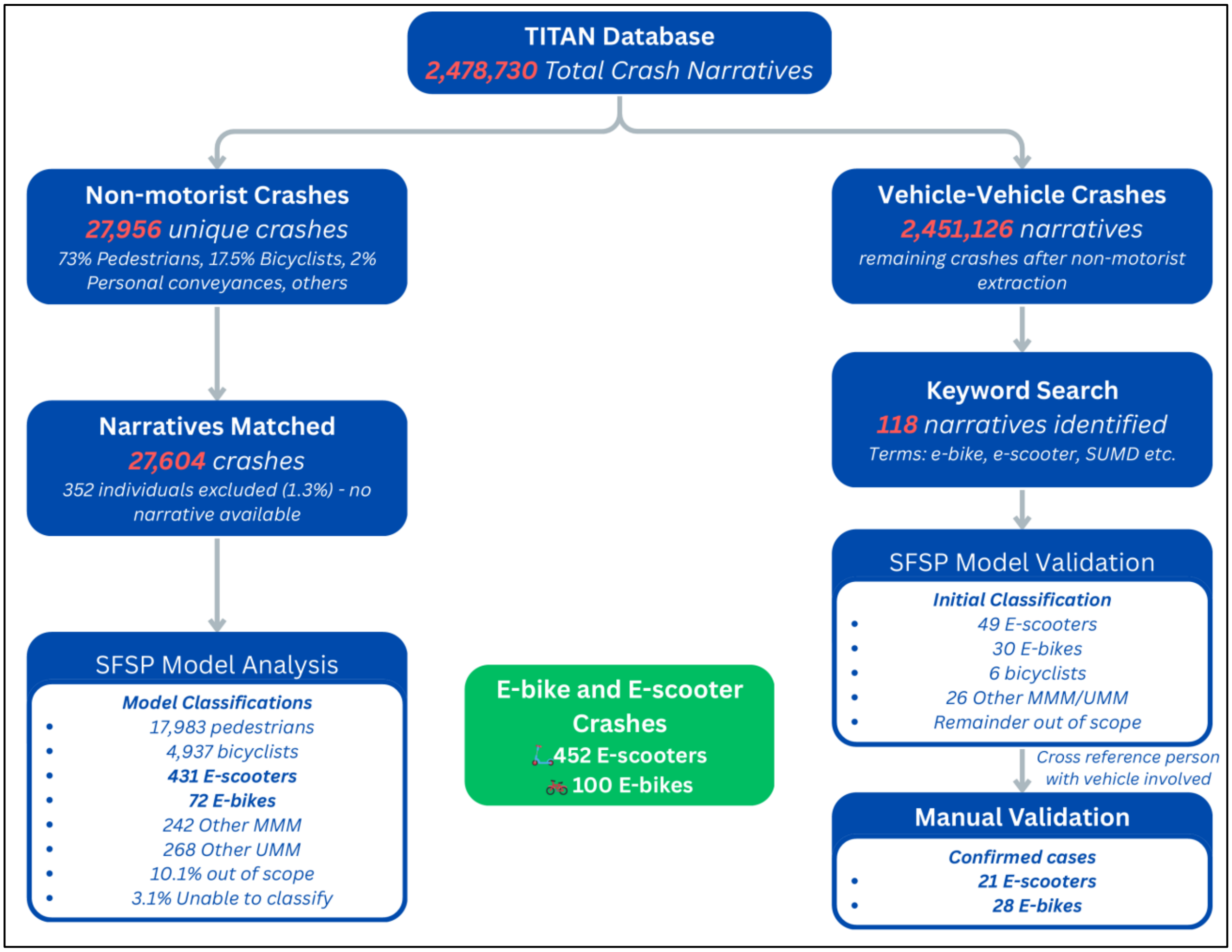
While the SFSP model demonstrated generally high accuracy, it exhibited limitations in distinguishing certain motor vehicles from micromobility devices. Specifically, the model sometimes misclassified crashes involving motor vehicles transporting micromobility devices (on racks or trailers) as micromobility-related collisions. This suggests the need to incorporate such scenarios into future model prompts.

Identifying non-motorists within vehicle–vehicle crashes presented additional challenges, as multiple individuals were often involved in a single incident. Among the 118 crashes analyzed, 314 persons were coded as motorists. To isolate actual non-motorists, the corresponding vehicle units in each crash were cross-referenced and motor vehicle status was verified by examining vehicle type codes, VIN presence, license plate numbers, and other identifying details. This validation process yielded only 28 e-bikes and 21 e-scooters as confirmed non-motorist cases.

