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Risk analysis of crashes related to e-scooters: proposal of a predictive model

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Risk analysis of crashes related to e-scooters: proposal of a predictive model

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Al Magnifico Rettore
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EXTENDED ABSTRACT (eng)

The rapid expansion of electric scooters has revolutionized urban mobility while raising significant safety concerns, particularly regarding crashes. This thesis presents a comprehensive study on the risk analysis of crashes involving electric scooters and proposes a predictive model to estimate the likelihood of crashes on urban road segments and intersections. Conducted in Bari, Italy, this research addresses gaps in the literature by integrating data on electric scooter traffic, road geometric characteristics, and infrastructure within a robust statistical framework.

The study begins with an analysis of crash data provided by the Local Police of Bari for the period 2021–2023. Descriptive statistics reveal critical insights into crash dynamics: 70% of the events resulted in injuries, highlighting the vulnerability of scooter users. Crashes predominantly occurred on undivided roads, underscoring potential infrastructure-related risks. The analysis also considers temporal and spatial patterns, providing useful insights for identifying high-risk conditions.

Data collection for this research followed an innovative approach, addressing the scarcity of standardized data on electric scooter traffic. Through collaboration with Vento Mobility Srl (TIER), access to usage statistics was secured, complemented by field surveys to estimate traffic volumes for both shared and private scooters. Additional information on road characteristics, vehicle traffic, and infrastructure was meticulously gathered using tools such as QGIS and Google Maps, ensuring a comprehensive dataset.

A binomial logistic regression model was developed to predict the likelihood of crashes based on key variables such as daily traffic volumes, road geometry, and the presence of specific infrastructure like bicycle crossings or turning lanes. Models were separately developed for road segments and intersections, ensuring greater contextual

relevance. Variables were selected based on statistical significance to enhance the model accuracy while maintaining interpretability.

The predictive model results highlight key factors influencing the risk of crashes involving electric scooters. For intersections, high volumes of vehicular and scooter traffic significantly increase crash likelihood. Similarly, for road segments, variables such as segment length and traffic density emerge as critical predictors. These findings underscore the importance of targeted infrastructure improvements and traffic management strategies to reduce risks.

This thesis provides a validated predictive model that can support policymakers, urban planners, and transportation authorities. The study offers a practical tool to identify high-risk areas and implement safety interventions, promoting sustainable and safe micromobility in urban contexts.

By addressing both data collection challenges and the methodological limitations of previous studies, this research lays the groundwork for future studies on electric scooter safety. It advocates for the standardization of data collection and the adaptation of infrastructure to support the safe integration of scooters into urban transportation systems, even if changes in regulations should be taken into account in future studies.

Key words: Road safety, electric scooters, predictive model

EXTENDED ABSTRACT (ita)

La rapida diffusione dei monopattini elettrici ha rivoluzionato la mobilità urbana, sollevando al contempo significative preoccupazioni in materia di sicurezza, in particolare riguardo agli incidenti. Questa tesi presenta uno studio approfondito sull'analisi del rischio legato agli incidenti che coinvolgono i monopattini elettrici e propone un modello predittivo per stimare la probabilità di incidenti su segmenti stradali urbani e incroci. Condotta a Bari, in Italia, questa ricerca colma le lacune della letteratura integrando dati sul traffico di monopattini elettrici, caratteristiche geometriche della strada e infrastrutture in un solido quadro statistico.

Lo studio inizia con l'analisi dei dati sugli incidenti forniti dalla Polizia Locale di Bari per il periodo 2021-2023. Le statistiche descrittive rivelano importanti informazioni sulle dinamiche degli incidenti: il 70% degli eventi ha causato feriti, evidenziando la vulnerabilità degli utenti di monopattini. Gli incidenti si verificano prevalentemente su strade non suddivise, mettendo in luce potenziali rischi infrastrutturali. L'analisi considera inoltre i pattern temporali e spaziali, offrendo spunti utili per identificare le condizioni più critiche.

La raccolta dei dati per la ricerca ha seguito un approccio innovativo, affrontando la scarsità di dati standardizzati sul traffico di monopattini elettrici. Grazie alla collaborazione con Vento Mobility Srl (TIER), è stato possibile accedere a statistiche sull'utilizzo dei monopattini, integrate da rilievi sul campo per stimare i volumi di traffico dei monopattini condivisi e privati. Ulteriori informazioni sulle caratteristiche stradali, il traffico veicolare e le infrastrutture sono state raccolte meticolosamente utilizzando strumenti come QGIS e Google Maps, garantendo un dataset completo.

È stato sviluppato un modello di regressione logistica binomiale per prevedere la probabilità di incidenti in base a variabili chiave come i volumi di traffico giornaliero, la geometria della strada e la presenza di infrastrutture specifiche come attraversamenti ciclabili o corsie di svolta. Il modello adotta un approccio distinto per segmenti stradali e incroci, assicurando una maggiore rilevanza contestuale. Le variabili sono state selezionate in base alla significatività statistica, con l'obiettivo di migliorare la precisione del modello mantenendone al contempo l'interpretabilità.

I risultati del modello predittivo evidenziano i fattori chiave che influenzano il rischio di incidenti con monopattini elettrici. Per gli incroci, elevati volumi di traffico veicolare e di monopattini aumentano significativamente la probabilità di incidenti. Analogamente, per i tronchi stradali, variabili come la lunghezza del segmento e la densità del traffico emergono come predittori critici. Questi risultati sottolineano l'importanza di miglioramenti infrastrutturali mirati e strategie di gestione del traffico per ridurre i rischi.

Questa tesi fornisce un modello predittivo validato che può supportare decisori politici, pianificatori urbani e autorità di trasporto. Lo studio offre uno strumento pratico per identificare le aree ad alto rischio e implementare interventi di sicurezza, promuovendo una micromobilità sostenibile e sicura nei contesti urbani.

Affrontando sia le sfide nella raccolta dei dati che le limitazioni metodologiche degli studi precedenti, questa ricerca getta le basi per futuri studi sulla sicurezza dei monopattini elettrici. Promuove la standardizzazione nella raccolta dei dati e l'adattamento delle infrastrutture per supportare l'integrazione sicura dei monopattini nei sistemi di trasporto urbano.

Parole chiave: Sicurezza stradale, monopattini elettrici, modello predittivo

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INTRODUCTION

The increasing prevalence of e-scooters in urban areas has raised concerns regarding road safety. Statistics on e-scooter crashes are still limited, and the lack of specific data makes it challenging to assess risk and implement effective preventive measures.

In this scenario, it is impossible to underestimate the safety issue related to micromobility, as it is undeniable that users must be considered vulnerable road users.

A priority e-scooter safety issue is to analyze the recurring crash patterns, factors, and circumstances in the urban environment starting from crash datasets, also relying on surrogate safety measures (Brownson et al., 2019), to identify dedicated countermeasures.

For this reason, the first objective of this study is to analyze e-scooter crash data, by identifying causes and circumstances of e-scooter crashes. This analysis starts from the urban crash dataset available for the city of Bari (Italy). Such studies can be useful for the practical aim of proposing potential safety measures to prevent e-scooter crashes and enhance road safety and sustainable mobility. Results could be a useful resource for policymakers, urban planners, designers, and transportation authorities in Bari and other cities facing similar e-scooter safety challenges.

This research aims to fill a critical gap in the literature by providing a robust predictive model for e-scooter crashes. The study focuses on developing a binomial logistic model capable of predicting the likelihood of crashes for both intersections and road segments. By inputting geometric and traffic-related variables into the model, it becomes possible to estimate the likelihood of an e-scooter crash occurring on any given intersection or road segment. This dual-focus model - one for intersections and one for road segments - is an innovative contribution to understanding and mitigating e-scooter-related crash risks.

The study was conducted using data from the urban area of Bari, Italy, focusing on a three-year period from January 2021 to December 2023. Crash data was collected from the Local Police of Bari, resulting in a comprehensive dataset that formed the foundation for this research. A preliminary crash analysis was conducted to understand

the dynamics of e-scooter crashes in the city, which culminated in a scientific article (Longo, et al., 2024).

The findings from the crash analysis informed the construction of a detailed database encompassing the most relevant characteristics of intersections and road segments. This database includes geometric features and traffic-related variables, essential for building a predictive model tailored to the urban context of Bari, Italy.

One of the key challenges in this research was obtaining reliable e-scooter traffic data, which is not commonly available due to the absence of insurance requirements or standardized reporting systems for e-scooter users. To address this, the research involved an innovative data collection process that integrated multiple sources:

- **Crash Data:** Information on crashes involving e-scooters was provided by the Local Police of Bari.
- **Road Characteristics:** Detailed geometric and infrastructural characteristics of intersections and road segments were collected using tools such as Google Maps and QGIS.
- **Vehicle Traffic Data:** Data on vehicle traffic volumes were obtained from the Sustainable Urban Mobility Plan (SUMP) of the Metropolitan City of Bari. Where SUMP data were unavailable, direct field surveys were conducted.
- **E-Scooter Traffic Data:** Collaboration with Vento Mobility Srl (TIER) played a pivotal role. The company provided annual e-scooter usage data, which was converted into daily values. Additionally, field surveys were conducted in 11 selected road sections to estimate both shared and private e-scooter traffic volumes.

To ensure the validity and robustness of the statistical model, the study adhered to the guidelines provided by Srinivasan et al. (2013). Specifically:

- **Intersections:** A sample of 401 intersections was selected, of which 131 sites had recorded at least one crash.
- **Road Segments:** A sample of 875 road segments was analyzed, including 137 sites with at least one crash.

These samples exceed the minimum requirements recommended for developing safety performance functions (SPFs). The collected data was categorized and standardized to create a comprehensive database, including variables such as:

- **Traffic Volume Variables:** Daily traffic volumes for vehicles and e-scooters, categorized into ranges using percentiles.
- **Geometric Features:** Road lengths, number of lanes, presence of one-way traffic, and other design elements.
- **Infrastructural Features:** Presence of bicycle lanes, traffic separators, turning lanes, and specific traffic signs.

The binomial logistic model was selected for its ability to handle count data with overdispersion, making it suitable for analyzing crash frequencies. The model was implemented using the R environment and calibrated to ensure statistical validity. Key features of the model include:

- **Dual Focus:** Separate models for intersections and road segments.
- **Integration of E-Scooter Traffic Data:** A novel aspect of this study, addressing the lack of e-scooter-specific traffic data in existing literature.
- **Robust Variable Selection:** Variables for which coefficient estimates are associated with high p-values were excluded to enhance model precision and reduce complexity, focusing only on statistically significant predictors.

1 BACKGROUND

In recent years, mobility and roadways have undergone significant changes. In particular, with the advent of COVID-19, people began to move away from shared transportation modes, such as buses, and increasingly embraced more individual means of transport. With the aim of promoting sustainability, many sustainable transportation modes, such as bicycles and e-scooters, have emerged in this context. Moreover, both local and international companies have pushed towards the sharing of bicycles and e-scooters.

The landscape of urban mobility is evolving rapidly with the introduction of innovative transport modes like e-scooters, particularly for short-distance, last-mile commutes (Baek et al., 2021; McQueen & Clifton, 2022; Zuniga-Garcia et al., 2022).

Classifying e-scooters as a hybrid transportation method introduces unique challenges, particularly since their users are often categorized as vulnerable road users (VRUs). Their legal status, however, is inconsistent across jurisdictions, complicating efforts to regulate their use effectively. For instance, the ambiguity over whether e-scooters should be treated as bicycles or motorized vehicles creates uncertainty, especially concerning their access to cycle paths and other shared spaces.

Both e-scooters and bicycles have emerged as pivotal elements in the global shift toward sustainable urban transportation (Baek et al., 2021). These environmentally friendly alternatives play a significant role in reducing greenhouse gas emissions and alleviating traffic congestion (Glavić et al., 2021; Mclean et al., 2021; Bieliński & Ważna, 2020). Furthermore, they enhance urban connectivity by bridging gaps between public transit hubs and final destinations (Baek et al., 2021; McQueen & Clifton, 2022; Zuniga-Garcia et al., 2022; Bieliński & Ważna, 2020).

Speed regulations also impact accessibility, particularly regarding age restrictions. Unlike bicycles, e-scooters are often subject to minimum age requirements or licensing rules in certain countries, influencing their adoption and usage patterns (D'andreagiovanni et al., 2022). Clearer and more consistent regulations could address these issues, allowing e-scooters to operate safely within urban environments (Baek et al., 2021; Bieliński & Ważna, 2020; D'andreagiovanni et al., 2022; Huemer et al., 2022; Prencipe et al., 2022).

Behavioral studies comparing e-scooter and bicycle users reveal additional differences. For instance, research by Li et al. (2023) highlights significant variations in braking and steering performance, depending on the type of vehicle and the urgency of maneuvers. Lightweight e-scooters, in particular, show poorer braking performance than bicycles. However, steering capabilities are comparable, and in some cases, steering is safer than braking for e-scooter riders. Another study by Vetturi et al. (2023) emphasizes that e-scooters are less comfortable than bicycles due to their sensitivity

to pavement irregularities, with factors like speed, rider height, and age influencing comfort levels. Similarly, Ventura et al. (2023) found that higher speeds and certain physical attributes—such as being tall or young—exacerbate vibrational discomfort for e-scooter riders, while heavier users experience fewer vibrations at lower speeds (Vella et al., 2024).

The approach of this research is in line with some other studies in the literature (Stigson et al., 2021) that, starting from the analysis of crash reports, attempted to reproduce e-scooter crash patterns through simulations for the aim of safety assessments (Brunner et al., 2020) or to investigate the most common injury mechanisms to propose specific policies, such as mandatory helmets (Ptak et al., 2022). Clearly, this depends on the availability of crash datasets, which can be at the national or local level (Stigson et al., 2021) or taken from a retrospective analysis of hospital data (Brownson et al., 2019). Previous research dealt with the investigation of e-scooter crash dynamics by covering topics such as rider behavior, the role of infrastructure, and possible safety measures. Sun et al. (2023) focused on crashes involving e-scooters used for deliveries, identifying clusters of factors influencing crash severity. Their contribution was valuable in outlining heterogeneity in the involved variables. Das et al. (2023) provided an in-depth look into traffic collision patterns of e-scooter users, highlighting risks associated with driving behaviors and possible collisions with motorists. The application of the Perceptual Cycle Model (PCM) allowed analyzing causal factors in detail, by providing crucial policy recommendations to enhance road safety. A different approach, always focused on crash-driving factors, was pursued by White et al. (2023). In this analysis, a naturalistic approach was adopted, emphasizing the importance of infrastructure, behavioral, and environmental factors. Findings indicate the need for educational programs and infrastructure improvements to mitigate safety risks. Another important issue related to e-scooter misbehaviors was tackled by Oshanreh et al. (2024). They focused on evaluating the effectiveness of an artificial intelligence-based feedback system in reducing sidewalk riding by shared e-scooter drivers. This study provides practical insights into the potential of technological interventions to improve user behavior and compliance with regulations. Kuskapan et al. (2023) pushed forward the

investigation of e-scooter sidewalk riding, introducing the use of Inertial Measurement Unit (IMU) coupled with machine learning algorithms for detecting improper sidewalk usage. Moreover, this analysis ended with an insight into the pandemic effects on the e-scooter user behavior. The latter study represents a step forward in applying innovative technologies to promote safer behaviors.

The integration of e-scooters into shared infrastructures gives rise to notable safety concerns. A number of cities have been adversely affected by the introduction of shared e-scooter schemes as a consequence of injuries caused by isolated falls, collisions, conflicts with other road users on shared paths, and parking issues, which include cluttering and blocked sidewalks (Reinhardt and Deakin, 2020, Shichman et al., 2022, Traynor et al., 2022). E-scooter injuries presenting to emergency departments (EDs) have soared after the introduction of shared e-scooter schemes. For instance, a retrospective study conducted in Israel between May 2017 and February 2020 revealed a sixfold increase in e-scooter-related injuries presenting to a level 1 trauma centre following the introduction of shared e-scooter services in August 2018. Among the 3331 patients with e-scooter injuries during this period, the average monthly injuries increased from an average of 26.9 injuries per month before the shared e-scooter program to 152.6 afterwards (Shichman et al., 2022). A consistent global trend demonstrates increased e-scooter-related ED visits following the introduction of electric scooter-sharing services (Badeau et al., 2019, Beck et al., 2020, Farley et al., 2020, Hennocq et al., 2020, Kappagantu et al., 2021, LaGreca et al., 2022, Mayhew and Bergin, 2019, Raubenheimer et al., 2023, Traynor et al., 2022).

Human behaviour is a prominent factor in e-scooter safety issues, as riders often place themselves and other road users at risk through unlawful riding and inconsiderate parking practices (Kazemzadeh et al., 2023, Siebert et al., 2021, Ventsislavova et al., 2024). In addition to rider behaviours, the design-related features of e-scooters themselves also contribute to their potential hazards since riders need to maintain balance while standing on a narrow deck, relying on small-sized wheels and operating at potentially high speeds (Janikian et al., 2024, McGuinness et al., 2021, Tischler et al., 2023). In the process of conducting the background analysis for this research, the

article "Exploring Implications and Current Practices in E-Scooter Safety: A Systematic Review" by Danish et al. (2024) played a key role, particularly in shaping the initial part of the literature review. This systematic review provides a comprehensive and current synthesis of existing knowledge on e-scooter safety, offering valuable insights into critical themes, gaps, and implications. However, while Danish et al. (2024) serves as a foundational reference, the background analysis was also informed by other studies that address related aspects of e-scooter safety, regulatory practices, and infrastructure design.

This chapter reports about literature studies related to e-scooters, divided into the following main topics:

- Crash patterns and aberrant rider behaviors
- Safety-related human factors
- Infrastructure-related issues
- Policies
- Predictive safety models

1.1. Crash patterns and aberrant e-scooter rider behaviors

E-scooter safety has become an increasingly pressing issue due to their growing interactions with various road users, including vehicles, pedestrians, and cyclists (Kazemzadeh et al., 2022). While the benefits of e-scooters in reducing environmental impact and alleviating traffic congestion are well-documented, understanding their crash dynamics remains incomplete (Liu et al., 2019; Glavić et al., 2021; Latinopoulos et al., 2021; Mclean et al., 2021). Research highlights a pattern of illegal and risky behaviors among e-scooter riders, including riding in prohibited areas, traveling against traffic, carrying passengers, and disregarding traffic laws (Siebert et al., 2021). Additionally, factors such as helmet non-use, speeding, and operating under the influence of substances are frequently linked to e-scooter injuries (Graef et al., 2021; Sanders & Nelson, 2023).

Shared e-scooter riders, in particular, exhibit higher levels of risky behavior compared to private owners and other micromobility users, such as cyclists and e-bike

riders (Kim & Campbell, 2021). This discrepancy underscores the challenges posed by inexperienced or casual riders who are more likely to misuse shared devices. Parking issues compound these challenges, leading to pedestrian injuries and traffic disruptions in urban areas (Hardinghaus & Oostendorp, 2023; James et al., 2019). Observational studies further emphasize that e-scooter riders are less likely than cyclists to wear helmets and more likely to ride in motorized lanes or on sidewalks, contravening regulations (Bai et al., 2015). Surveys consistently show that e-scooter riders are perceived as riskier compared to cyclists, reinforcing the public concerns about their safety (Siebert et al., 2021).