The limited recovery of e-scooter incidents may also reflect changes in TITAN's coding practices. Since the system began specifically coding e-scooters in 2020, many earlier e-scooter–related narratives may have been revised or reclassified, potentially affecting the linkage results.

In the next phase of this study, the focus shifted exclusively to micromobility users, specifically e-scooter and e-bike users, based on the crash narrative information analyzed with AI. Using this approach, 452 e-scooter users and 100 e-bike users, along with 242 other MMM and 268 other UMM users, were identified from January 1, 2014, to September 30, 2024. Figure C3 illustrates the AI classification workflow for both non-motorist and motorist coding in the narratives.

Figure C3: TITAN Crash Data Analysis Workflow



Case Study II | Extended HDDS Demographics

This appendix provides demographic and injury characteristic data for e-scooter and e-bike riders recorded in the Tennessee HDDS. While the main body of this report focuses on high-level injury severity and crash mechanics, the tables below provide a granular view of the populations affected by non-motor-vehicle collisions, falls, and stationary-object impacts. Demographic variables such as race, ethnicity, residency, and urbanicity are preserved in this expanded dataset to assist researchers and policymakers in identifying potential disparities in micromobility safety outcomes and to better inform localized, equitable infrastructure planning.

Table C3: E-Scooter Riders with Injury Incidents Recorded in HDDS (October 1, 2020–December 31, 2024)

	Total *N* = 776 Count (%)	Fall *n* = 685 Count (%)	Collision: Vehicle *n* = 49 Count (%)	Collision: Stationary Object *n* = 35 Count (%)	Collision: Non-Motorist *n* = 7 Count (%)
Visit Type					
Hospitalization	38 (4.9)	30 (4.4)	4 (8.2)	4 (11.4)	0 (0.0)
Emergency department visit	738 (95.1)	655 (95.6)	45 (91.8)	31 (88.6)	7 (100.0)
Number of Injuries Sustained					
0 injuries	36 (4.6)	26 (3.8)	7 (14.3)	2 (5.7)	1 (14.3)
1 injury	303 (39.0)	271 (39.6)	14 (28.6)	15 (42.9)	3 (42.9)
2 injuries	200 (25.8)	177 (25.8)	13 (26.5)	8 (22.9)	2 (28.6)
3 injuries	124 (16.0)	113 (16.5)	8 (16.3)	3 (8.6)	0 (0.0)
4 or more Injuries	113 (14.6)	98 (14.3)	7 (14.3)	7 (20.0)	1 (14.3)
Number of Body Regions Injured (6 Possible: Head/Neck, Spine/Back, Torso, Extremities, Unclassifiable by Body Region, Unspecified)					
0 body regions injured	36 (4.6)	26 (3.8)	7 (14.3)	2 (5.7)	1 (14.3)
1 body regions injured	540 (69.6)	481 (70.2)	27 (55.1)	28 (80.0)	4 (57.1)
2 body regions injured	171 (22.0)	158 (23.1)	9 (18.4)	2 (5.7)	2 (28.6)
3 or more body regions injured	29 (3.7)	20 (2.9)	6 (12.2)	3 (8.6)	0 (0.0)
Age Group					
0–15 years	218 (28.1)	202 (29.5)	8 (16.3)	7 (20.0)	1 (14.3)
16–19 years	56 (7.2)	46 (6.7)	7 (14.3)	2 (5.7)	1 (14.3)
20–29 years	190 (24.5)	163 (23.8)	14 (28.6)	10 (28.6)	3 (42.9)
30–39 years	124 (16.0)	107 (15.6)	10 (20.4)	6 (17.1)	1 (14.3)
40–49 years	78 (10.1)	70 (10.2)	5 (10.2)	3 (8.6)	0 (0.0)
50–59 years	51 (6.6)	47 (6.9)	1 (2.0)	3 (8.6)	0 (0.0)
60+ years	59 (7.6)	50 (7.3)	4 (8.2)	4 (11.4)	1 (14.3)