Efforts to mitigate risks have increasingly focused on improving rider behavior and infrastructure. Proposed measures include pre-ride training, smartphone alerts for risky behaviors, and advanced monitoring systems integrated into shared e-scooters to encourage safer practices (Brunner et al., 2020). However, evidence evaluating the long-term effectiveness of these measures is still limited. Additionally, infrastructure inadequacies and poor road conditions remain major contributors to e-scooter injuries. Collisions with motor vehicles, while infrequent, often occur at intersections or during vehicle turns, underscoring the importance of improving rider protection in these scenarios (Rafael Chontos et al., 2024). Meanwhile, pedestrian injuries caused by e-scooters, though less common, are frequently severe, with traumatic brain injuries being a predominant concern (Crowe & Elkbuli, 2021).

Urban planning initiatives aimed at creating safer shared spaces for e-scooters have shown promise. For instance, research in Singapore demonstrated that encouraging "keep left" behaviors on shared paths can significantly reduce conflicts without requiring substantial infrastructure changes. Furthermore, studies reveal that e-scooter speeds naturally decrease in areas with higher pedestrian density, reinforcing the value of well-designed, multi-use spaces (Liu et al., 2022; Pazzini et al., 2022).

Despite advancements in e-scooter designs, such as improved suspensions and larger wheels, further research is necessary to determine their effectiveness in injury prevention. Crash data often lacks key contextual details, such as precise crash locations or rider characteristics, making comprehensive analysis challenging.

Addressing these gaps in data collection and analysis is critical for developing effective safety interventions and enhancing the understanding of e-scooter-related risks (Karpinski et al., 2024).

1.2. Safety related human factors of e-scooters riders

Studies indicate that socio-demographic factors such as gender and age influence e-scooter usage and safety. Male riders tend to exhibit riskier behavior, and younger riders are more likely to engage in aggressive riding compared to older individuals (Bai et al., 2015; Kazemzadeh et al., 2023). This may be linked to higher riding frequency, risk-taking tendencies, and lower perceived risk (Tian et al., 2022). However, some studies show no significant differences in e-scooter usage based on demographic factors such as age, gender, income, and education (Bieliński and Wazna, 2020; Clewlow, 2019). A study in Spain found that gender, age, and education had no significant impact on risk perceptions, except for knowledge of traffic rules (Useche et al., 2022a).

Although demographic data is sparse, the literature consistently suggests that men are more involved in e-scooter injuries, possibly due to their riskier behaviors (Azimian and Jiao, 2022; ITF, 2020). Despite these behavioral differences, injury profiles between male and female riders are similar (ITF, 2024), with women more likely to report safety concerns and less involved in severe crashes (Caspi, 2021). Pediatric injuries related to e-scooters are common, often due to underage riders bypassing age restrictions (Cohen et al., 2022). Age restrictions are frequently disregarded without strict enforcement.

Factors such as time of day and trip duration also play significant roles in accident frequency. E-scooter riders tend to ride faster on weekdays (Genc Yavuz et al., 2022), while weekend crashes are less likely to be fatal due to more recreational use (Gao & Zhang, 2024). However, night rides are often associated with higher injury rates, especially when alcohol is involved (Gan-El et al., 2022). Studies suggest that longer trips increase the likelihood of risky behavior (Gioldasis et al., 2021).

E-scooter trips are typically undertaken for fun, saving time, or commuting (Cicchino et al., 2021a; Glenn et al., 2020). However, medical records rarely document trip

purposes, limiting insights into their role in injury occurrences. Recreational riders often ride slower than commuters (Almannaa et al., 2020). Further research is needed to understand the relationship between trip purpose and risky behavior.

Interventions like app-controlled speed limits, restricted operating hours, and citywide bans have been implemented to improve e-scooter safety (Leyendecker et al., 2023). However, their effectiveness is unclear due to limited long-term data. Future studies should examine the sustained impact of regulations, safety culture, and rider behavior changes over time.

Concerning helmet usage, despite mandatory laws in regions like Australia, compliance remains low, with only 43% of injured riders wearing helmets at the time of their crashes (Raubenheimer et al., 2023; see also Christoforou et al., 2021). On the other hand, e-scooter riders often suffer head, face, and neck injuries, highlighting the need to investigate helmet usage (see also Beck et al., 2020;). It should be also considered that standard bicycle helmets may not adequately protect against the facial fractures commonly seen in e-scooter accidents (Bresler et al., 2019; Faraji et al., 2020). Developing better protective gear tailored to e-scooter risks is a critical research gap.

Intoxication and lack of experience are additional major contributors to e-scooter accidents. Studies confirm that even low blood alcohol concentrations impair performance, increasing the likelihood of crashes (Zube et al., 2022). Night and weekend rides see higher rates of alcohol-related injuries, particularly among male riders (Namiri et al., 2021). For instance, 75% of patients injured during midnight hours in Finland were intoxicated (Vasara et al., 2022). Similar trends are observed in other regions, where alcohol-related injuries often involve head trauma (Shiffler et al., 2021; Karpinski et al., 2024). Efforts to address this issue include sobriety tests before unlocking shared e-scooters (Beam, 2023) and public education campaigns on the risks of intoxicated riding (Mehdizadeh et al., 2023). However, underreporting and the lack of systematic documentation hinder comprehensive analyses of intoxication-related accidents.

To enhance safety for less-experienced riders, some providers offer "Beginner Mode," which limits speed to help new users gain confidence (Beam, 2023). Research also highlights that pre-ride tutorials significantly improve risk perception and help reduce crashes among novice riders (Brunner et al., 2020). While promising, the impact of such measures on specific demographics, like women and older riders, remains underexplored. Dynamic speed limits, adjusted for traffic density and behavioral patterns, could further improve urban integration (Dozza et al., 2022).

1.3. *Infrastructure issues*

Several recent studies have emphasized the critical role of road infrastructures in influencing crash frequency and severity. A specific section will be dedicated to crash predictions in the following. However, crash data modelling is only a portion of research which focuses on infrastructure-related issues from both a geometric perspective and the quality of pavement. For example, systematic road safety inspections (RSIs) have proven to be an effective tool for identifying infrastructure deficiencies and their correlation with crash rates. Specifically, issues such as inadequate road markings and high-density private access points have been strongly linked to increased crash risks, underscoring the need for rigorous maintenance and compliance with safety standards (Vaiana & Perri, 2022).

Specifically focusing on e-scooters, the ongoing debate among major municipalities revolves around the establishment of safe travel zones for e-scooter riders and the diverse regulations governing e-scooter operations across countries, states, and cities. A critical aspect of this discussion concerns the increased risk of pedestrian injuries when e-scooters are allowed on sidewalks. Challenges include significant e-scooter-pedestrian speed differences, leading to dissatisfaction, conflicts, and injuries, as well as navigation difficulties caused by narrow, obstacle-filled pathways (Liao and Correia, 2020; Ma et al., 2021; Sokolowski, 2020; Uluk et al., 2022). To address these issues, some municipalities have redirected e-scooter traffic from sidewalks to roads. However, this shift has introduced new challenges, such as e-scooter riders reporting near misses with motor vehicles, especially where road usage is mandated (Sucha et al., 2023). Both riders and non-riders frequently report feeling unsafe when e-scooters

operate in vehicle lanes (Pourfalamatoun, Ahmed, & Miller, 2023). Studies confirm that crashes involving motor vehicles often lead to severe or fatal injuries for e-scooter riders, with collisions at intersections being a primary contributor (Cicchino et al., 2021b; Neuroth et al., 2022). Moreover, some studies identify primary roads and traffic signals as common sites for accidents (Cicchino et al., 2021b), while others point to sidewalks (Cicchino et al., 2021a). Improved infrastructure, such as well-marked, wide bike lanes separated from traffic, seems crucial for enhancing e-scooter safety.

In fact, from an infrastructural perspective, bicycles may generally benefit from dedicated lanes that enhance safety and organization in urban traffic environments. E-scooters, however, often lack such guidelines and must integrate into existing traffic flows, creating potential conflicts with pedestrians, cyclists, and motor vehicles (Pazzini et al., 2022). This infrastructural deficiency is further exacerbated by differences in speed capabilities. While e-scooters can achieve higher speeds than traditional bicycles, this advantage necessitates stricter speed management policies to ensure safety for all road users (Bieliński & Ważna, 2020; Huemer et al., 2022; D'andreagiovanni et al., 2022).

Observational research reveals that e-scooter riders generally prefer bike lanes over sidewalks or motorized roads (Cicchino et al., 2021b; Siebert et al., 2021; Tian et al., 2022; Zhang et al., 2021). However, some studies indicate that e-scooter riders feel uncomfortable or unwelcome in bike lanes, highlighting the need for thorough assessments before fully incorporating e-scooters into cycling infrastructure (Feler, 2020; Lyons et al., 2020). Proposals to balance competing demands in shared cycling spaces include allocating more space to cycling infrastructure, implementing traffic-calmed zones, and adding physical separators to prevent footpath intrusions. Additional measures such as increasing space between parking lanes and bike paths, maintaining vegetation, and widening bike lanes have also been suggested (Blazanin et al., 2022; Laa and Leth, 2020; Pérez-Zuriaga et al., 2023).

Street conditions are another key determinant in preventing e-scooter injuries. Many riders cite poor surface quality and obstacles on shared paths as primary safety

hazards (Cicchino et al., 2021a; Liao and Correia, 2020). Smoother roads and well-maintained pathways can significantly reduce risks for e-scooter users.

Additionally, parking-related issues associated with dockless e-scooter systems create challenges in urban environments. While the flexibility of dockless systems is a major appeal for riders, it has resulted in illegal parking practices, with e-scooters blocking pedestrian pathways and creating hazards (James et al., 2019; Sikka et al., 2019; Stigson et al., 2021). In densely populated areas, designated parking zones are critical to minimizing these disruptions (Zou et al., 2020). Some cities have implemented measures to regulate e-scooter parking, such as geofencing and incentives for using specified parking zones. Providers have introduced features like virtual docking systems and rider incentives for proper parking, but these measures primarily target shared e-scooters, leaving the issue of privately owned e-scooters largely unaddressed (Zakhem & Smith-Colin, 2024).

Despite these advancements, further research is needed to evaluate the effectiveness of these measures. Understanding how e-scooter infrastructure, regulations, and rider behavior interact with each other will be crucial for shaping safer and more efficient urban mobility systems.

1.4. Policies related to e-scooters

The legal classification of e-scooters remains ambiguous across many regions, leading to inconsistent regulatory approaches. In some areas, e-scooters are treated similarly to pedestrians, while in others, they are categorized as bicycles or motorized vehicles. This lack of uniformity has favoured debates surrounding speed limits, helmet use, location restrictions, and legal requirements (Serra et al., 2021). While there is significant support for aligning e-scooter regulations with those of bicycles, notable differences in usage patterns, injury mechanisms, and riding dynamics complicate such comparisons (Caspi, 2021; McGuinness et al., 2021). Some safety strategies, such as promoting helmet use and enforcing alcohol restrictions, are applicable to both e-scooter riders and cyclists (Barker et al., 2022; Pepper et al., 2022).

One critical factor contributing to e-scooter-related risks is the lack of awareness of existing regulations among both riders and non-riders. Studies reveal

widespread ignorance regarding rules such as proper riding paths, helmet mandates, and age restrictions (Glenn et al., 2020; James et al., 2019). This gap in knowledge leads to non-compliance and, consequently, higher crash risks. While educational campaigns are essential, simply informing the public may not suffice. Social norms, risk perception, and behavioral tendencies also play a significant role in unsafe riding practices (Phipps & Hamilton, 2024).

To address these challenges, both policymakers and e-scooter companies have implemented several interventions. Shared e-scooter providers have introduced safety measures, including in-app safety tutorials, helmet locks, and mandatory training courses for new riders. Beam, for instance, enforces a three-strikes policy to penalize riders who repeatedly violate traffic laws or engage in dangerous behavior (Beam, 2023). Additionally, some jurisdictions have extended DUI laws to include e-scooter riders, although enforcement remains inconsistent (Ma, 2021). Technological solutions, such as geofencing and onboard sensors, are also being employed to monitor rider behavior and ensure compliance with local regulations, including speed limits and restricted zones (Beam, 2022). However, research evaluating the long-term effectiveness of these technological interventions remains limited.

Elaborating more on some real examples; Paris banned shared e-scooters after studies revealed that 87% of traumatic injuries were linked to behaviors such as speeding, substance use, and helmet noncompliance (Leyendecker et al., 2023). Other cities have opted for regulatory measures, such as speed limits, access restrictions, and improved traffic flow management, rather than outright bans (Bozzi & Aguilera, 2021; Che et al., 2020). Despite these safety concerns, shared e-scooter programs remain popular due to their potential to decrease car dependency and enhance urban mobility (Choron & Sakran, 2019).

It is crucial for policymakers to establish and enforce clear, comprehensive regulations that address the specific safety needs of e-scooter riders. These policies should include provisions for speed limits, helmet mandates, minimum age requirements, and restrictions on alcohol consumption. Improved integration of e-scooters into urban spaces, supported by robust enforcement and advanced technology, will be

pivotal in ensuring safe usage. Future research should prioritize assessing the impact of interventions like geofencing and onboard sensors on rider behavior and overall safety outcomes.

In this context, Italy has recently introduced comprehensive regulations to enhance the safety and governance of electric scooters within urban environments. On November 20, 2024, the Italian Parliament enacted significant reforms to the Highway Code, which have officially come into force, introducing several key measures for e-scooter riders.

One of the most noteworthy updates is the extension of the mandatory helmet requirement to all e-scooter riders, regardless of age, aiming to reduce head injuries in crashes. Additionally, electric scooters must now display a visible, non-removable, laminated identification sticker issued by the Istituto Poligrafico e Zecca dello Stato (Italian State Mint and Polygraphic Institute), with further details about this measure to be outlined in upcoming decrees.

Electric scooters are also now required to carry third-party liability insurance under Article 2054 of the Civil Code. This aligns their insurance obligations with those of motor vehicles, offering greater protection in the event of crashes. The new regulations also limit e-scooter usage to urban roads with speed limits below 50 km/h and prohibit operation on bike lanes, on pedestrian areas, and rural roads, aiming to create safer operational environments. Furthermore, penalties for improper parking have been increased to prevent public space obstructions and encourage more responsible behavior.

These regulatory changes are especially relevant to the future development of the predictive models proposed in this thesis. The mandatory registration and insurance of e-scooters represent a significant advancement, facilitating improved data collection related to accidents, crash dynamics, and traffic patterns. Such measures will also simplify the estimation of e-scooter traffic volume, enabling more accurate risk assessments.

Despite shared contributions to sustainable mobility, e-scooters and bicycles differ markedly in their legal and operational characteristics. E-scooters, unlike

bicycles, are often inconsistently classified as motor vehicles, personal mobility devices, or bicycles, depending on the jurisdiction, complicating their integration into existing infrastructure and policy frameworks (D'andreagiovanni et al., 2022). Clearer legal definitions and regulatory consistency are essential for addressing these challenges and ensuring the safe incorporation of e-scooters into urban mobility systems.

Policies may also focus on how e-scooters are designed and built. In fact, e-scooters present unique challenges related to stability and safety due to their narrow decks, small wheels, and standing posture, which increase the risk of accidents compared to seated vehicles like bicycles. These design features result in a higher susceptibility to crashes and injuries, particularly during rapid braking (see Paudel & Fah Yap, 2021) or transitions between different surface types. Moreover,

Transitioning between surfaces poses significant risks (White et al., 2023). Small wheels are particularly prone to getting stuck in tram tracks and potholes, leading to a higher rate of isolated falls compared to bicycles (McGuinness et al., 2021; Tischler et al., 2023). E-scooter riders also experience more severe vibrations than cyclists, reducing comfort and control, especially on uneven terrain (Lentzen et al., 2021).

However, the absence of universal e-scooter design standards exacerbates these issues. In fact, these design limitations are intricately connected to policy considerations, as regulations governing e-scooter design and performance standards are essential to address these challenges effectively. To mitigate these challenges, major e-scooter providers have introduced new-generation models featuring larger wheels, enhanced suspension systems, and beginner modes aimed at novice riders. While shared e-scooter providers often impose speed limits to reduce risks, privately owned e-scooters can bypass these limits, emphasizing the need for stricter regulations (ITF, 2024). In particular, International organizations stress the need for a standardized definition of micro-mobility and universal design requirements for e-scooters (ITF, 2024; SAE International, 2019). Currently, regulatory frameworks vary significantly across regions, complicating efforts to improve device reliability and user safety (Serra et al., 2021; Kamphuis & Schagen, 2020).

Addressing these safety challenges through better design, stricter regulations, and collaborative international standards is pivotal to enhancing public safety and the overall user experience.

1.5. Predictive safety models

Crash prediction models are statistical tools used to estimate the likelihood of crashes based on various factors, such as traffic volume, road geometry, and context-based variables. These models are also commonly applied to understand crash dynamics and support the development of preventive measures.

The approach focuses on identifying key variables, such as traffic flow, environmental conditions, and intersection configurations, to build a modelling framework that may predict crash frequency, severity and/or likelihood of specific crash types on road segments and intersections. These models go beyond describing risk, offering quantitative tools to evaluate the impact of infrastructure or regulatory changes on road safety.

Generally, crash frequency predictions (see e.g., Lord and Mannering, 2010) are based on count data models based on the Poisson distribution (or, more frequently, on the Negative Binomial distribution of errors). A typical example is given by Safety Performance Functions (SPFs), which are crash prediction models based on a consolidated baseline framework (AASHTO, 2010). Crash injury severity predictions (Savolainen et al., 2011) are based on binary or multinomial logit approaches where the choice alternatives are the different injury severity levels (e.g., fatal, injury and property-damage-only), with different levels of detail in the model specification. The same (and other) methodologies can be also applied to predict the likelihood of specific crash types (see e.g., Intini et al., 2020).

In the literature, models have been extensively developed for specific categories of road users, such as motor vehicles, cyclists, and pedestrians. For instance, various studies have analyzed the risks faced by cyclists in urban contexts, incorporating data related to motorized vehicle speeds, the presence of bike lanes, and traffic density.

The study by Intini et al. (2021) developed Safety Performance Functions (SPFs) to predict crash frequency in urban settings, focusing on road segments and

intersections in the city of Bari, Italy. Using negative binomial count models, the researchers identified various crash predictors for different subgroups of road segments and intersections. The findings indicate that the presence of vertical signage on minor roads, critical sight distance, bicycle crossings, and the maintenance of pavement and signage significantly influence crash frequency. Moreover, the study highlights that local characteristics can alter the relationship between established predictors and crash frequency, suggesting the need for context-specific models for different urban environments.

Building on this theme, Dolatsara (2014), which developed Safety Performance Functions (SPFs) for non-motorized traffic, focused on pedestrians and cyclists in four cities in Michigan: Ann Arbor, East Lansing, Flint, and Grand Rapids. The analysis determined that the area of influence for crashes is 240 feet for motorized vehicles and 137 feet for non-motorized vehicles. For pedestrians, the SPFs revealed that increased exposure, a higher number of left-turn lanes, the presence of on-street parking, and bus stops contribute to pedestrian crash frequency, while the presence of speed limit signs reduces it. For cyclists, exposure, the presence of bike lanes, bus stops, and the number of left-turn lanes are positively associated with crash frequency. A structural equation model showed that although bike lanes are associated with an increase in crashes, this correlation is due to higher cyclist volumes, indicating that bike lanes do not compromise safety.

Chen et al. (2020) developed Safety Performance Functions (SPFs) for cyclists using tracking app data, focusing on intersection safety and evaluating risk based on factors like intersection layout and motorized traffic speed. Their innovative approach demonstrated that integrating digital data can enhance the precision of safety models, providing insights into real-world cyclist behavior. Key findings highlighted how complex intersection designs and high motorized traffic speeds increase crash risks for cyclists. Moreover, the study adaptable framework makes it applicable across various urban contexts, offering a valuable tool for city planners to design safer infrastructure. This research is particularly relevant as it showcases how technology can address data limitations in traditional safety analysis, paving the way for more accurate and adaptable

models. Including this study emphasizes the potential of data-driven approaches to improve safety for vulnerable road users and underlines the importance of expanding such methodologies to other emerging mobility modes, like electric scooters.

Also, Nordback et al. (2014) developed Safety Performance Functions (SPFs) tailored to urban cyclists in the US context, focusing on the influence of bike lanes and motorized traffic density on crash risks. Their findings revealed that the presence of bike lanes significantly reduces crash frequency, demonstrating their protective effect for cyclists. However, areas with high motorized traffic density were associated with an increased risk of crashes, emphasizing the importance of separating cycling infrastructure from vehicular traffic. This study underscores the role of dedicated infrastructure in enhancing cyclist safety, offering a foundation for urban planning decisions. Citing this research highlights the need for evidence-based strategies in managing interactions between vulnerable road users and motorized traffic, which is a critical consideration for expanding these approaches to emerging micromobility modes like electric scooters.

Despite the rapid increase in the use of electric scooters in urban areas, no specific models, to the best of the current author's knowledge, have been developed to assess crash risks for this growing category of vulnerable road users. This absence represents a notable gap in the current body of research, especially given the expanding adoption of electric scooters and the associated safety challenges.

This study focuses on developing model able to predict the likelihood of crashes with electric scooters involved. Unlike traditional Safety Performance Functions (SPFs) discussed in the literature, which predict the crash frequency based on various factors, this model is designed to estimate a probability value between 0 and 1. This value represents the likelihood that a crash will occur under specific conditions on segments and intersections.

By identifying and integrating the most influential variables, such as traffic characteristics, road geometry, and infrastructure conditions, the model provides a robust probabilistic framework. This approach not only fills a critical gap in the scientific literature but also offers a practical tool for improving road safety. Local authorities and

urban planners can leverage this model to implement targeted interventions, optimize infrastructure planning, and develop effective policies to mitigate risks for electric scooter users.

2 METHODOLOGY

2.1 Research Approach

This research adopts different approaches for studying safety-related aspects of e-scooters with particular regard to traffic crashes. Ultimately, it proposes a binomial logistic model designed to predict the crash likelihood and evaluate the safety conditions of roads. The methodology is particularly innovative as it integrates a wide range of data, including detailed traffic volumes, which has not been extensively addressed in prior studies. This uniqueness is underscored by the bibliographic analysis, which highlights the gap in existing literature regarding the inclusion of comprehensive traffic-related variables in predictive safety models.

The research approach is divided into different stages, which are briefly introduced as follows. This chapter is organized into sub-sections corresponding to the bullet points of the list reported below.

1. Identification of a Study Area

Bari, Italy, serves as the study area due to its complex urban road network and increasing adoption of e-scooters. The city characteristics, including the presence of bike lanes, signalized intersections, and varying traffic densities, provide a rich context for analysis. Access to localized crash data further supports the selection of Bari as an ideal case study.

2. Crash Data Analysis

Crash data provided by the Local Police of Bari forms the foundation for this study. Analysis focuses on:

- a. Frequency and Types of Crashes - Identifying common crash scenarios.
- b. Severity Analysis - Categorizing crashes based on injury outcomes.
- c. Pattern Recognition -Examining temporal and spatial trends to uncover contributing factors. This analysis provides critical inputs for the predictive modeling phase.

3. Data Collection

A multi-faceted approach was employed to collect the required data:

- a. **Crash Data:** Police reports detailing crash types, locations, and contributing factors.
 - b. **Vehicle Traffic Data** - Extracted from Bari Sustainable Urban Mobility Plan (SUMP) and complemented by field surveys.
 - c. **E-Scooter Traffic Data:** Obtained through collaboration with local operators and field observations.
 - d. **Road Characteristics:** Collected via Google Maps and QGIS, including lane configurations, traffic signs, and pavement conditions. This extensive dataset ensures a holistic understanding of the factors influencing crash risks.
4. **Predictive Model Development**
- The study employs binomial logistic regression models to predict crash likelihood. The methodology includes:
- a. **Variable Selection** - Identification of significant predictors, such as traffic volume and road geometric and context-related variables
 - b. **Model Building** - Ensuring accuracy and robustness through statistical validation.
 - c. **Dual approach** - Development of distinct models for intersections and road segments to address their unique dynamics.

2.2 Study Area (Bari, Italy)

The study area selected for this research is the city of Bari, a major urban center in southern Italy with a population of approximately 320,000 inhabitants. Bari is characterized by a complex road network, including main road arterials, secondary streets, signalized and unsignalized intersections, and an increasing presence of infrastructures dedicated to sustainable mobility, such as bicycle lanes and pedestrian areas.

The selection of Bari as the study area was motivated not only by the introduction of e-scooters in 2020 but also by the advantage of conducting research under the Politecnico di Bari. Operating within the territory allowed easier access to crash data,

on-site surveys, and direct observation of specific road characteristics. This approach enabled a more in-depth and contextualized understanding of crash dynamics and infrastructural conditions.

To correlate crash data with surrounding conditions, various static and dynamic variables were considered. These included road types, the presence of bicycle infrastructures, and average hourly traffic flows. The integration of these variables with spatial data related to crash locations (latitude and longitude) allowed the identification of different critical issues concerning road safety. The ability to directly observe the characteristics of the area further enhanced the accuracy of the analysis, providing a more detailed understanding of risk factors and conditions affecting the safety of e-scooters in the city of Bari.

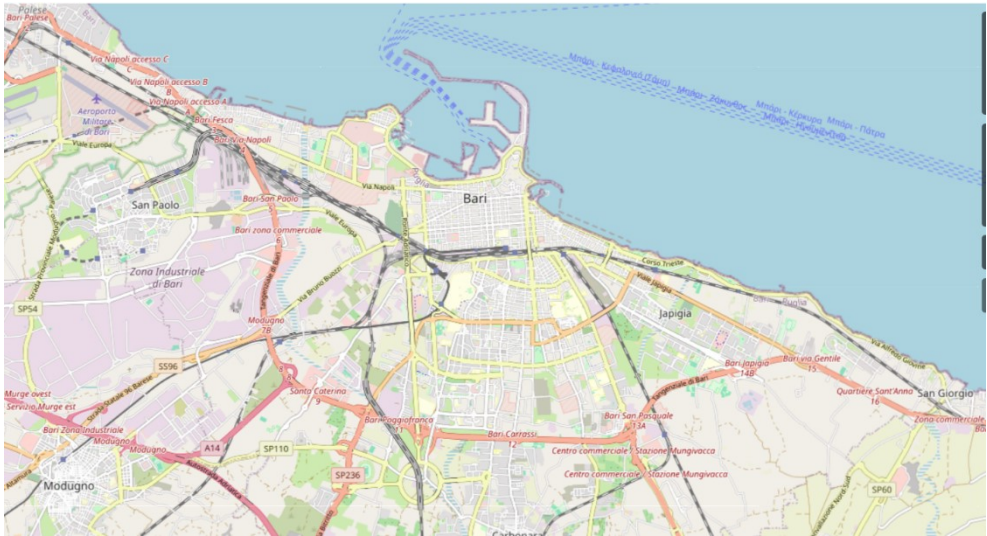


Fig. 1 - Map of the urban area of Bari, Italy, extracted from OpenStreetMap.

2.3 Starting Point of the Research: Crash data Analysis

The research began with an analysis of crash data provided by the Local Police of Bari. This analysis allowed for the collection of detailed information on crashes involving e-scooters and led to the drafting of a scientific article already published (Longo, et al., 2024).

2.3.1 Data source for crash data analysis

The methodology used in this study aims at identifying e-scooter crash patterns based on a crash dataset and police reports. This methodology differs from commonly used methods in the previous literature, which focused on hospital reports (Brownson, et al., 2019) or insurance company reports (Stigson, et al., 2021).

The reports used in this study were provided by the Local Police of the Municipality of Bari and relate exclusively to e-scooter crashes. The availability of these reports allowed for the use of a more detailed dataset, including also property-damage-only (PDO) crashes. Thus, the following injury severity levels were considered: fatal, injury, and no-injury crashes. Injury crashes were not further differentiated into more disaggregated severity classes, as this information was available only for very limited cases in the crash reports.

During the investigated period, from July 2020 to November 2022 (December 2022 was not available at the time of data collection for the crash analysis; data up to December 2023 were later integrated for the final study of this thesis), 257 e-scooter crashes were recorded by the Local Police in the City of Bari area (Ranieri, et al. 2022) (Table 1).

E-scooters were introduced in the City of Bari at the beginning of 2020, when the COVID-19 pandemic restrictions were loosened. For this reason, the crash analysis is based on two years of recorded data. These data were initially analyzed by grouping crashes to define the most frequent scenarios and crash factors.

Table 1 - Distribution of crashes in the period July 2020–November 2022

Year	Number of Crashes
2020 (from July to December)	41
2021 (from January to December)	118
2022 (from January to November)	98
Total	257

The available dataset provides all the following information, in addition to those already mentioned: latitude, longitude, crash date, time, type of crash, type of vehicles involved, street name, road type, crash severity, number of injured persons, number of deaths, and type of violation. Additional variables, not found in the original dataset, were considered and retrieved through on-site visual surveys: average hourly traffic, one-way or two-way road, pavement conditions, presence of cycle paths, and signalized or unsignalized intersections (presence of traffic lights). Details about the data collection process will be provided in the following sections.

2.3.2 Study Variables

Descriptive statistics of the e-scooter crash dataset are presented as follows, according to the study variables defined with the help of the information found in local police reports.

For the aim of the further statistical analyses performed, variables have been grouped into more parsimonious classes, as follows:

- Injury severity: No, Yes.
- Road category: Undivided two-way, Undivided one-way, Divided multi-lane, Pedestrian zone.
- Day hour: Calm hours(6 a.m.-7 a.m., 9 a.m.-1 p.m., 4 p.m. – 10 p.m.) , Peak hour (7 a.m.–9 a.m., 1 p.m.–3 p.m.), Night hours (10 p.m.–6 a.m.).
- Week day: Weekday, Weekend and Holiday (including Sundays).
- Season: Summer, Autumn, Winter, Spring.
- Road Geometry: Segment (including bridges, tunnels), Unsignalized intersection, Signalized intersection, Roundabout.
- Crash Type: Single-vehicle, Angle, Sideswipe, Pedestrian hit, Other.
- Pavement: Dry, Wet/Slippery.
- Age: <18, 18–30, 31–40, >40, Unspecified.
- Sex: Man, Woman, Unspecified.
- Passengers: No, Yes, Unspecified.
- Sharing: Private, Sharing, Unspecified.

- Dynamics: Crash not caused by the e-scooter, Irregular e-scooter behavior, Other, Road surface issues.
- Crash on a cycle path: No, Yes, Unspecified.
- Presence of cycle paths: No, Yes.

The above-reported classification of factors aim to provide a structured framework for analyzing and interpreting data.

2.3.3 Statistical Methods

In this research, which focuses on understanding the dynamics of e-scooter crashes, one of the primary objectives is to identify the variables that most significantly influence crash types and injury severity. To achieve this, the following statistical modeling approaches were applied:

- Binary Logit Model: This model uses injury severity as the dependent variable (categorized as "injuries: yes or no") with the crash-related variables previously defined serving as potential predictors.
- Multinomial Logit Model: This model considers crash type as the dependent variable (with "single-vehicle crashes" as the reference category, and other types including angle, sideswipe, pedestrian hit, and others) and the above-defined crash-related variables as predictors.

Following the multinomial logit approach, the probability of observing a given crash type among the set of alternative crash types is given as follows:

$$P(t = j) = \frac{e^{(\beta_0 + \sum_{i=1}^n \beta_i X_i)_j}}{\sum_{t=0}^m e^{(\beta_0 + \sum_{i=1}^n \beta_i X_i)_t}} \quad 1)$$

where:

- t = crash type;
- X_i = i -th independent variable;
- β_i = i -th coefficient (β_0 is the intercept) associated with the j -th crash type chosen among the set of alternative m crash types.

If the probability of observing the crash type $t = j$ is compared with the probability of observing the base alternative "0" (single-vehicle crashes in this case):

$$\frac{P(t = j)}{P(t = 0)} = e^{(\beta_0 + \sum_{i=1}^n \beta_i X_i)_j} \quad 2)$$

where all the terms are as previously defined in Equation (1).

Based on the logit transformation, if each β_i included in the model is exponentiated, the relative risk ratio (with respect to the base outcome) for a one-unit change in the modality of the variable (all variables considered here are categorical) with respect to the base modality is obtained.

For the binary logit model, the equations simplify since only two possible outcomes exist. In this case, a single set of coefficients estimates the probability of observing injury crashes versus property-damage-only crashes.

Predictors were retained in the final models if at least one coefficient associated with a variable category was statistically significant at the 10% level, reflecting the exploratory nature of the study. The model goodness-of-fit was assessed using likelihood ratio tests and pseudo-R² values. All statistical analyses were conducted in the STATA environment.

2.4 Additional data collection stage

The data used for the first part of the research (preliminary crash data analysis study) were presented in the previous sub-sections. However, for the development of the predictive crash model, focused on road segments and intersections, it was necessary to acquire new, more updated, and comprehensive data compared to those already available. Specifically, a sample covering a three-year observation period, from January 2021 to December 2023, was utilized to ensure an adequate data foundation for building the model.

The collected data include information related to sites where at least one e-scooter crash occurred during the observation period. Over the three years of observation, crashes were recorded at 131 intersections and on 137 road segments. However, to properly develop the predictive model, additional sites (divided into road segments and intersections) where no crashes occurred should necessarily be included. A sample of these sites were randomly selected and integrated into the dataset to provide a more comprehensive representation of road conditions and risk dynamics. The inclusion of sites without crashes allows for a more precise estimation of the *likelihood of crash occurrence*.

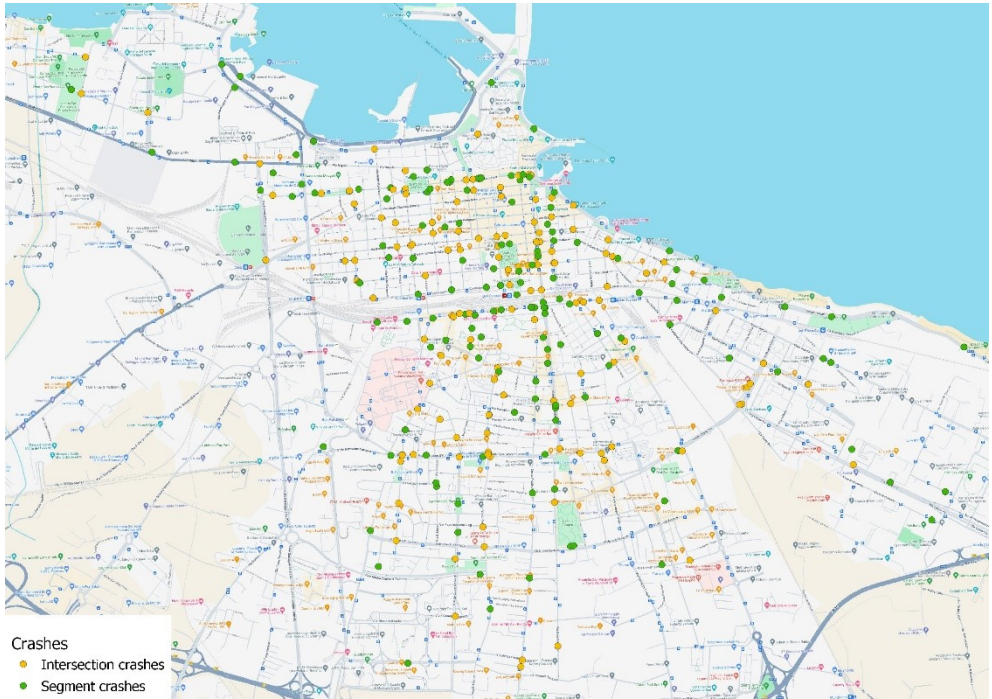


Fig. 2 - Distribution of e-scooter crashes across the urban area of Bari.

This methodology of data selection and integration aims to enhance the accuracy of the predictive model, considering not only the infrastructural and traffic characteristics associated with crash sites but also those sites without crashes. This approach enables the identification of factors that most significantly influence crash risk and allows for more reliable predictions to support road safety management.

To ensure the statistical validity of the model, the sampling approach was guided by recommendations in the literature. According to Srinivasan et al. (2013), a sample of at least 400 intersections is necessary to obtain reliable results in predictive modeling. The dataset prepared for this study meets this requirement, with the final sample consisting of 401 intersections, of which 131 experienced at least one crash.

For road segments, the guideline suggests a sample of at least 160 km of road network. Instead of a length-based approach, this study focuses on site-based sampling, resulting in a final sample of 875 road segments, of which 137 experienced at least one crash. Although the total road network length included in the sample is

approximately 115 km, the study encountered a structural limitation due to the absence of additional segments with traffic data. This has limited further expansion and prevented achieving the minimum required number of segments. The development of the predictive crash model involved selecting the binomial logistic model. This statistical approach was applied to crash data and road characteristics to estimate the likelihood of crash occurrence across the sampled sites. This methodology of data selection, integration, and modeling ensures a strong foundation for analyzing crash risk and provides valuable insights into road safety management in the context of e-scooters.

2.4.1 Sampling of Road Segments and Intersections:

The sampling process for road segments and intersections required the collection of specific information to ensure a comprehensive and detailed dataset for analysis.

For intersections, particular attention was given to gathering key characteristics and contextual variables that influence crash dynamics. The information collected included:

- Intersection Type: determined by Google Maps
- Average Daily Traffic (ADT) of vehicles (see next sub-sections for more details) on:
 - the main road -Road 1-
 - the secondary road -Road 2-
- Average Daily Traffic (ADT) of e-scooters through field surveys and data provided by e-scooter services (see next sub-sections for more details) on:
 - the main road -Road 1-
 - the secondary road -Road 2-
- Presence of Infrastructure and Road Signs:
 - Turning Lane: Google Maps
 - Bicycle Crossing: Google Maps

- Traffic Light: Google Maps
 - Stop Sign: Google Maps
 - Yield Sign: Google Maps
 - Roundabout: Google Maps
- Whereas, for the sampling of road segments, the following information were collected:
 - Average Daily Traffic (ADT) of vehicles
 - Average Daily Traffic (ADT) of e-scooters
 - Number of Lanes: determined by Google Maps.
 - One-Way Traffic : verified by Google Maps.
 - Length: measured using QGIS.
 - Presence of specific Infrastructure Characteristics:
 - Traffic Separator: Google Maps
 - Access Points: Google Maps
 - Parking (One Side, Both Sides): Google Maps
 - Bicycle Lane (Type): Google Maps
 - Bus Lane: Google Maps

2.4.2 Vehicle Traffic Data

Vehicle traffic data was a critical component of the study, as it provided insights into traffic volumes and patterns across urban roads. The primary source for this data was the Sustainable Urban Mobility Plan (SUMP) of the Metropolitan City of Bari. The SUMP offered detailed information on traffic volume and other essential variables for the urban road network, forming a robust basis for analyzing vehicle flow and its relationship to crash risk.