	Total *N* = *776* Count (%)	Fall *n = 685* Count (%)	Collision: Vehicle *n = 49* Count (%)	Collision: Stationary Object *n = 35* Count (%)	Collision: Non-Motorist *n* = *7* Count (%)
Sex					
Female	349 (45.0)	314 (45.8)	17 (34.7)	13 (37.1)	5 (71.4)
Male	427 (55.0)	371 (54.2)	32 (65.3)	22 (62.9)	2 (28.6)
Race					
White	530 (68.3)	473 (69.1)	27 (55.1)	25 (71.4)	5 (71.4)
Black	171 (22.0)	145 (21.2)	16 (32.7)	9 (25.7)	1 (14.3)
Other	51 (6.6)	44 (6.4)	6 (12.2)	0 (0.0)	1 (14.3)
Unknown	24 (3.1)	23 (3.4)	0 (0.0)	1 (2.9)	0 (0.0)
Ethnicity					
Hispanic origin	31 (4.0)	28 (4.1)	2 (4.1)	1 (2.9)	0 (0.0)
Non-Hispanic origin	710 (91.5)	626 (91.4)	44 (89.8)	33 (94.3)	7 (100.0)
Hispanic origin unknown	35 (4.5)	31 (4.5)	3 (6.1)	1 (2.9)	0 (0.0)
Residency					
Tennessee resident	557 (71.8)	492 (71.8)	36 (73.5)	24 (68.6)	5 (71.4)
Non-Tennessee resident	219 (28.2)	193 (28.2)	13 (26.5)	11 (31.4)	2 (28.6)
Urbanicity (Based on Residence)					
Large central metro	240 (30.9)	216 (31.5)	18 (36.7)	4 (11.4)	2 (28.6)
Large fringe metro	109 (14.0)	99 (14.5)	3 (6.1)	7 (20.0)	0 (0.0)
Medium metro	107 (13.8)	92 (13.4)	8 (16.3)	6 (17.1)	1 (14.3)
Small metro	24 (3.1)	20 (2.9)	3 (6.1)	1 (2.9)	0 (0.0)
Micropolitan	59 (7.6)	49 (7.2)	4 (8.2)	4 (11.4)	2 (28.6)
Non-core	18 (2.3)	16 (2.3)	0 (0.0)	2 (5.7)	0 (0.0)
Non-Tennessee resident	219 (28.2)	193 (28.2)	13 (26.5)	11 (31.4)	2 (28.6)

Table C4: E-Bike Riders with Injury Incidents Recorded in HDDS (October 1, 2022–December 31, 2024)

	Total *N = 441* Count (%)	Non-Collision *n = 201* Count (%)	Other/ Unspecified *n = 141* Count (%)	Collision: Vehicle *n = 57* Count (%)	Collision: Stationary Object *n = 29* Count (%)	Collision: Non-Motorist/animal *n = 13* Count (%)
Visit Type						
Hospitalization	53 (12.0)	27 (13.4)	15 (10.6)	5 (8.8)	6 (20.7)	0 (0.0)
Emergency department visit	388 (88.0)	174 (86.6)	126 (89.4)	52 (91.2)	23 (79.3)	13 (100.0)
Number of Injuries Sustained						
0 injuries	21 (4.8)	9 (4.5)	5 (3.5)	5 (8.8)	2 (6.9)	0 (0.0)
1 injury	145 (32.9)	67 (33.3)	43 (30.5)	21 (36.8)	8 (27.6)	6 (46.2)
2 injuries	100 (22.7)	45 (22.4)	37 (26.2)	7 (12.3)	7 (24.1)	4 (30.8)
3 injuries	63 (14.3)	31 (15.4)	22 (15.6)	7 (12.3)	2 (6.9)	1 (7.7)
4 or more injuries	112 (25.4)	49 (24.4)	34 (24.1)	17 (29.8)	10 (34.5)	2 (15.4)
Number of Body Regions Injured (6 Possible: Head/Neck, Spine/Back, Torso, Extremities, Unclassifiable by Body Region, Unspecified)						
0 body regions injured	21 (4.8)	9 (4.5)	5 (3.5)	5 (8.8)	2 (6.9)	0 (0.0)
1 body regions injured	240 (54.4)	113 (56.2)	76 (53.9)	31 (54.4)	12 (41.4)	8 (61.5)
2 body regions injured	133 (30.2)	61 (30.3)	47 (33.3)	14 (24.6)	8 (27.6)	3 (23.1)
3 or more body regions injured	47 (10.7)	18 (9.0)	13 (9.2)	7 (12.3)	7 (24.1)	2 (15.4)
Age Group						
0–15 years	73 (16.6)	32 (15.9)	23 (16.3)	10 (17.5)	4 (13.8)	4 (30.8)
16–19 years	25 (5.7)	10 (5.0)	9 (6.4)	5 (8.8)	1 (3.4)	0 (0.0)
20–29 years	66 (15.0)	25 (12.4)	22 (15.6)	12 (21.1)	5 (17.2)	2 (15.4)
30–39 years	58 (13.2)	26 (12.9)	16 (11.3)	11 (19.3)	3 (10.3)	2 (15.4)
40–49 years	67 (15.2)	36 (17.9)	18 (12.8)	8 (14.0)	4 (13.8)	1 (7.7)
50–59 years	60 (13.6)	25 (12.4)	23 (16.3)	6 (10.5)	5 (17.2)	1 (7.7)
60+ years	92 (20.9)	47 (23.4)	30 (21.3)	5 (8.8)	7 (24.1)	3 (23.1)