Fig. 3- Logo of the Sustainable Urban Mobility Plan (PUMS) for the Metropolitan City of Bari

For roads where SUMP data were unavailable, direct field surveys were conducted to fill in the gaps. These surveys involved on-site observations and measurements specifically focusing on traffic volumes during daylight hours. The data collected were then calibrated against traffic values from roads with similar geometric and urban characteristics to ensure consistency. This approach ensured that vehicle traffic information was comprehensive and accurate across the study area. By combining SUMP data with targeted field surveys, the study ensured reliable and detailed traffic data for use in the predictive modeling process.



Fig. 4 - Snapshot from video footage used for traffic surveys, illustrating the methodology for collecting and analyzing vehicle and e-scooter flow data in the study area.

2.4.3 E-scooter traffic data

The collection of e-scooter traffic data represented one of the most significant, innovative, and complex challenges of this research. The primary difficulty stemmed from the scarcity of information available in the literature regarding e-scooter traffic patterns. Unlike traditional vehicles, e-scooters are not subject to insurance policies, registration requirements, or standardized tracking systems, which complicates the acquisition of reliable and detailed data.

To overcome this challenge, a strategic collaboration was established with Vento Mobility Srl, the operator of the TIER e-scooter sharing service in Bari. This partnership proved essential in obtaining crucial traffic data specific to e-scooters, enabling a more comprehensive understanding of their usage patterns in the urban environment.



Fig. 5 - Combined images showcasing the logo of TIER Mobility and a TIER e-scooter.

Through this partnership, TIER provided annual data on the number of e-scooters actively used in Bari. This information was processed and converted into daily values to facilitate a more granular analysis of traffic flows. By utilizing this data, the research was able to incorporate an innovative perspective on e-scooter mobility, which is often underrepresented in traditional traffic studies.

In addition to data provided by TIER, field surveys were conducted in 11 specific sections of the urban area of Bari to complement and validate the data. These surveys captured detailed measurements, including:

- the number of TIER shared e-scooters.
- the number of shared e-scooters from other companies operating in the area.
- the number of privately owned e-scooters.

The integration of field survey data allowed for a comprehensive estimate of e-scooter traffic across the selected sections. This approach not only accounted for the shared e-scooter fleet but also included private e-scooter users, ensuring a complete representation of e-scooter mobility in Bari. This dual-source methodology provided a robust and reliable dataset for subsequent analysis and modeling of e-scooter traffic dynamics.

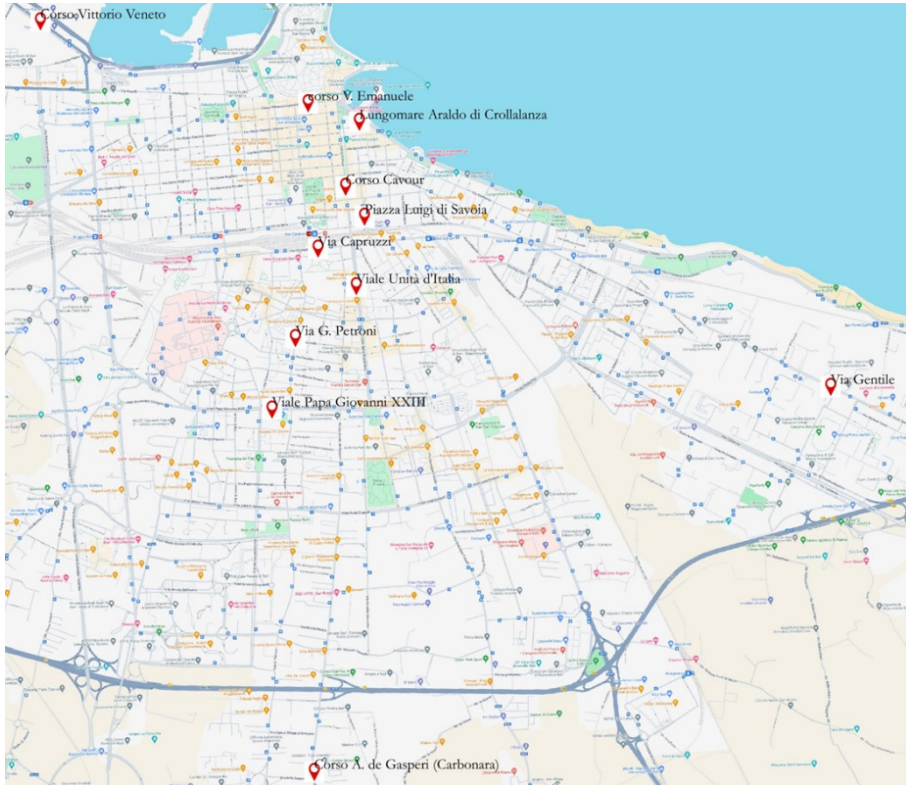


Fig. 6 - Map showing the survey points across the urban area of Bari.



Fig. 7 - Representation of the tools used for traffic surveys.

The analysis of e-scooter traffic data aimed to estimate the average number of e-scooters active during daytime hours, providing a detailed understanding of their usage patterns. The data provided by TIER played a key role in this calculation, with the company specifying that 83% of total daily e-scooter traffic occurs during daytime hours.

To further refine the calculation, field surveys were conducted, during which the number of e-scooters was recorded in two distinct time periods: a peak hour and a calm hour. The counts from these two hours were summed up and then multiplied by 8 to account for the 16 daytime hours (from 6:00 AM to 10:00 PM). This method allowed for an accurate estimation of total daytime daily traffic, incorporating variations in traffic intensity throughout the day.

The urban area of Bari was divided into several zones of interest to facilitate localized analysis. However, the peripheral areas of Bari were excluded from the study due to their distinct urban characteristics, which differed significantly from the rest of the city and made them less representative for the purposes of this research.

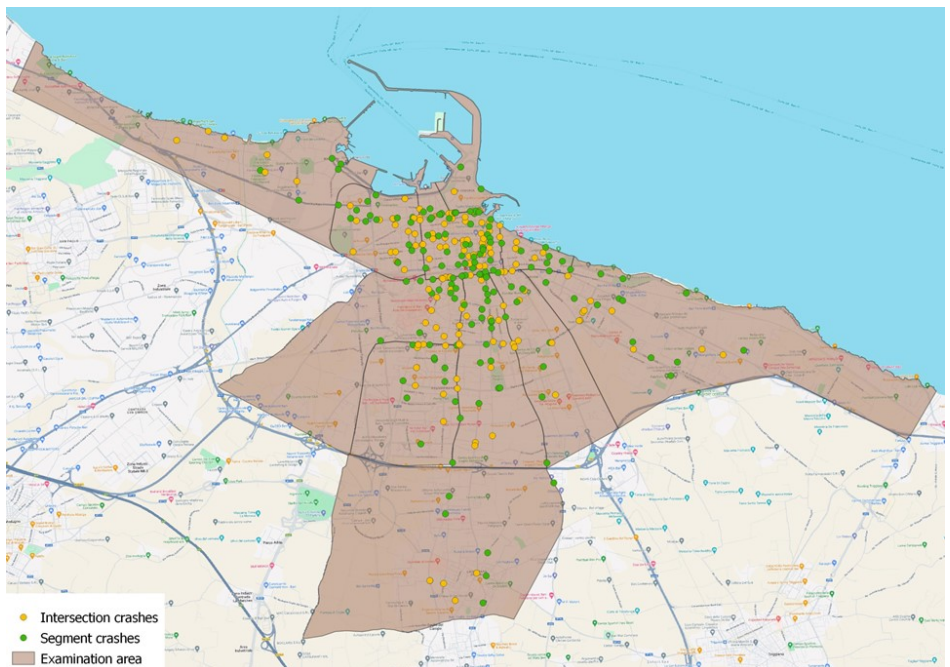


Fig. 8 - Spatial distribution of e-scooter crashes across the study area.

The remaining urban area was divided using QGIS software, employing the Thiessen polygon method, also known as the Voronoi diagram. This approach involves partitioning the space into polygons such that every point within a given polygon is closer to the observation point (each of the 11 survey points shown in the figure 9) associated with that polygon than to any other observation point. This method ensured that the urban area was divided logically and systematically, based on the spatial distribution of the observation points.

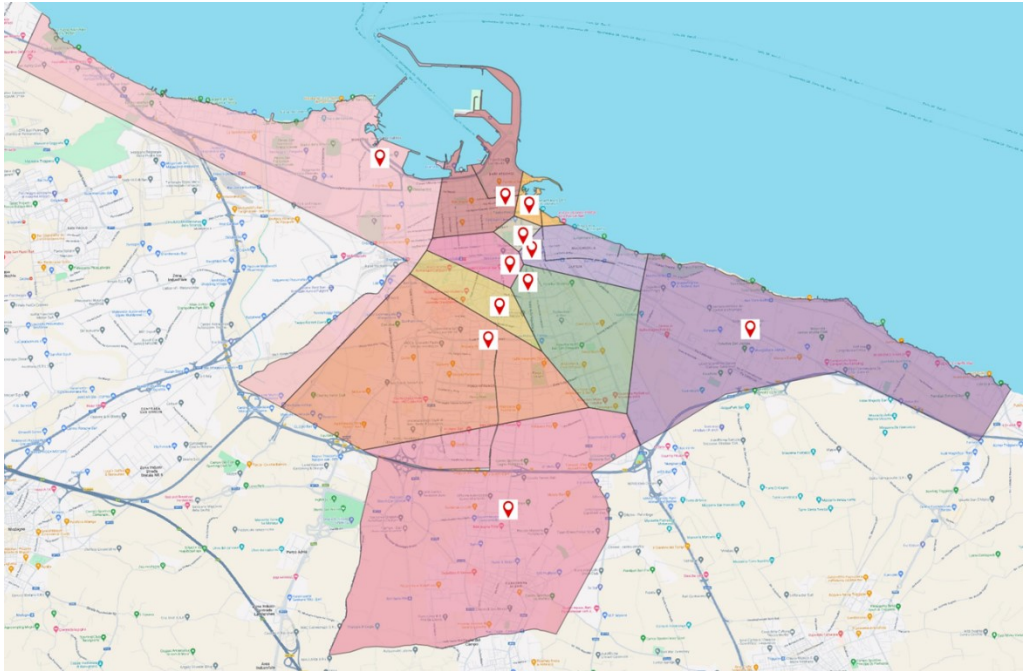


Fig. 9 - Map of the study area divided into Thiessen polygons based on the spatial distribution of the 11 survey points.

The daytime average daily traffic was calculated using the survey data collected across the 11 surveyed sections of the urban area. This calculation involved the following steps:

1. Determination of Daily TIER E-Scooter Traffic

For each survey point, an average was calculated between the daily number of TIER e-scooters recorded during field surveys and the daily number

of TIER e-scooters provided by TIER. This value allowed for a precise estimation of the percentage of TIER e-scooters out of the total daily e-scooter traffic surveyed in site.

2. Estimation of Total Traffic per Polygon

The calculated percentage of TIER e-scooters over the total e-scooter traffic was then applied to the data provided by TIER across all relevant roads within each polygon. This process enabled the estimation of total daily traffic (including both private and shared e-scooters) for each road in the polygon.

3. Calculation of Overall Traffic for the Entire Study Area

By aggregating the total traffic values from all polygons, the overall daily e-scooter traffic for the entire study area was determined. This approach provided a comprehensive view of e-scooter mobility patterns across Bari, considering both shared and private e-scooter users.

This multi-step methodology ensured that the data collected and analyzed were representative of e-scooter traffic in Bari, enabling a detailed and accurate assessment of their usage across different zones of the city.

All the steps outlined above represent a detailed and structured methodology for estimating e-scooter traffic and its distribution across the urban area of Bari. However, it is worth noting that this complex approach to data collection and estimation might be significantly simplified in the future, thanks to the introduction of new regulations for e-scooters in Italy. These regulations mandate the use of license plates and insurance for e-scooters, which could enable more systematic and reliable data collection.

With these regulatory changes, it may become possible to access comprehensive datasets directly through official records, eliminating the need for extensive field surveys and manual calculations. This would greatly enhance the efficiency of future studies on e-scooter traffic and safety, providing researchers and policymakers with more accessible and precise data for urban planning and road safety initiatives.

2.5 Development of the e-scooter crash likelihood prediction model

The implementation of the collected data sample into the statistical model represents a critical step in this research.

In detail, the objective was to develop a logistic regression framework capable of predicting crash occurrences ("n_crashes" with two outcomes: no crash versus 1 + crashes) based on a set of selected variables. Logistic regression is particularly suitable for analyzing the probability of events, such as the occurrence of road crashes, when the response variable is binary or categorical. In this case, the model utilized the *glm()* function in R, specifying a binomial family distribution with a logit link function. This approach allowed the prediction of the binary variable "n_crashes" based on the combination of predictive variables.

The final database developed for this study provides a detailed and comprehensive dataset, structured to facilitate the analysis and predictive modeling of e-scooter crash likelihood. It integrates data from both road segments and intersections, using variables that reflect traffic volumes, infrastructural characteristics, and e-scooter activity.

2.5.1 Road Segments database

The database used for modeling includes a total of 875 road segments, of which 137 recorded at least one e-scooter crash during the observation period. The variables collected (or computed from collected variables) for road segments are as follows:

Table 2 – Variables of road segments database

Variable Name	Description
vehicular_traffic	Total vehicular traffic for the segment (vehicles/day).
traffic_range	Categorical variable indicating the range of average daily traffic (ADT) based on quartiles:

Variable Name	Description
	<ul style="list-style-type: none"> - 25th Percentile: 2,807 vehicles/day - 50th Percentile: 6,154 vehicles/day - 75th Percentile: 10,630 vehicles/day - Maximum Value: 44,921 vehicles/day.
num_lanes	Number of lanes on the segment.
adt_per_lane	Average daily traffic per lane, calculated as vehicular_traffic divided by num_lanes (vehicles/day).
one_way	Presence of a one-way direction on the segment.
median_pre- sence	Presence of a median on the segment.
side_access	Presence of side access points.
parking_avai- lability	Availability of parking along the segment.
bike_lanes	Presence of a bicycle lane along the segment. The variable was not further categorized based on the type of bicycle lane (e.g., segregated bike path or painted bike lane), as the number of sites with bicycle lanes was limited. This decision ensured simplicity in the model while maintaining its robustness.
pref_lanes	Presence of reserved lanes, such as those for public transport.
seg- ment_length	Length of the segment in meters.
e_scoo- ter_traffic	Average daily traffic of e-scooters.

2.5.2 Intersections database

The database includes 401 intersections, of which 131 recorded at least one e-scooter crash. The variables collected (or computed from collected variables) for intersections are as follows:

Table 3 – Variables of intersections database

Variable Name	Description
rangeadt1	Categorical variable indicating the range of ADT on the main intersecting street based on quartiles: - 25th Percentile: 5,915 vehicles/day - 50th Percentile: 9,508 vehicles/day - 75th Percentile: 15,690 vehicles/day - Maximum Value: 44,921 vehicles/day.
ADT2	Vehicular traffic on the secondary intersecting street.
rangeadt2	Categorical variable indicating the range of ADT on the secondary street based on quartiles: - 25th Percentile: 1,838 vehicles/day - 50th Percentile: 3,749 vehicles/day - 75th Percentile: 6,693 vehicles/day - Maximum Value: 22,338 vehicles/day.
adtvehtot	Total vehicular traffic, calculated as the sum of ADT1 and ADT2.
rangeadttot	Categorical variable indicating the range of total ADT at the intersection based on quartiles: - 25th Percentile: 8,690 vehicles/day - 50th Percentile: 13,597 vehicles/day - 75th Percentile: 22,724 vehicles/day - Maximum Value: 55,833 vehicles/day.

Variable Name	Description
intersec- tion_type	Type of intersection (e.g., three- or four-legged).
turning_lanes	Presence of turning lanes at the intersection.
signage	Type of signage at the intersection: <ul style="list-style-type: none"> - Presence of Yield Sign (or Roundabout) - Presence of Traffic Signal - Presence of Stop Sign.
bike_crossing	Presence of bicycle crossings at the intersection.
adtmon1	Average daily traffic of e-scooters on the main street.
rangeadt- mono1	Categorical variable indicating the range of e-scooter traffic on the main street based on quartiles: <ul style="list-style-type: none"> - 25th Percentile: 98 e-scooters/day - 50th Percentile: 264 e-scooters/day - 75th Percentile: 508 e-scooters/day - Maximum Value: 1,648 e-scooters/day.
adtmon2	Average daily traffic of e-scooters on the secondary street.
rangeadt- mono2	Categorical variable indicating the range of e-scooter traffic on the secondary street based on quartiles: <ul style="list-style-type: none"> - 25th Percentile: 39 e-scooters/day - 50th Percentile: 129 e-scooters/day - 75th Percentile: 296 e-scooters/day - Maximum Value: 1,406 e-scooters/day.
adtmonotot	Total daily e-scooter traffic, calculated as the sum of ADTmono1 and ADTmono2.
rangeadtmo- notot	Categorical variable indicating the range of total e-scooter traffic at the intersection based on quartiles: <ul style="list-style-type: none"> - 25th Percentile: 166 e-scooters/day

Variable Name	Description
	<ul style="list-style-type: none"> - 50th Percentile: 499 e-scooters/day - 75th Percentile: 773 e-scooters/day - Maximum Value: 2,234 e-scooters/day.

This final database, with standardized and clearly defined variables, forms a solid foundation for analyzing crash occurrences and developing predictive models.

2.5.3 Statistical techniques

The transition from crash analysis to the development of a predictive model required careful consideration of the available data and methodological choices. The Logit model was selected for this study instead of traditional count data models (i.e., those based on the Negative Binomial distribution of errors) used for Safety Performance Functions (SPFs). This decision was justified by the limited number of crashes observed in the dataset. For instance, almost all road segments with recorded crashes experienced only one crash over the three-year observation period.

Given these constraints, the development of a traditional SPF, which predicts the crash frequency, was deemed impractical. Instead, the Logit model was chosen to estimate the likelihood of a crash occurrence (“n_crashes” variable), expressed as a value between 0 and 1. This approach is particularly suitable for binary outcomes (e.g., 0 = no crash, 1 = at least one crash), allowing the model to predict the likelihood that a specific road segment or intersection will experience at least one crash.

By focusing on probabilities rather than absolute crash counts, the Logit model provides a more realistic and interpretable framework for assessing crash risk, given the sparsity of crash data in the study. This probabilistic perspective also aligns with the study objective of identifying high-risk locations to inform road safety management and preventive measures.

The selection of the model focused on the statistical significance of the included variables. The p-value was the primary metric for assessing each variable significance. A p-value of the coefficient estimates below 0.05 was considered to indicate a

statistically significant effect of the related variables on crash occurrences, while values approaching 0.1 suggested marginal significance. Variables with higher p-values were excluded from the final model, as they did not significantly contribute to explaining the variability in the crash likelihood. Including such variables could reduce the model precision and unnecessarily increase its complexity without providing meaningful improvements.

During the modeling process, some variables considered in earlier iterations were excluded from the final model due to their lack of statistical significance. These variables, when combined with others, demonstrated p-values above 0.05, indicating that they did not meaningfully enhance the model predictive accuracy.

The final logistic regression model focused on statistically significant variables, ensuring a balance between precision and simplicity. This approach provided a robust and reliable tool for predicting e-scooter crash likelihood and understanding the underlying factors contributing to road safety issues.

3 RESULTS AND DISCUSSION

In this section, results from the different analysis stages shown in the methodological section are presented and discussed. In particular, they are divided according to the preliminary crash data analysis conducted (3.1) and the model built to predict crash likelihood (3.2).

3.1 Results and discussion of the crash data analysis

Crash data analysis was firstly conducted in terms of descriptive analyses, shown immediately below. After, results from the modelling of e-scooter crash injury severity and crash types are shown.

3.1.1 Results from the Descriptive Analysis

The majority of e-scooter crashes resulted in injuries (70%), while no fatal crashes were recorded during the observation period. However, it is important to acknowledge that property-damage-only crashes may be under-reported. For instance, individuals who experience minor falls without injuries often choose not to report such incidents to the authorities.

Table 4 - Descriptive statistics of the e-scooter crash dataset (Severity).

Crash-Related Variable	Number	Percentage
Severity		
Fatal	0	0%
With injuries to involved users	181	70%
No injuries	76	30%

A significant proportion of e-scooter crashes (91%) occurred on undivided roads, almost evenly distributed between one-way and two-way roads, while only 9% of crashes took place on divided roads. Considering that divided roads constitute only 23 km (approximately 2%) of the 1321 km road network in the City of Bari, the lower percentage of crashes on divided roads is somewhat expected. However, this finding

simultaneously suggests that divided roads may be less safe for e-scooter users compared to undivided roads.

Interestingly, 1% of e-scooter crashes were recorded in pedestrian zones, even though riding an e-scooter in these areas constitutes a traffic violation under local regulations.

Table 5 - Descriptive statistics of the e-scooter crash dataset (Severity).

Crash-Related Variable	Number	Percentage
Road type		
Undivided one-way	115	45%
<i>Undivided one-way with cycle path</i>	9	4%
<i>Undivided one-way w/o cycle path</i>	106	41%
Undivided two-way	117	45%
<i>Undivided two-way with cycle path</i>	28	11%
<i>Undivided two-way w/o cycle path</i>	89	34%
Divided multi-lane	19	7%
<i>Divided multi-lane with cycle path</i>	5	2%
<i>Divided multi-lane w/o cycle path</i>	14	5%
Three+ Carriageways	4	2%
<i>Three+ Carriageways with cycle path</i>	1	0%
<i>Three+ Carriageways without cycle path</i>	3	1%
Pedestrian zone	2	1%

The study also analyzed the timing of crashes to assess the influence of road traffic patterns. Using the local definition of peak hours (7 a.m.–9 a.m., 1 p.m.–3 p.m.) and calm hours, as outlined by Ranieri et al. (2022), it was found that 19% of crashes occurred during peak hours, 10% at night (10 p.m.–6 a.m.), and the remaining 71% during other calm hours. This distribution highlights the temporal variation in crash

occurrences and underscores the need for targeted safety interventions based on traffic flow dynamics.

Table 6 - Descriptive statistics of the e-scooter crash dataset (Motor-vehicle traffic conditions).

Crash-Related Variable	Number	Percentage
Motor-vehicle traffic conditions		
Peak hours (7 a.m.–9 a.m., 1 p.m.–3 p.m.)	48	19%
Night hours (10 p.m.–6 a.m.)	26	10%
Other calm hours	183	71%

Several significant patterns. Most e-scooter crashes occurred during the summer and during daylight hours, reflecting seasonal and temporal usage trends. Regarding the road environment, 52% of crashes took place at road segments, 42% at intersections (with 31% at unsignalized intersections), and 4% at roundabouts.

Table 7 - Descriptive statistics of the e-scooter crash dataset (Season, Lighting conditions, road elements).

Crash-Related Variable	Number	Percentage
Season		
Summer	102	40%
Autumn	70	27%
Winter	29	11%
Spring	56	22%
Lighting conditions		
In presence of natural light	191	74%
In absence of light	66	26%
Road elements		
Signalized intersection	27	11%

Unsignalized intersection	80	31%
Curve	2	1%
Segment (incl. bridges, tunnels)	135	52%
Roundabout	9	4%
Bridge	4	2%

When examining crash types, the most frequent was the single-vehicle crash (31%), where the e-scooter rider lost control and crashed alone. The second most common type was angle collisions with other vehicles (27%), followed by sideswipe crashes (22%).

Table 8 - Descriptive statistics of the e-scooter crash dataset (crash type).

Crash-Related Variable	Number	Percentage
Crash type		
Single-vehicle	82	31%
Rear-end	16	6%
Angle	69	27%
Sideswipe	56	22%
Pedestrian hit	22	9%
Head-on	12	5%

The data also highlight demographic trends among those involved in crashes. Most e-scooter riders in crashes were young, aged between 18 and 30 (37%), and the majority were male (60% of total crashes, increasing to 73% when missing data are excluded). Additionally, 5% of crashes involved a second passenger on the e-scooter, an unsafe behavior akin to riding in pedestrian zones.

Crash dynamics and contributing factors also provide valuable insights. Excluding unspecified factors (4%), the majority of crashes (65%) were attributed to the e-

scooter riders themselves. Among these, distraction was a significant factor, contributing to 23% of crashes, while road pavement issues and failure to yield the right of way accounted for 11% each. This finding aligns with prior research, such as Abou-Senna et al. (2022), which links failure to yield with higher pedestrian crash rates.

Table 9 - Descriptive statistics of the e-scooter crash dataset (pavement conditions, e-scooter driver age, sex, private or shared e-scooter, causes).

Crash-Related Variable	Number	Percentage
Pavement conditions		
Dry	246	96%
Wet/Slippery	11	4%
E-scooter driver age		
<18	24	9%
18–30	96	37%
31–40	42	16%
>40	49	19%
Unspecified	46	18%
E-scooter driver sex		
Man	154	60%
Woman	57	22%
Unspecified	46	18%
Passenger on board		
Yes	12	5%
No	245	95%
Private or shared		
Shared	71	28%

Crash-Related Variable	Number	Percentage
Private	158	72%
Unspecified	28	11%
Crash causes		
Not caused by e-scooter	67	26%
E-scooter failure	3	1%
Distracted driving	58	23%
Drunk driving	2	1%
Irregular behavior	26	10%
External turbulence	17	7%
Parked e-scooter obstructing	7	3%
Failure to yield	27	11%
Road surface issues	27	11%
Unspecified	23	9%

Regarding bicycle infrastructure, e-scooters were allowed during the observation period to use dedicated lanes, but challenges remain. In Bari, only 32 km (about 2%) of the total road network length (1321 km) consists of bike paths. Of the 257 crashes analyzed, 19% occurred on roads with bike paths. Notably, 47 crashes occurred on such roads, but only 25 happened on the bike paths themselves, with the remaining 22 (47%) occurring outside. Despite the availability of bike paths, on-site traffic surveys showed that 9% of e-scooter users opted to ride outside these paths, even when present. This behavior may significantly increase risk: the 9% of users riding outside bike paths were involved in almost the same number of crashes as the 91% who used the paths. Thus, riding outside bike paths appears to be approximately 10 times more dangerous than using them.

Table 10 - Descriptive statistics of the e-scooter crash dataset (cycle path).

Crash-Related Variable	Number	Percentage
Cycle path		
Crash on cycle path	25	10%
No cycle path	232	90%
<i>Cycle path present</i>	22	9%
<i>No cycle paths</i>	210	81%

Spatial analysis further identifies crash-prone areas, particularly in the city center near the railway station. High-traffic urban arterial segments and intersections in this zone exhibit a high density of injury crashes, particularly single-vehicle and angle types. Predictably, angle crashes are concentrated at intersections, while single-vehicle crashes cluster along road segments. This spatial clustering underscores the need for targeted interventions in high-traffic areas to address these recurring patterns.

3.1.2 Results of the injury severity and crash type models

The findings from the binary logistic regression model examining e-scooter crash injury severity are presented in Table 11.

Table 11 - Results of the logistic regression model for injury severity.

Explanatory Variable	Coeff. Estimate	Std. Error	z Value	p-Value
Day hour: peak hour (ref.: calm hour)	0.617	0.758	1.51	0.131
Day hour: night hours (ref.: calm hour)	1.451	2.639	2.35	0.019
Crash type: angle (ref.: single-vehicle)	-0.607	0.256	-1.29	0.196
Crash type: sideswipe (ref.: single-vehicle)	-0.384	0.324	-0.81	0.420

Explanatory Variable	Coeff. Estimate	Std. Error	z Value	p-Value
Crash type: pedestrian hit (ref.: single-vehicle)	2.141	7.572	2.40	0.016
<i>Crash type: other (ref.: single-vehicle)</i>	<i>-1.001</i>	<i>0.210</i>	<i>-1.76</i>	<i>0.079</i>
Age: <18 (ref.: 18–30)	0.936	1.503	1.59	0.113
Age: 31–40 (ref.: 18–30)	0.593	0.845	1.27	0.205
Age: >40 (ref.: 18–30)	0.350	0.622	0.80	0.424
Age: Unspecified (ref.: 18–30)	-0.069	0.070	-3.17	0.002
Sharing: sharing (ref.: private)	-0.235	0.290	-0.64	0.522
Sharing: Unspecified (ref.: private)	2.247	8.452	2.52	0.012
Dynamics: irregular e-scooter behavior (ref.: Crash not caused by the e-scooter)	0.143	0.445	0.37	0.711
Dynamics: other (ref.: Crash not caused by the e-scooter)	0.848	1.781	1.11	0.266
<i>Dynamics: Road surface issues (ref.: Crash not caused by the e-scooter)</i>	<i>1.601</i>	<i>4.334</i>	<i>1.83</i>	<i>0.067</i>

Likelihood ratio test (reference: null model): $\chi^2(15) = 43.22$, $p < 0.001$, $R^2 = 0.1385$.

Note: Estimated coefficients associated with a p-value < 0.05 are highlighted in bold, while estimated coefficients with a p-value < 0.10 are reported in italics.

Significant statistical associations were identified for the variables "Day Hour," "Crash Type," "Age," "Sharing," and "Dynamics." The analysis indicates that injury severity increases during night hours and when crash dynamics are associated with road

surface issues. These results highlight the need to consider both temporal factors and road surface conditions in e-scooter safety evaluations.

The outcomes of the multinomial logistic regression model analyzing e-scooter crash types are presented in Table 12.

Table 12 - Results of the multinomial logistic regression model for crash types.

Explanatory Variable – Crash Type	Coeff. Estimate	Std. Error	z Value	p-Value
Crash type: angle (base outcome: single-vehicle)				
<i>Road type (ref.: undivided two-way)</i>				
<i>Undivided one-way</i>	0.717	0.409	1.75	0.080
Divided multi-lane	0.619	0.771	0.02	0.981
Pedestrian zone	1.136	88,084.55	0.00	1.000
<i>Day hour (ref.: calm hour)</i>				
Peak hours	-0.146	0.499	-0.29	0.769
Night hours	-0.566	0.617	-0.92	0.359
Road geometry (ref.: segment)				
Unsignalized intersection	2.793	0.473	5.90	<0.001
Signalized intersection	2.626	0.687	3.82	<0.001
Roundabout	2.106	0.960	2.19	0.028
<i>Age (ref.: 18–30)</i>				
<18	1.153	0.905	1.27	0.203
31–40	0.271	0.538	0.50	0.614
>40	-0.563	0.551	-1.02	0.307
Unspecified	-0.562	0.587	-0.96	0.338

Explanatory Variable – Crash Type	Coeff. Estimate	Std. Error	z Value	p-Value
Crash type: sideswipe (base outcome: single-vehicle)				
Undivided one-way	0.297	0.391	0.76	0.447
Divided multi-lane	0.274	0.696	0.39	0.693
Pedestrian zone	-0.133	89,385.11	0.00	1.000
<i>Day hour (ref.: calm hour)</i>				
Peak hours	-0.160	0.484	-0.33	0.741
Night hours	-1.301	0.731	-1.78	0.075
<i>Road geometry (ref.: segment)</i>				
<i>Unsignalized intersection</i>	1.222	0.470	2.60	0.009
<i>Signalized intersection</i>	1.318	0.684	1.93	0.054
<i>Roundabout</i>	0.649	1.054	0.62	0.538
<i>Age (ref.: 18–30)</i>				
<18	1.357	0.900	1.51	0.132
31–40	-0.166	0.518	-0.32	0.748
>40	-0.363	0.499	-0.73	0.466
Unspecified	-0.543	0.578	-0.94	0.347
Crash type: pedestrian hit (base outcome: single-vehicle)				
<i>Road (ref.: undivided two-way)</i>				
Undivided one-way	0.038	0.580	0.07	0.947
Divided multi-lane	0.511	1.011	0.51	0.613
Pedestrian zone	22.995	60,640.19	0.00	1.000
<i>Day hour (ref.: calm hour)</i>				

Explanatory Variable – Crash Type	Coeff. Estimate	Std. Error	z Value	p-Value
Peak hours	-0.485	0.766	-0.63	0.527
Night hours	-14.041	638.874	-0.02	0.982
Road geometry (ref.: segment)				
Unsignalized intersection	-0.080	0.777	-0.10	0.918
Signalized intersection	-13.587	509.270	-0.03	0.979
Roundabout	-13.521	938.137	-0.01	0.989
Age (ref.: 18–30)				
<18	1.107	1.369	0.81	0.419
31–40	-1.371	1.118	-1.23	0.220
>40	-1.528	1.121	-1.36	0.173
Unspecified	1.300	0.626	2.08	0.038
Crash type: other (base outcome: single-vehicle)				
Road (ref.: undivided two-way)				
Undivided one-way	-0.700	0.544	-1.29	0.198
Divided multi-lane	0.448	0.730	0.61	0.540
Pedestrian zone	-0.400	118,229.3	0.00	1.000
Day hour (ref.: calm hour)				
Peak hours	0.457	0.571	0.80	0.423
Night hours	0.262	0.717	0.37	0.714
<i>Road geometry (ref.: segment)</i>				
Unsignalized intersection	0.871	0.587	1.49	0.138
<i>Signalized intersection</i>	1.330	0.778	1.71	0.087

Explanatory Variable – Crash Type	Coeff. Estimate	Std. Error	z Value	p-Value
Roundabout	0.717	1.294	0.55	0.579
Age (ref.: 18–30)				
<18	1.251	1.004	1.25	0.213
31–40	-0.636	0.739	-0.86	0.389
>40	0.161	0.595	0.27	0.787
Unspecified	-0.830	0.800	-1.04	0.299

Likelihood ratio test (reference: null model): $\chi^2(48) = 123.43$, $p < 0.001$, $R^2 = 0.1599$

Note: estimated coefficients associated with a p-value < 0.05 are highlighted in bold, while estimated coefficients with a p-value < 0.10 are reported in italics.

In the second model, "single-vehicle" crashes are used as the reference category for comparing other crash types. The analysis shows that angle crashes are more likely than single-vehicle crashes on undivided one-way roads compared to undivided two-way roads. Similarly, angle crashes are more likely at intersections and roundabouts than at segments. Additionally, sideswipe crashes are found to be more likely than single-vehicle crashes during night hours compared to calm hours and at intersections rather than segments.

3.1.3 Discussion about the results of crash data analysis

This section provides a detailed discussion of the findings from both the descriptive and statistical analyses presented earlier.

E-scooter crashes are observed to occur more frequently on undivided roads compared to divided roads. However, when accounting for the relative lengths of the road networks, divided roads appear to pose a relatively higher risk. This is likely due to the higher vehicular speeds typically observed on divided roads compared to undivided ones. Divided roads tend to encourage drivers to travel at faster speeds, which

can create hazardous conditions when vehicles encounter slower-moving e-scooters. The significant speed disparity between e-scooters and regular vehicles increases the probability of high-risk conflicts, as quick evasive actions become more challenging.

Additionally, the physical separation of traffic on divided roads may encourage riskier behavior among e-scooter riders. For instance, they have been observed to travel not only on the side of the rightmost lane but also on the right side of each lane on multi-lane divided roads. This behavior, along with the distinction between one-way and two-way roads, will be further analyzed in this section by examining crash dynamics and contributing factors to provide deeper insights into this phenomenon.

When analyzing the distribution of crashes across various time slots during the day, it is essential to note that, unlike motor-vehicle traffic volumes, which are well-documented to fluctuate significantly throughout the day (with peak hours accounting for up to 10% of total daily traffic, as noted by Wolshon & Pande, 2016), the same variability does not apply to e-scooters. In situ traffic monitoring surveys conducted in 11 sections of the municipality of Bari during the spring of 2023 provide valuable insights. These surveys were carried out during two one-hour periods: 7:45 a.m.–8:45 a.m., representing motor-vehicle peak hours, and 3:00 p.m.–4:00 p.m., corresponding to calm hours. The selected sections were those with the highest e-scooter traffic and crash occurrences.

The findings reveal that the total number of e-scooters crossing these sections during the calm hour was only about 10% lower than during the peak hour. Additionally, data from an e-scooter sharing provider in Bari (Vento Mobility srl) indicates that night runs (10:00 p.m.–6:00 a.m.) account for nearly 20% of all e-scooter trips. This notable percentage can be attributed to the reduced availability of other public transportation options during nighttime hours.

In summary, e-scooter traffic volume shows significant differences between day and night but remains relatively consistent throughout the day. This observation aligns with findings from surveys conducted in other cities, which highlight broad peak hour slots that are not evenly distributed across the day, particularly on weekdays (Feng et al., 2022; Zou et al., 2020; Younes et al., 2023; Foissaud et al., 2022). However, in

Bari, the uniformity of e-scooter traffic during daytime hours contrasts with the fluctuations in motor-vehicle traffic volumes between peak and calm hours, potentially influencing interactions between e-scooters and other vehicles.

The classification of crashes into specific time periods, as shown in Table 7, must be interpreted in this context. Nighttime crashes account for 10% of the total, compared to nearly 20% of the estimated e-scooter traffic during night hours. Given the near-constant e-scooter traffic volume across the sixteen daytime hours, one would expect an even distribution of crashes, approximately 14.5 per hour. However, only 48 crashes occurred during the four peak hour slots, lower than the expected 58 (14.5×4 peak hour slots). This suggests that peak hour traffic may have a protective effect on e-scooter safety.

When considering average traffic speeds, this finding is less surprising (Sun et al., 2023). During motor-vehicle peak hours, reduced traffic speeds make it easier to avoid collisions involving e-scooters. This supports the idea that speed differentials between vehicles are a critical road safety concern in mixed traffic scenarios (Aarts & Van Schagen, 2006; Quddus, 2013). Additionally, congested traffic conditions naturally limit maneuvering space for motor vehicles, further reducing the likelihood of conflicts.

Conversely, the night period appears less hazardous for e-scooters in terms of crash frequency, as motor-vehicle traffic volume is minimal, even lower than during calm hours. However, crashes occurring at night are associated with greater severity. This aligns with existing literature that highlights the heightened risks of nighttime crashes, even though they are fewer than those occurring during daytime hours (Shah et al., 2021; Shah & Cherry, 2022). Furthermore, sideswipe crashes are more prevalent during night hours compared to single-vehicle crashes.

Thus, while e-scooter traffic and crash frequencies are lower at night, the literature (Gao & Zhang, 2024) underscores critical issues related to injury severity and conflicts leading to sideswipe crashes during these hours.

The majority of crashes took place during summer (see also Shah et al., 2021; Yang et al., 2020; Störmann et al., 2020) and during daylight hours. This outcome can be attributed to the increased use of e-scooters during warmer weather and daylight

periods. Aggregate data from "Vento Mobility srl," an e-scooter sharing provider in Bari (2022 data), indicate seasonal variations in e-scooter usage rates that align with the percentages shown in Table7 and depicted in Figure 10. Additionally, the figure illustrates the combined effect of season and lighting conditions.