	Total *N = 441* Count (%)	Non-Collision *n = 201* Count (%)	Other/ Unspecified *n = 141* Count (%)	Collision: Vehicle *n = 57* Count (%)	Collision: Stationary Object *n = 29* Count (%)	Collision: Non-Motorist/animal *n = 13* Count (%)
Sex						
Female	120 (27.2)	54 (26.9)	49 (34.8)	8 (14.0)	7 (24.1)	2 (15.4)
Male	321 (72.8)	147 (73.1)	92 (65.2)	49 (86.0)	22 (75.9)	11 (84.6)
Race						
White	363 (82.3)	167 (83.1)	115 (81.6)	43 (75.4)	27 (93.1)	11 (84.6)
Black	50 (11.3)	19 (9.5)	18 (12.8)	9 (15.8)	2 (6.9)	2 (15.4)
Other	18 (4.1)	9 (4.5)	6 (4.3)	3 (5.3)	0 (0.0)	0 (0.0)
Unknown	10 (2.3)	6 (3.0)	2 (1.4)	2 (3.5)	0 (0.0)	0 (0.0)
Ethnicity						
Hispanic origin	19 (4.3)	9 (4.5)	7 (5.0)	3 (5.3)	0 (0.0)	0 (0.0)
Non-Hispanic origin	411 (93.2)	188 (93.5)	130 (92.2)	52 (91.2)	28 (96.6)	13 (100.0)
Hispanic origin unknown	11 (2.5)	4 (2.0)	4 (2.8)	2 (3.5)	1 (3.4)	0 (0.0)
Residency						
Tennessee resident	382 (86.6)	169 (84.1)	123 (87.2)	54 (94.7)	26 (89.7)	10 (76.9)
Non-Tennessee resident	59 (13.4)	32 (15.9)	18 (12.8)	3 (5.3)	3 (10.3)	3 (23.1)
Urbanicity (Based on Residence)						
Large central metro	77 (17.5)	41 (20.4)	17 (12.1)	11 (19.3)	5 (17.2)	3 (23.1)
Large fringe metro	105 (23.8)	44 (21.9)	33 (23.4)	18 (31.6)	7 (24.1)	3 (23.1)
Medium metro	78 (17.7)	35 (17.4)	28 (19.9)	8 (14.0)	6 (20.7)	1 (7.7)
Small metro	24 (5.4)	10 (5.0)	8 (5.7)	4 (7.0)	2 (6.9)	0 (0.0)
Micropolitan	63 (14.3)	22 (10.9)	24 (17.0)	12 (21.1)	3 (10.3)	2 (15.4)
Non-core	35 (7.9)	17 (8.5)	13 (9.2)	1 (1.8)	3 (10.3)	1 (7.7)
Non-Tennessee resident	59 (13.4)	32 (15.9)	18 (12.8)	3 (5.3)	3 (10.3)	3 (23.1)

Appendix D: Typical Stakeholder Interview/Focus Group Script and Sample Questions (modified depending on stakeholder group)

General

1. How familiar are you with the different kinds of micromobility devices, including both shared and privately owned e-scooters, e-bikes, and boards (such as electric skateboards, hoverboards, and other small, standing electric vehicles)?
2. Is there a clear understanding or definition of micromobility devices in your agency or community?
    - Are some parts more ambiguous?
3. Can you give an example of when you've needed information on e-bikes or e-scooters in your work? What kind of information was most useful—or missing?
4. Where do you typically go to learn more about micromobility? What types of resources would be most helpful to you, e.g., research reports, example policies, safety data, etc.?
    - *Optional follow-up: Do you know how to access resources that currently exist?*

Safety Trends

5. What safety trends (if any) have you observed related to e-scooter or e-bike use?
6. Are there notable differences in risk or outcomes between shared and personally owned devices?
7. What gaps related to micromobility safety data/information have the greatest impact on your ability to serve your audience?

Safety Efforts

8. Have micromobility safety trends influenced any of your funded initiatives, outreach priorities, or public education efforts?
9. What policies do you think are the most important for improving driver-micromobility safety? Does your organization have any of those policies or tools?
    - *If so, what have been the results of those efforts?*
    - *If not, what resources or information would be helpful to develop those policies or tools?*
10. Are there other efforts your organization has supported or undertaken to improve driver and micromobility safety relative to one another? If so, please tell us about them.

Closing

11. What additional research and/or regulatory efforts would you like to see to help improve micromobility safety?
12. What data or information would help you make better decisions about micromobility safety?
13. Is there anything else you would like to add to this interview?
14. Is there another person or organization that you think we should engage during this study?