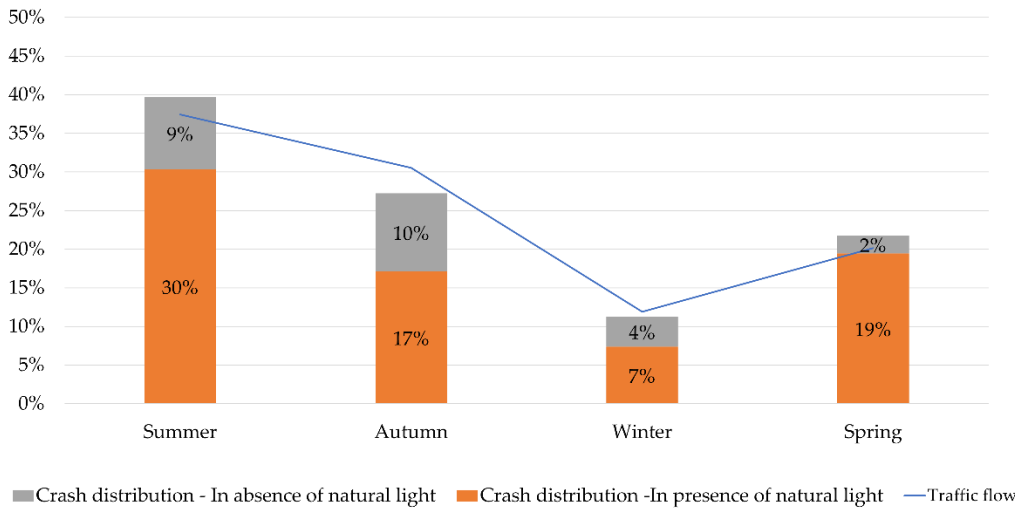


Fig. 10 - Distribution of e-scooter crashes according to the combination of seasons and lighting conditions, plotted together with the distribution of the e-scooter runs (“traffic flow”: blue line in figure) in the four seasons, according to aggregate statistics provided by “Vento mobility srl”, a sharing e-scooter provider in Bari (Longo et al., 2022).

To analyze the combination of these variables, it is important to note that during autumn and winter, the average number of daylight hours is similar (less than 11 hours), whereas daylight hours are also comparable during spring and summer (approximately 14 hours). Therefore, similar proportions of crashes occurring without natural light would be expected between the two seasonal groups: (1) spring–summer, and (2) autumn–winter. However, as indicated by the percentages in the figure, while autumn and winter crashes align with this expectation (approximately 37% of crashes in both seasons occurred without natural light), summer crashes deviate significantly. Specifically, crashes without natural light accounted for 9% of total summer crashes

(about 23%), which is notably higher than the equivalent figure for spring, where only 2% of total crashes (less than 10%) occurred in the absence of natural light.

This discrepancy could again be linked to the higher e-scooter usage rates during summer evenings compared to spring, as corroborated by the aggregate data from the e-scooter provider. Based on these findings, no clear influence of season and natural lighting conditions on e-scooter safety can be identified.

Regarding different road elements, these were analyzed alongside crash types to provide insights into planning and design implications. Figure 11 illustrates the distribution of e-scooter crashes across geometric road elements (segments or intersections, including roundabouts). The bar chart also compares these findings to the distribution of crashes involving other vehicles in the same city, as reported by Intini et al. (2021).

Two key aspects emerge from this analysis: (a) the classification of e-scooter crash types by road elements, and (b) the differences between e-scooter crashes and crashes involving other vehicles. Concerning the first point, e-scooter crashes involving single vehicles and pedestrians are more frequent at segments than at intersections. This trend is distinct to e-scooters, as it is not as pronounced for other vehicle crashes. The higher proportion of e-scooter single-vehicle crashes at segments could be attributed to greater speeds and lower attentiveness, which are often higher at traffic nodes like intersections. Similarly, the higher share of pedestrian-related crashes at segments may result from the limited maneuvering space available to e-scooter riders (who typically travel near the edge of the carriageway) when attempting to avoid pedestrians crossing the road. This observation highlights the importance of designing pedestrian crossings with care, particularly on narrow streets frequented by e-scooters and bordered by parking spaces on both sides.

On the other hand, e-scooter angle crashes are significantly more frequent at intersections than at segments, a trend also observed in crashes involving other vehicles. This is expected, given that angle crashes are inherently linked to intersecting

traffic flows. Statistical analyses confirm this tendency, and crash reports frequently cite distracted driving as a contributing factor in angle collisions at intersections.

A further distinction of e-scooter crashes compared to other vehicle crashes is the disproportionately high share of single-vehicle crashes (approximately one-third of all e-scooter crashes) and, to a lesser extent, the notably lower frequency of rear-end crashes. The higher prevalence of single-vehicle crashes underscores the vulnerability of e-scooter riders to losing control, which can be exacerbated by poor road conditions, distraction, or sudden evasive maneuvers to avoid obstacles, vehicles, or pedestrians. Improving road design and maintaining existing infrastructure are widely regarded as effective strategies to mitigate such crashes (White et al., 2023). Conversely, rear-end crashes involving e-scooters are less frequent compared to other vehicles, likely due to the shorter stopping distances associated with their lower speeds.

The peculiar situation of pedestrian hits can be also solved by reducing the interactions between pedestrians and e-scooters that, in other contexts, were also due to e-scooters irregularly travelling on sidewalks (Kuskapan et al., 2023).

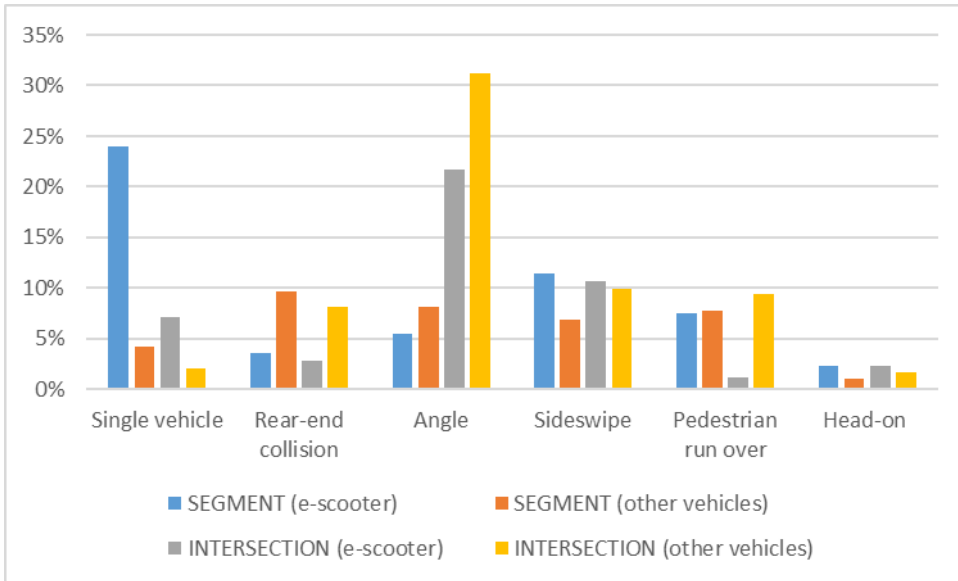


Fig. 11 - Distribution of e-scooter crashes (blue and grey bars, summing up to 100%) and crashes to other vehicles (orange and yellow bars, summing up to 100%) by crash type, coupled with road elements (Longo et al., 2022).

Most e-scooter crashes are single-vehicle accidents, and their frequency can be compared to the proportion of crashes on wet or poorly maintained pavements (see Table 9). However, it should be noted that crashes on wet pavements represent only 3% of total e-scooter crashes, and “road surface issues” were cited as a contributing factor in only 11% of police reports. While pavement maintenance is undoubtedly crucial for e-scooter safety (White et al., 2023), other factors seem to account for the high share of single-vehicle crashes. Furthermore, the low percentage of crashes on wet pavements suggests that adverse weather conditions discourage e-scooter use, as riders often avoid using e-scooters during such conditions (Bieliński & Ważna, 2020). Statistical analyses also show that crashes attributed to road surface dynamics tend to have higher severity compared to crashes not caused by e-scooters, which carries significant practical implications.

The average age of e-scooter users involved in crashes aligns with previous research, with an average of 31 years (Bieliński & Ważna, 2020; Störmann et al., 2020). The age factor can also impact crash severity, as highlighted by Sun et al. (2023). A study conducted in Denmark (Blomberg et al., 2019) focused on young users aged 18–25 years, correlating severe head and musculoskeletal injuries with risky behaviors influenced by alcohol and drug consumption. These findings suggest that awareness campaigns targeting young e-scooter users are essential.

Regarding gender, the data confirms trends seen in the literature, with men more likely to be involved in e-scooter crashes (Blomberg et al., 2019; Vetturi et al., 2023). Additionally, 5% of crashes involved a second passenger on the e-scooter, which constitutes a traffic violation, as carrying passengers is prohibited. Such behaviors, including wearing headphones, talking while riding, or using a mobile phone, are considered user-related risky practices (Huemer et al., 2022). A potential countermeasure to address this issue could involve equipping e-scooters with weight-control devices to prevent overloading.

E-scooters in Italy are available in shared and private forms. Shared e-scooter services have been permitted since 2019, following national legislation (D’andreagiovanni et al., 2022). This legislation mandates several technical requirements, such as

limiting speed to 20 km/h and capping power at 0.5 kW. E-scooters are permitted in specific areas, including shared bicycle-pedestrian lanes and 30 km/h zones, provided they are equipped with speed limiters for pedestrian zones (D'andreaiovanni et al., 2022).

3.1.4 Discussion about influencing factors on e-scooter crashes

To analyze the influence of e-scooter types on crash statistics, in situ traffic surveys were conducted in spring 2023, revealing that 23% of all e-scooters observed were shared vehicles. Comparing this figure to crash data from the last semester of 2022 shows a matching 23% share of crashes involving shared e-scooters, aligning with the surveyed proportions. This suggests that the e-scooter type does not significantly influence crash risk. Shared e-scooters are limited to 20 km/h, but their users may be less experienced, which potentially offsets the safety benefits of the speed limitation. Thus, the current speed cap for shared e-scooters appears to be an effective safety measure for novice riders.

The information about crash-contributing factors and dynamics can be analyzed in conjunction with infrastructure-related variables to extract valuable insights. Figure 12 illustrates these interactions. E-scooter crashes are more prevalent on undivided roads compared to divided ones. However, a notable share of crashes caused by distracted riding occurs on divided roads, while very few crashes on these roads are not caused by the e-scooter driver (Sun et al., 2023; White et al., 2023). This reinforces the hypothesis that speed differentials on divided roads increase crash risks. Most crashes on divided roads are not attributed to the e-scooter driver, yet their distraction may result in severe outcomes. Consequently, implementing speed reduction measures on divided roads or constructing dedicated e-scooter paths is critical.

The classification of crashes by one-way versus two-way roads (yellow and grey bars in Figure 5) shows crashes are almost evenly distributed between the two types. However, a peculiar observation is that crashes caused by “e-scooter falls due to external turbulence” are more frequent on two-way roads, likely due to the increased risk of traffic conflicts (Blomberg et al., 2019). Additionally, a small number of crashes involving parked e-scooters being struck (labeled as “e-scooter obstacles”) were only

reported on two-way roads. This highlights the necessity for safe parking practices and dedicated parking zones, particularly on two-way roads (White et al., 2023).

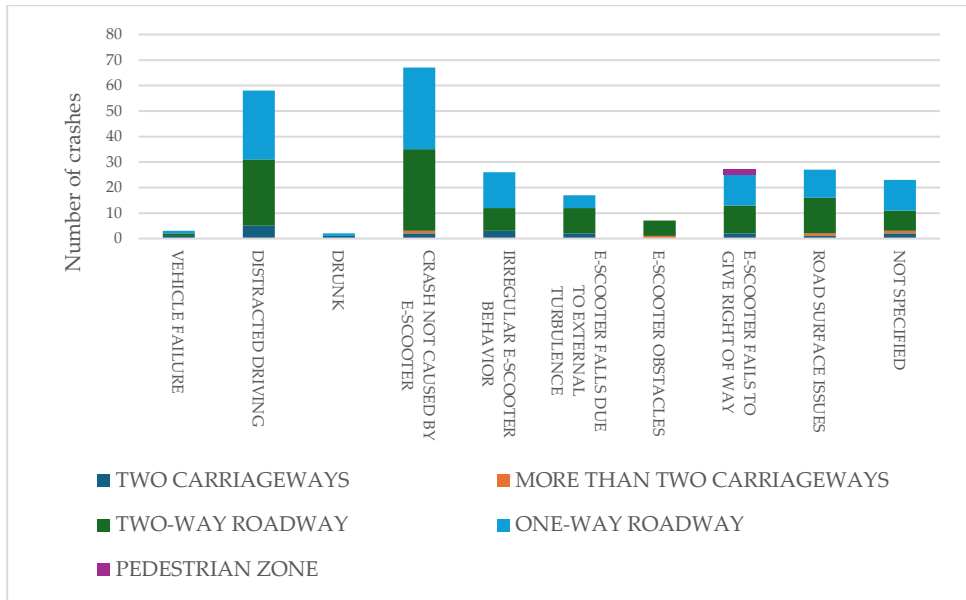


Fig. 12 - Crash dynamics in relation to road type (divided roads, further divided into two or more than two carriageways; undivided roads, further divided into one-way and two-way; and pedestrian zones) for e-scooter crashes (Longo et al., 2022).

Riding outside the designated bike path appears hazardous, as highlighted in prior studies (Sun et al., 2023; Tian et al., 2022). Enhancing the visibility and effectiveness of bike path signage could play a critical role in guiding both cyclists and other road users toward safer behavior. This could include implementing clear, frequent, and universally recognizable symbols and colors to mark bike paths. Public awareness campaigns and educational programs should also be developed to emphasize the importance of adhering to bike path usage for improving overall road safety and traffic efficiency. Collaborating with local authorities, community groups, and cycling advocacy organizations can support a comprehensive strategy to increase compliance with bike path usage. However, this aspect is strictly connected to the regulations operated in each specific country/region.

3.2 Crash likelihood model for Road Segments: Results and Discussion

The analysis of data related to road segments led to the construction of a predictive model that employs a binomial regression model. This model aims to identify the main factors influencing crash risk in road segments and represents an important contribution to understanding road safety, especially in terms of micromobility and mixed traffic.

Before building the model, it was necessary to load and prepare the data. The dataset, called `segments.csv`, was loaded into R with the following command:

```
d <- read.csv("segments.csv", sep = ";", header = TRUE, stringsAsFactors = FALSE)
```

In this step:

- `sep = ";"` specifies that the field separator is a semicolon, consistent with the CSV format used.
- `header = TRUE` indicates that the first row of the file contains the column names.
- `stringsAsFactors = FALSE` prevents automatic conversion of strings into factors, allowing more precise control over the data type and applicable transformations.

The original dataset included various variables related to road segment characteristics, which were subsequently transformed and categorized to optimize the statistical analysis.

3.2.1 Descriptive analysis of road segment variables

To provide a comprehensive understanding of the dataset, a descriptive analysis was conducted, summarizing the key characteristics of both categorical and numerical variables. Table 13 presents the distribution of the categorical variables, related to road segment characteristics, distinguishing between segments where crashes occurred and those without crashes. The variables include number of lanes, presence of one-way streets, medians, side accesses, parking availability, bike lanes, and preferential lanes. For each category, absolute and percentage frequencies are reported, allowing to assess the variability in infrastructure characteristics across the analyzed road segments.

Table 14 reports the descriptive statistics for the numerical variables, such as the mean and standard deviation, which allow a better understanding of the data variability and central tendency. This table summarizes key traffic and road segment characteristics, including vehicular traffic, average daily traffic per lane (ADT per lane), segment length, and e-scooter traffic. The statistics distinguish between segments with and without crashes, enabling the analysis of differences in traffic flow and infrastructure conditions across the dataset.

Table 13 - Descriptive statistics for categorical variables (segments)

<i>Category*</i>	0	1	2	3	Total
num_lanes					
Total	0 (0%)	434 (50%)	331 (38%)	110 (13%)	875 (100%)
Crashed	0 (0%)	66 (48%)	44 (32%)	27 (20%)	137 (100%)
Not Crashed	0 (0%)	368 (50%)	287 (39%)	83 (11%)	738 (100%)
one_way					
Total	358 (41%)	517 (59%)	0 (0%)	0 (0%)	875 (100%)
Crashed	77 (56%)	60 (44%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	281 (38%)	457 (62%)	0 (0%)	0 (0%)	738 (100%)
median_presence					
Total	802 (92%)	73 (8%)	0 (0%)	0 (0%)	875 (100%)
Crashed	116 (85%)	21 (15%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	686 (93%)	52 (7%)	0 (0%)	0 (0%)	738 (100%)
side_access					
Total	437 (50%)	438 (50%)	0 (0%)	0 (0%)	875 (100%)
Crashed	99 (72%)	38 (28%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	338 (46%)	400 (54%)	0 (0%)	0 (0%)	738 (100%)
parking_availability					
Total	173 (20%)	194 (22%)	508 (58%)	0 (0%)	875 (100%)
Crashed	38 (28%)	32 (23%)	67 (49%)	0 (0%)	137 (100%)
Not Crashed	135 (18%)	162 (22%)	441 (60%)	0 (0%)	738 (100%)
bike_lanes					

Category*	0	1	2	3	Total
Total	815 (93%)	60 (7%)	0 (0%)	0 (0%)	875 (100%)
Crashed	116 (85%)	21 (15%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	699 (95%)	39 (5%)	0 (0%)	0 (0%)	738 (100%)
pref_lanes					
Total	827 (95%)	48 (5%)	0 (0%)	0 (0%)	875 (100%)
Crashed	120 (88%)	17 (12%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	707 (96%)	31 (4%)	0 (0%)	0 (0%)	738 (100%)

*num_lanes: 1=1 lane, 2 = 2 lanes, 3=more than 2 lanes;
 one_way: 0=Two-way traffic, 1= one way;
 median_presence: 0=Absent, 1=Present;
 side_access: 0=Absent, 1=Present;
 parking_availability: 0=Absent , 1=Present on one side only, 2=Present on both sides;
 bike_lanes: 0=Absent, 1=Present;
 pref_lanes: 0=Absent, 1=Present.

Table 14 - Descriptive statistics for numerical variables

	vehicular_traffic	adt_per_lane	segment_length	e_scooter_traffic
Mean	8146	4956	157	274
<i>Mean crashed</i>	9595	6199	212	335
<i>Mean not crashed</i>	7878	4725	146	263
Standard deviation	7353	4214	201	274
<i>Standard deviation Crashed</i>	8080	6496	328	320
<i>Standard deviation Not crashed</i>	7184	3596	165	264

3.2.2 Results of the road segment model building

Some of the loaded variables were transformed into factors to correctly represent discrete data in the model and optimize the handling of binary variables. The transformation was performed for the following variables:

```
traffic_range <- factor(traffic_range)
```

```
num_lanes <- factor(num_lanes)
one_way <- factor(one_way)
median_presence <- factor(median_presence)
side_access <- factor(side_access)
parking_availability <- factor(parking_availability)
bike_lane <- factor(bike_lane)
pref_lanes <- factor(pref_lanes)
ncrashes <- factor(ncrashes).
```

These variables represent different infrastructural aspects of the road segment:

- traffic_range and num_lanes are respectively the ADT range and the number of lanes, two factors related to traffic and road configuration.
- one_way, median_presence, side_access, parking_availability, bike_lane, and pref_lanes are binary variables that respectively indicate the presence (1) or absence (0) of a one-way direction, median, access points, parking, bicycle lane, and preferential lanes.

For some numeric variables, a logarithmic transformation was created, based on previous research (e.g., Intini et al., 2021). The transformed variables are:

```
log_vehicular_traffic <- log(vehicular_traffic)
log_e_scooter_traffic <- log(e_scooter_traffic)
log_adt_per_lane <- log(adt_per_lane).
```

These logarithmic variables were included in the model to improve data distribution and refine the predictive accuracy of the final model.

Following data preparation, several combinations of variables were tested. Combinations were analyzed in terms of statistically significant variables (p -value < 0.05). After studying results from several different competitive models, the model that maximized the number of significant variables, optimizing the goodness of fit, was chosen. At the end of this process, the selected model includes the following variables:

- *adt_per_lane*,
- *median_presence*,
- *bike_lane*,
- *side_access*,
- *segment_length*,

- *e_scooter_traffic*,

This model (table 15) includes the highest number of significant variables and best represents the factors associated with crash risk in road segments.

Table 15 - E-scooter crash likelihood prediction model for road segments

Variable	Estimate	Std. Error	z value	Pr(>z)
(Intercept)	-2,14E+03	2,03E+02	-10.525	< 2e-16 ***
adt_per_lane	5,86E-02	2,10E-02	2.783	0.005381 **
median_presence1	9,81E+02	3,03E+02	3.240	0.001197 **
bike_lane1	8,05E+02	3,18E+02	2.532	0.011355 *
side_access1	-1,29E+03	2,19E+02	-5.904	3.54e-09 ***
segment_length	1,57E+00	4,43E-01	3.552	0.000383 ***
e_scooter_traffic	6,98E-01	3,30E-01	2.117	0.034279 *

3.2.3 Alternative models

In this sub-section, alternative competitive models, seemingly containing more and less complex variables, are presented. For example, the traffic and the number of lanes (considered separately), were found to lack statistically significant variables (table 16). For this reason, and for the reasons listed below, the model presented in Table 15 was selected.

Table 16 - Alternative model 1 (segments)

Variable	Estimate	Std. Error	z value	Pr(>z)
(Intercept)	-1,80E+03	1,95E+02	-9.199	<2e-16 ***
adt	1,41E-02	1,40E-02	1.010	0.312695
median_presence1	9,54E+02	3,62E+02	2.637	0.008357 **
bike_lane1	8,93E+02	3,23E+02	2.764	0.005710 **
side_access1	-1,30E+03	2,19E+02	-5.938	2.89e-09 ***
segment_length	1,73E+00	4,65E-01	3.721	0.000199 ***
e_scooter_traffic	8,52E-01	3,44E-01	2.477	0.013245 *

n_lanes2	-4,93E+02	2,38E+02	-2.072	0.038233 *
n_lanes3	-3,20E+02	3,56E+02	-0.899	0.368506

This model is not appropriate because some variables, such as *adt* and *n_lanes3*, are not statistically significant ($p\text{-value} > 0.05$), indicating they do not contribute meaningfully to explaining the variability in crash occurrence. Including these variables can reduce the model precision and unnecessarily increase complexity. Additionally, some of standard errors suggest potential multicollinearity or insufficient data quality, which may undermine the reliability of the estimated coefficients.

To ensure that the selected model was the most suitable, several likelihood ratio tests were performed using the R *lmtest* library. The tests compared the selected model with alternative models and produced the following results:

- Comparison between *m1* and *m10*:
 - The *m1* model includes the variables *vehicular_traffic*, *one_way*, *median_presence*, *side_access*, *bike_lane*, *pref_lanes*, *segment_length*, *e_scooter_traffic*, and *adt_per_lane*, while *m10* (model shown in Table 15) includes only the variables selected as significant.
 - The test showed a significant difference ($\text{Chisq} = 26.533$, $p < 0.001$), confirming that the final model (*m10*) is preferable for its parsimony and variable significance.
- Comparison between *m2* and *m10*:
 - The *m2* model is similar to *m1* but replaces *e_scooter_traffic* with its logarithmic version, *log_e_scooter_traffic*.
 - In this case, too, the test confirmed the superiority of the final model (*m10*), with a significant difference ($\text{Chisq} = 27.011$, $p < 0.001$).
- Comparison between *m1* and *m2*:
 - The test showed a significant difference, favouring the use of the logarithmic variable for e-scooter traffic.

In conclusion, the resulting model incorporates a series of key variables that provide significant information on factors influencing crash likelihood on road segments in the city of Bari.

3.2.4 Interpretation of the Variables included in the selected segment model

In this paragraph, the variables included in the selected model are described, interpreted and discussed.

- Intercept
 - The intercept term has an estimated value of -2.137 with a standard error of 0.2030. The associated z-value is -10.525, with a high level of significance (p-value < 2e-16), indicating that the intercept is significantly different from zero.
 - From an interpretive standpoint, the intercept represents the predicted base risk when all other variables are set to zero. However, this serves primarily as a reference point, as the model includes contextual factors that significantly influence accident risk.
- Average Daily Traffic per Lane (adt_per_lane):
 - Variable type: Numeric.
 - Description: This variable represents the average daily traffic (ADT) exclusively for vehicles on the segment, divided by the number of lanes present, providing a measure of traffic volume per single lane.
 - Coefficient interpretation: With an estimated coefficient of 5.855e-05, it suggests that for every increase of one vehicle in the daily average traffic per lane, there is a predicted increase in crash likelihood. Although the coefficient is small, the cumulative effect on large traffic volumes can be significant, demonstrating that as lane traffic increases, accident risk rises.
- Median Presence (median_presence):
 - Variable type: Binary categorical.

- Description: This binary variable has a value of 0 when the median is absent and 1 when present, distinguishing segments with traffic medians that separate traffic flows from those without.
- Coefficient interpretation: With a coefficient of 0.9809, the model suggests that the presence of a median increases accident frequency. Although medians separate traffic flows, they may also introduce risks, such as lateral collisions or crashes resulting from lane changes.
- Bicycle Lane Presence (bike_lane):
 - Variable type: Binary categorical.
 - Description: This variable indicates the presence (1) or absence (0) of a bicycle lane along the segment.
 - Coefficient interpretation: The positive coefficient (0.8053) suggests that the presence of bicycle lanes might be associated with an increased crash risk. This could result from interactions between vehicles and cyclists in contiguous or mixed spaces, highlighting the need for separate and safe spaces.
- Side Access Points (side_access):
 - Variable type: Binary categorical.
 - Description: This variable indicates the presence (1) or absence (0) of side access points along the road segment.
 - Coefficient interpretation: The negative coefficient (-1.290) implies that side access points are associated with a decrease in crashes. Although counterintuitive, it may suggest that segments with access points require reduced speeds and more cautious driving behaviors.
- Segment Length (segment_length):
 - Variable type: Numeric.
 - Description: This variable represents the length of the road segment in meters.

- Coefficient interpretation: The coefficient of 0.001573 suggests that with each additional meter in segment length, the accident risk slightly increases. Longer segments logically imply greater exposure to accident risk as a result of increased exposure.
- E-Scooter Traffic (e_scooter_traffic):
 - Variable type: Numeric.
 - Description: This variable represents the average daily number of e-scooters passing through the segment.
 - Coefficient interpretation: With a positive coefficient (0.0006975), it suggests that an increase in e-scooter traffic is associated with a higher risk of crashes. This association reflects how the rise of micromobility in urban areas leads to complex interactions between various road users.

The pseudo- R^2 value of 0.16 indicates that the model explains approximately 16% of the variability in crash data. While this might seem relatively low, it is important to recognize that road crashes are influenced by a multitude of factors, many of which are stochastic or external to the recorded parameters. In the context of road safety models, such pseudo- R^2 values are not unusual and are considered acceptable, as they reflect the inherently complex and multifactorial nature of crash data. Note also that this is one of the first attempts, based on limited available data, to predict e-scooter crashes based on traffic, geometric and context-related variables.

3.2.5 Discussion of Results: Model for Road Segments

The predictive model for road segments, developed using binomial regression, highlights several key factors influencing crash risk. The model includes variables related to traffic volume, lane configurations, and the presence of infrastructural elements such as medians and bike lanes. The results show a significant relationship between traffic density (for both traditional vehicles and electric scooters) and the frequency of accidents on road segments.

This section discusses the results of the road segment model. Two exposure-related significant variables in the model are `adt_per_lane` (average daily traffic per lane) and `e_scooter_traffic`. Both are associated with crash risk, suggesting that higher traffic volumes increase the likelihood of crashes. The increase in vehicular and e-scooter traffic directly correlates with a heightened risk of non-compliance with traffic rules, leading to reduced road safety and a probable rise in crash frequency (Siebert et al., 2021; Useche et al., 2022a, 2022b).

This finding underscores the growing importance of micromobility in urban transportation and the necessity for infrastructures that can accommodate both traditional vehicles and emerging transportation modes, such as electric scooters. The rise in e-scooter usage results in greater exposure, which is in turn linked to higher crash rates, a fact that may be exacerbated in areas where micromobility-dedicated infrastructures are underdeveloped.

The presence of a median (`median_presence`) on the road was found to increase the risk of e-scooter crashes. While this finding may seem counterintuitive, as medians are generally considered safety measures that separate traffic flows, it can be explained by the dynamics they introduce in high-traffic environments. In such contexts, medians may lead to abrupt lane changes or risky overtaking maneuvers on the separated carriageways, increasing the likelihood of crashes (Li & Sun, 2017). Specifically, in high-traffic areas, medians can contribute to side-swipe crashes or those arising from lane-changing behavior. These findings suggest that the presence of medians may require careful consideration, particularly in areas with dense traffic where they could inadvertently contribute to crash risks, with particular regard to e-scooters.

Conversely, the model revealed a negative relationship between the presence of side accesses (`side_access`) and the occurrence of crashes. While this might initially seem counterintuitive, it is likely attributable to lower driving speeds and more cautious behavior in road segments with side accesses. Roads with multiple side accesses may inherently promote safer driving due to the potential for vehicles entering or exiting the road, which encourages drivers to slow down and proceed with greater caution. This

inverse relationship highlights how side accesses can contribute to safer driving environments by mitigating e-scooter crash risks.

Road segment length was found to be positively correlated with crash risk, indicating that longer road segments tend to have higher crash likelihood. This relationship likely stems from greater exposure to traffic flow and an increased number of potential conflict points over a longer distance. Interestingly, while longer road segments are associated with higher speeds, which directly contribute to increased crash risk, road segments with side accesses are linked to reduced speeds and safer driving behaviors. This contrast underscores the complex interplay between speed, road design, and crash risks (Jasiūnienė & Tumavičė, 2022; Chen et al., 2020). Together, these findings highlight the importance of designing roadways that balance speed management and access control to optimize safety outcomes.

On the other hand, the presence of bike lanes (`bike_lane`) has shown an increase in the risk of e-scooter crashes. While bike lanes are generally considered an element that enhances cyclist safety, our findings suggest that, in some cases, they may introduce conflicts between cyclists and other road users, such as motorists or pedestrians, in mixed environments. These results are supported by the existing literature, as also referenced in the background chapter.

In fact, recent studies, such as Blazanin et al. (2022), suggest that shared bike lanes can introduce conflicts when not adequately designed. Proposed solutions include physical separation between bike lanes and motor vehicle lanes, increasing the space between parking lanes and bike lanes, and improving the maintenance of existing infrastructure. Furthermore, Laa and Leth (2020) and Pérez-Zuriaga et al. (2023) propose the introduction of traffic-calmed zones to mitigate conflicts in high-density urban contexts.

To support the model result indicating that the presence of bicycle lanes increases the risk of crashes for electric scooters, a detailed analysis was conducted on road segments with bicycle lanes where accidents involving electric scooters occurred. This analysis was based on the dataset used to develop the model, aiming to understand the reasons behind this result, which at first glance may appear counterintuitive.

From the detailed descriptive analysis of the 20 sites (in the database for developing the model), where at least one crash occurred in presence of bicycle lanes:

- Some of the so-called "bicycle lanes" included in the study are, in fact, not properly defined as such. In many cases (25%), the crashes occurred in areas referred to as cycle paths or lanes, often lacking a raised curb. This variability in design allows vehicles to encroach on spaces meant for cyclists, increasing the risk of collisions. Notably, some of these lanes were appropriately designed during the COVID-19 period, when traffic flows were lower. They were developed with the aim of promoting the use of eco-friendly modes of transportation, such as bicycles and electric scooters, which during that time were also emerging as an alternative to public transport (figure 13).



Fig. 13- Cycling lane on Corso Vittorio Emanuele II in Bari, source: Google Street View.

- In some crashes (10%), the electric scooter rider was presumably (based on police reports or the type of accident) outside the designated bicycle lane (Longo et al., 2024), which was allowed to travel until the recent modifications in the Highway Code.

When e-scooters circulated outside the bike lane, as observed in some cases, there is an additional safety concern. The presence of a bike lane often results in a narrower adjacent road lane, especially when the bike lane has been

added after the road original construction. This reduced lane width increases the risks for e-scooters mixing with motorized traffic.

In the broader analysis of crashes on roads with bicycle lanes, unless the police report specifically indicates the location of the crash, it is often impossible to determine with certainty whether the incident occurred on or outside the bike lane. This limitation highlights the need for more precise data collection and reporting to better understand crash dynamics in such contexts.

- Interruptions in bicycle lanes, both at medians to allow vehicles to perform U-turns and at side access points where the lane runs along the edge of the road, pose significant safety risks for e-scooter riders. These interruptions should be carefully redesigned to prevent conflicts between vehicles and riders/cyclists, ensuring that vulnerable road users can navigate these areas safely (figure 14).



Fig. 14- Bike lane on Viale Unità d'Italia in Bari, source: Google Street View.

- In some cases (15%), crashes occurred due to pedestrians entering the bicycle lane. In these scenarios, the issue is not the interaction between electric scooters and vehicles but rather conflicts between scooters and pedestrians.
- In other cases (40%), electric scooters fell without external involvement, either due to rider distraction or poor road surface conditions on the bicycle lanes or paths.

Finally, with the introduction of the new Highway Code reform in Italy (Law approved on November 20, 2024), electric scooters will no longer be allowed to circulate on bike lanes. This significant regulatory change renders many of the concerns raised about e-scooter interactions on bike lanes less relevant for future road safety analysis. However, these findings remain valuable for understanding past dynamics and for considering potential implications if similar mixed-use infrastructure is allowed elsewhere. Policymakers must ensure that future infrastructure design adequately separates different road users and/or provide the necessary traffic calming measures for mixed traffic to reduce conflicts and enhance overall safety.

These observations suggest that the real issue with bicycle lanes often lies in design-related or external factors, which contribute significantly to the increased risk for electric scooter riders. However, based on these remarks, the idea that bicycle lanes are less safe for e-scooters, if properly designed and operated, should be rejected.

The findings of this study contribute to the growing body of literature on road safety by quantifying the relationships between traffic volume, infrastructural characteristics, and e-scooter crash risk on urban road segments. While some results, such as the positive correlation between traffic volume and crashes, align with previous studies, others, such as the higher risk associated with the presence of bike lanes and medians, highlight areas that require further investigation and improvements in road design. These findings provide valuable insights for urban planners and policymakers, emphasizing the need for an integrated infrastructure that accommodates both traditional vehicles and new forms of transportation, such as electric scooters.

3.3 Crash likelihood model for Road Intersections: Results and Discussion

The analysis of data related to road intersections led to the construction of a predictive model using logistic regression. This model aims to identify the main factors influencing the risk of e-scooter crashes at road intersections and represents a significant contribution to understanding road safety, with particular focus on mixed vehicular traffic and micromobility.

Before building the model, it was necessary to load and prepare the data. The dataset, named `intersection.csv`, was loaded into R with the following command:

```
d <- read.csv("intersection.csv", sep = ";", header = TRUE, stringsAsFactors = FALSE)
```

In this step:

- `sep = ";"` specifies that the field separator is a semicolon, in accordance with the CSV format used.

- `header = TRUE` indicates that the first row of the file contains the column names.

- `stringsAsFactors = FALSE` prevents the automatic conversion of strings to factors, allowing more control over data types and applicable transformations.

The original dataset included several variables related to the characteristics of the road intersections, which were subsequently transformed and categorized to optimize statistical analysis.

3.3.1 Descriptive analysis of road intersection variables

To offer a thorough overview of the dataset related to road intersections, a descriptive analysis was performed to summarize the main characteristics of both categorical and numerical variables. Table 17 displays the distribution of categorical variables, detailing the frequency and percentage of occurrences for each category. This table provides key insights into the characteristics of the intersections analyzed, including intersection type (three-legged or four-legged), presence of turning lanes, types of signage (yield sign, traffic signal, or stop sign), and bicycle crossings. The data are organized by distinguish between intersections where crashes occurred and those without incidents, allowing for an assessment of how different infrastructure elements may relate to crash occurrence. Notably, the majority of intersections are four-legged,

and turning lanes are present in only a small fraction of cases. The distribution of signage types suggests that yield signs and traffic signals are more common than stop signs, while bicycle crossings are relatively rare. Table 18 provides descriptive statistics for numerical variables, including measures such as the mean and standard deviation, which help capture the central tendency and variability of the data. This table summarizes key traffic metrics for intersections, including vehicular traffic on the main and secondary intersecting streets (ADT1 and ADT2), total vehicular traffic (adtvehtot), and e-scooter traffic on the main and secondary streets (adtmon1 and adtmon2), as well as their total (adtmonotot). The values are further broken down into intersections where crashes occurred and those without crashes.

Table 17 - Descriptive statistics for categorical variables (intersections)

<i>Category*</i>	0	1	2	3	4	Total
intersec- tion_type						
Total	0 (0%)	0 (0%)	0 (0%)	168 (42%)	233 (58%)	401
Crashed	0 (0%)	0 (0%)	0 (0%)	57 (44%)	74 (56%)	131
Not Crashed	0 (0%)	0 (0%)	0 (0%)	111 (41%)	159 (59%)	270
turning_lanes						
Total	363 (91%)	38 (9%)	0 (0%)	0 (0%)	0 (0%)	401
Crashed	113 (86%)	18 (14%)	0 (0%)	0 (0%)	0 (0%)	131
Not Crashed	250 (93%)	20 (7%)	0 (0%)	0 (0%)	0 (0%)	270
signage						
Total	180 (45%)	39 (10%)	110 (27%)	72 (18%)	0 (0%)	401
Crashed	76 (58%)	11 (8%)	34 (26%)	10 (8%)	0 (0%)	131
Not Crashed	104 (39%)	28 (10%)	76 (28%)	62 (23%)	0 (0%)	270
bike_crossing						

Category*	0	1	2	3	4	Total
Total	378 (94%)	23 (6%)	0 (0%)	0 (0%)	0 (0%)	401
Crashed	117 (89%)	14 (11%)	0 (0%)	0 (0%)	0 (0%)	131
Not Crashed	261 (97%)	9 (3%)	0 (0%)	0 (0%)	0 (0%)	270

*intersection_type: 3 three-legged, 4 = four-legged;

turning_lanes: 0=Absent, 1=Present

signage: 0=Absent, 1= Yield Sign (or Roundabout), 2=Traffic Signal, 3=Stop;

bike_crossing: 0=Absent, 1=Present.

Table 18 - Descriptive statistics for numerical variables (intersections)

	ADT1	ADT2	adtvehtot	adtmon1	adtmon2	adtmonotot
Mean	11576	4974	16550	332	194	526
<i>Mean crashed</i>	11960	5017	16977	362	215	575
<i>Mean not crashed</i>	11390	4953	16342	317	185	502
Standard deviation	8267	4275	11062	308	206	416
<i>Standard deviation crashed</i>	8437	4607	11739	317	227	421
<i>Standard deviation not crashed</i>	8193	4113	10734	304	194	413

3.3.2 Results of the road intersection model building

The variables loaded from the `intersection.csv` file represent various infrastructure and traffic characteristics of the road intersections.

Some of the variables loaded were transformed into factors to correctly represent discrete data in the model and optimize the treatment of binary variables. The transformation was performed for the following variables:

- rangeadt1 <- factor(rangeadt1)
- rangeadt2 <- factor(rangeadt2)
- rangeadttot <- factor(rangeadttot)
- intersection_type <- factor(intersection_type)
- turning_lanes <- factor(turning_lanes)
- signage <- factor(signage)
- bike_crossing <- factor(bike_crossing)
- accidents <- factor(accidents)

These variables represent different aspects of the intersections:

- `rangeadt1`, `rangeadt2`, and `rangeadttot` represent the ADT ranges for the main, secondary street, and the total intersection, respectively.
- `intersection_type`, `turning_lanes`, `signage`, and `bike_crossing` are variables indicating the type of intersection, presence of turning lanes, signage, and bike crossings.

For some numerical variables, a logarithmic transformation was created, based on previous research (e.g., Intini et al., 2021). The transformed variables are:

- $\log_ADT1 <- \log(ADT1)$
- $\log_ADT2 <- \log(ADT2)$
- $\log_adtmon1 <- \log(adtmon1)$
- $\log_adtmon2 <- \log(adtmon2)$

These logarithmic variables were included in the model to enhance the predictive accuracy of the final model.

After data preparation, multiple combinations of variables were tested to determine their statistical significance ($p\text{-value} < 0.05$). Each combination was evaluated for its ability to maximize the inclusion of significant variables and improve the model overall fit. Through a comparative analysis of various candidate models, the final model was chosen based on its capacity to highlight the most critical variables influencing e-scooter crash risk specifically at road intersections. This approach ensures a robust representation of the factors contributing to crash dynamics in these traffic nodes.

At the end of the selection process, the resulting model was as in Tab. 19).

Table 19 - E-scooter crash likelihood prediction model for road intersections

Variable	Estimate	Std. Error	z value	Pr(>z)
(Intercept)	-51.163	21.956	-2.330	0.01979 *
signage1	-0.9405	0.4207	-2.235	0.02540 *
signage2	-0.6103	0.2761	-2.210	0.02707 *
signage3	-16.257	0.3839	-4.235	2.28e-05 ***
bike_crossing1	14.809	0.4750	3.118	0.00182 **
prop_adt1	26.985	11.874	2.273	0.02305 *
prop_adt_escooter2	10.220	0.5492	1.861	0.06278 .
log_ADT2	0.2848	0.1731	1.646	0.09986 .
ratio_e_scooter_vehicles_1	41.942	24.329	1.724	0.08471 .

3.3.3 Interpretation of the Variables included in the selected intersection model

In this paragraph, the variables included in the selected model are described, interpreted and discussed.

The intercept term represents the baseline crash risk at intersections when all other variables are set to zero. The estimate of the intercept is -5.1163, with a standard error of 2.1956, a z-value of -2.330, and a p-value of 0.01979 (*), indicating statistical significance. Considering that the intercept is negative, it primarily serves as a reference point, as the actual risk is significantly influenced by the other variables included in the model.

The presence of signage was modeled through three variables: *signage1*, *signage2*, and *signage3*. For *signage1*, representing the presence of roundabouts or yield signs, the estimate is -0.9405 with a standard error of 0.4207, a z-value of -2.235, and a p-value of 0.02540, indicating statistical significance. Similarly, *signage2*, which represents the presence of traffic signals, has an estimate of -0.6103, a standard error of 0.2761, a z-value of -2.210, and a p-value of 0.02707. For *signage3*, representing stop signs, the estimate is -1.6257 with a standard error of 0.3839, a z-value of -4.235, and a p-value of 2.28e-05. These results suggest that the presence of these types of signage, particularly stop signs, is associated with a reduction in crash likelihood compared to the absence of signage.

The presence of bicycle crossings is represented by the variable *bike_crossing1*, which has an estimate of 1.4809, a standard error of 0.4750, a z-value of 3.118, and a p-value of 0.00182. This positive coefficient indicates that intersections with bicycle crossings are associated with an increased crash likelihood, possibly due to interactions between vehicles and e-scooter riders in shared or adjacent spaces.

The proportion of traffic on the main street (*prop_adt1*) has an estimate of 2.6985, a standard error of 1.1874, a z-value of 2.273, and a p-value of 0.02305. This positive coefficient suggests that as the proportion of traffic on the main street increases, so does the likelihood of crashes, likely due to higher congestion and more frequent interactions between vehicles.

The proportion of e-scooter traffic on the secondary street ($\text{prop_adt_escooter2}$) is associated with an estimate of 1.0220, a standard error of 0.5492, a z-value of 1.861, and a p-value of 0.06278. Although the coefficient is positive, suggesting that higher e-scooter traffic on the secondary street might increase crash risk, the relationship is marginally significant and not conclusive at the 5% level.

The logarithmic transformation of vehicular traffic on the secondary street (log_ADT2) has an estimate of 0.2848, a standard error of 0.1731, a z-value of 1.646, and a p-value of 0.09986. This indicates a marginal association between increased traffic and a higher risk of crashes.

Finally, the e-scooter-to-vehicle traffic ratio on the main street ($\text{ratio_e_scooter_vehicles_1}$) has an estimate of 4.1942, a standard error of 2.4329, a z-value of 1.724, and a p-value of 0.08471. This suggests that an increased ratio of e-scooter traffic to vehicle traffic might be associated with a higher crash risk, though the relationship is not statistically significant at the 5% level.

The pseudo R^2 value of the model is 0.13, indicating that the model accounts for 13% of the variability in crash data. While this figure may appear modest, also in this case it is essential to recognize that road crashes are influenced by a multitude of factors, many of which are stochastic or external to the recorded parameters. In road safety modeling, pseudo R^2 values of this magnitude may be considered acceptable as they reflect the inherently complex and variable nature of crash data. This metric provides a meaningful measure of the model explanatory power within the context of such high variability. Moreover, also in this case, this is one of the first attempts to predict e-scooter crashes at intersections, based on traffic, geometric and context-related variables.

3.3.4 Alternative models

Similarly to what performed for segments, alternative models for intersections are presented in this sub-section.

Table 20 - Alternative model 1 (intersections)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-38.415	20.296	-1.893	0.05839 .
signage1	-0.9454	0.4195	-2.254	0.02422 *
signage2	-0.6199	0.2755	-2.250	0.02447 *
signage3	-16.389	0.3833	-4.275	1.91e-05 ***
bike_crossing 1	14.788	0.4743	3.118	0.00182 **
prop_adt1	25.607	11.775	2.175	0.02965 *
prop_adt_escooter1	-0.9259	0.5449	-1.699	0.08924 .
log_ADT2	0.2620	0.1713	1.529	0.12627
ratio_e_scooter_vehicles_1	38.324	24.177	1.585	0.11294

In this alternative model (table 20), there are several statistically significant coefficient estimates, but there are some issues to consider. In particular, the variables “prop_adt_escooter1” and “ratio_e_scooter_vehicles_1” do not show significant effects on the crash risk, meaning that the relationship with crashes is less clear in this model. In fact, this model suggests that signage and bike crossings are more important factors than e-scooter traffic. However, some variables, such as “prop_adt_escooter1”, are not significant, meaning further exploration was needed to possibly improve the model.

Table 21 - Alternative model 2 (intersections)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-29.762	16.231	-1.834	0.06671 .
signage1	-0.9470	0.4192	-2.259	0.02386 *
signage2	-0.6084	0.2748	-2.214	0.02685 *
signage3	-16.395	0.3839	-4.271	1.95e-05 ***
bike_crossing 1	14.815	0.4734	3.130	0.00175 **
prop_adt1	0.9895	0.8518	1.162	0.24537
prop_adt_escooter1	-0.9383	0.5492	-1.708	0.08755 .
log_ADT1	0.2598	0.1864	1.394	0.16324
ratio_e_scooter_vehicles_1	37.515	24.583	1.526	0.12699

In this model (table 21), the overall performance improves, but there are still variables that fail to provide meaningful insights. In particular:

- “prop_adt1” remains insignificant, showing that the traffic-to-lane ratio does not significantly influence accidents in this model.
- “log_ADT1”, “ratio_e_scooter_vehicles_1” - both these variables remain insignificant, suggesting that they do not have a strong influence on the crash likelihood.

Despite the improvements in the number of significant variables, the inclusion of these not statistically significant coefficient estimates might be diluting the overall model fit. Therefore, these variables may need to be excluded or reconsidered.

Table 22 - Alternative model 3 (intersections)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-32.330	16.393	-1.972	0.04859 *
signage1	-0.9247	0.4211	-2.196	0.02809 *
signage2	-0.5937	0.2760	-2.151	0.03146 *
signage3	-16.453	0.3855	-4.268	1.97e-05 ***
bike_crossing 1	14.649	0.4759	3.078	0.00208 **
prop_adt1	14.347	10.004	1.434	0.15154
prop_adt_escooter1	-12.490	0.6029	-2.072	0.03829 *
log_ADT1	0.2725	0.1896	1.437	0.15062
ratio_e_scooter_vehicles_1	53.328	28.015	1.904	0.05697 .
ratio_e_scooter_vehicles_2	-0.6211	0.7125	-0.872	0.38333

This model (Table 22) includes all the previous variables with the addition of “ratio_e_scooter_vehicles_2”. However:

- “prop_adt1” remains insignificant.
- “log_ADT1” also shows no effects on crashes, even when considered alongside other variables.

- “ratio_e_scooter_vehicles_2” remains insignificant, meaning it does not contribute to the model.

Although the model does introduce new factors like “ratio_e_scooter_vehicles_2”, they do not significantly impact the outcome. Also in this case, the presence of many not statistically significant variables hinders the interpretation of the model.

Table 23 - Alternative model 4 (intersections)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-36.786	21.769	-1.690	0.09107 .
signage1	-0.9258	0.4216	-2.196	0.02808 *
signage2	-0.6006	0.2770	-2.168	0.03016 *
signage3	-16.424	0.3852	-4.263	2.01e-05 ***
bike_crossing_1	14.657	0.4762	3.078	0.00209 **
prop_adt1	22.070	26.646	0.828	0.40752
prop_adt_escooter1	-12.160	0.6119	-1.987	0.04688 *
log_ADT2	0.1377	0.4404	0.313	0.75462
ratio_e_scooter_vehicles_1	52.246	28.238	1.850	0.06429 .
log_ADT1	0.1372	0.4724	0.290	0.77150
ratio_e_scooter_vehicles_2	-0.5465	0.7523	-0.726	0.46761

This model (Table 23) includes the variables from the previous models, but the effect of “prop_adt_escooter1” is significant here, paired with traffic-to-lane ratio and signage. However:

- “prop_adt1” remains insignificant.
- “log_ADT1” and “ratio_e_scooter_vehicles_2” do not significantly contribute to the model.

While this model includes additional variables, it still contains some not meaningful predictors. The model might be overfitting with too many variables, some of which do not add value.

After reviewing the performance of the models, it is clear that the most influential predictors of crash risk are:

- Signage (types of road signs);
- Bike crossings;
- Traffic-to-lane ratio (prop_adt1).

These variables consistently showed statistical significance in multiple models, indicating they are key drivers in explaining the crash likelihood. On the other hand, variables like “prop_adt_escooter1”, “log_ADT1” and “ratio_e_scooter_vehicles_1” failed to show consistent or meaningful relationships with the crash likelihood. These remarks were considered while choosing the final presented model, which was deemed more reliable and interpretable than the others shown here.

3.3.5 Discussion of Results: Model for Road Intersections

In this section, the results of the intersection model are discussed. A comparison with the literature helps contextualize the findings within a broader perspective on the issue of road safety.

The model revealed that the presence of any signage (with respect to their complete absence) is associated with a significant reduction in e-scooter crash risk. Among these signs, stop signs demonstrate the most substantial impact on improving safety. Stop signs effectively reduce vehicle speeds at intersections, fostering cautious behavior among all road users. This speed regulation contributes to minimizing the likelihood of crashes. Studies by Navarro et al. (2022) and Stipancic et al. (2021) confirm these findings, highlighting that stop-controlled intersections enhance safety by managing vehicle interactions and promoting better adherence to traffic rules. While traffic signals and roundabout or yield signs also play important roles in improving intersection safety, the presence of stop signs stands out as a particularly effective measure for mitigating e-scooter crash risks.

The variable bike_crossing1, representing the presence of bicycle crossings, displayed a positive coefficient, suggesting that bicycle crossings may increase the risk

of e-scooter crashes. This result aligns with the notion (already treated for bike lanes in the case of segments) that improperly designed bicycle crossings can pose safety risks due to interactions between riders/cyclists and vehicles. To mitigate these risks, it is essential to design well-separated and clearly marked bicycle crossings. Proper separation minimizes potential conflicts among road users and enhances overall safety at intersections. This underscores the importance of thoughtful infrastructure planning that prioritizes the safe coexistence of all transportation modes.

The variable `prop_adt1`, which represents the proportion of traffic on the main intersecting road related to the total traffic, was found to be positively correlated with the risk of e-scooter crashes. This suggests that a highly trafficked main road increases the probability of crashes, particularly for e-scooters. This elevated risk can be attributed to the tendency of vehicles on the main road to overlook those approaching from secondary roads, especially more vulnerable users like e-scooter riders. Such dynamics highlight the challenges e-scooters face in navigating intersections dominated by heavy main road traffic.

The logarithmic transformation of vehicular traffic on the roads showed a marginal but positive effect on crash risk. Although the effect is not statistically significant at the 5% level, the p-value close to 10% suggests a potential relationship, indicating that increased traffic may logically contribute, albeit slightly, to the risk of crashes.

The variable `prop_adt_escooter2`, which represents the proportion of e-scooter traffic on the secondary intersecting road relative to the total e-scooter traffic, also showed a positive coefficient. This suggests that a higher concentration of e-scooter traffic on the secondary road may increase the risk of crashes. For e-scooters, the most critical condition arises when their traffic is highly concentrated on the secondary road. This result is complementary to the findings for vehicular traffic on the primary road, highlighting how disparities in traffic volume and vehicle types between intersecting roads can increase crash risks for e-scooters. This dynamic is likely due to vehicles on the primary road being less likely to notice or yield to e-scooters coming from the secondary road. However, the marginal p-value indicates that this effect is not statistically significant at the 5% level, requiring further investigation to confirm this trend.

One of the most significant findings previously shown relate to the direct relationship between the vehicular traffic on the main intersecting roads and the higher risk of e-scooter crashes. If coupled with the general negative effect of exposure due to total traffic volumes, this finding aligns with previous studies, such as Nordback et al. (2014), which demonstrated a direct link between traffic volumes and crash frequency. In detail, that study, applied to Boulder, Colorado (USA) developed safety performance functions (SPFs) for cyclists, revealing that intersections with higher cyclist and motorist traffic volumes exhibit a greater number of collisions between these two road user groups. However, it is noteworthy that intersections with higher numbers of cyclists experience fewer collisions per cyclist, suggesting that increased cycling use may enhance motorist awareness and caution.

The detailed analysis of intersections where e-scooter crashes occurred, and which are marked by the presence of bicycle crossings, revealed a series of infrastructural and behavioural issues that help explain the high risk associated with these situations. Although the developed model indicates a positive correlation between the presence of bicycle crossings and the risk of crashes, this evidence must be interpreted within the context of the actual conditions of the analyzed infrastructures.

Most of the intersections (67%) analyzed and marked in the database as having bicycle crossings actually feature bicycle crossings located directly at the intersections. Specifically:

- Bicycle crossings should be designed to ensure the safety and visibility of vulnerable users, such as cyclists and e-scooter riders (the latter until the new regulations imposed in the Highway Code). However, due to the existing boundary conditions, many of these crossings are at the corner of the intersection, making it difficult for e-scooter riders and motor vehicles to see each other.



Fig. 15 - Bicycle crossing at Corso Vittorio Emanuele and Via Marchese di Montrone, Bari, source: Google Street View.

- The lack of traffic lights at the intersection may exacerbate the risk of dangerous interactions, especially in areas where vehicles make turns or lane changes.

At the same time, the presence of a bike lane or cycle track can give e-scooter riders a false sense of security, leading them to reduce their level of caution and attention. This behaviour could partly explain the risk associated with e-scooter crashes, especially in situations where the crossing design does not facilitate safe interactions with other road users.

A qualitative analysis of accident reports revealed that some crashes were caused by self-induced falls of e-scooter riders (17%), attributed to road surface deterioration or improper handling of the vehicle.

It was not possible to definitively determine this, but it is also likely that some crashes occurred because riders did not properly use the bicycle crossing or were outside the designated lane, thereby increasing their exposure to motorized traffic.

Once again, these data highlight that the issues related to bicycle crossings mainly stem from design-related or external factors, which contribute to the increased risk for e-scooter riders.

Structural interventions are essential to:

- Adapt bicycle crossings by improving visibility and safety.
- Particularly prioritize visibility at crossings, ensuring that users and motor vehicles can see each other from a safe distance.
- Implement clear signage at critical points or, if necessary, physical modifications to the intersections, such as raising the entire intersection or just the crossing.
- Raise awareness among vulnerable users about the importance of cautious behavior, even when using dedicated infrastructures.

Furthermore, with the introduction of the new Highway Code reforms in Italy (November 20, 2024), electric scooters will no longer be permitted to use bicycle crossings. This legislative change significantly impacts the findings and their implications, requiring a redefinition of safety strategies and infrastructural design considerations in line with the updated regulations and updated data-based studies.

These findings underscore the importance of carefully considering traffic distribution at intersections and the impact that high concentration on specific roads can have on safety, particularly with respect to micromobility and its associated risks.

CONCLUSIONS

This study provides an in-depth analysis of crash likelihood, severity and dynamics involving e-scooters in urban contexts, focusing particularly on the city of Bari, Italy. Through the development of predictive statistical models for road segments and intersections, the study identifies key factors influencing crash risk and highlights critical areas for improving urban mobility and safety. The findings reveal significant trends and relationships that can guide urban planning and future transportation policies.

From the specific analysis conducted in Bari, several important insights emerge. The dataset, which covered crashes from July 2020 to November 2022, revealed that 70% of recorded crashes involved injuries, although no fatalities occurred. Injury severity was higher at night and in crashes involving pedestrians or road surface issues. Divided roads appeared less safe than undivided ones, and calm hours, distinct from nighttime hours, emerged as the most dangerous period for crash occurrences. Single-vehicle crashes, particularly at road segments, were the most common type, and crashes involving pedestrians tended to have higher severity. Private e-scooters were involved in more crashes than shared ones, likely due to their greater usage rates. The analysis also highlighted that riders who did not use designated cycle paths faced significantly higher risks.

The analysis demonstrates that traffic volume plays a crucial role in determining crash risks. The positive correlation between vehicular traffic density and crash frequency underscores how increased traffic creates more conflict points, thereby elevating the likelihood of crashes. This result aligns with existing literature.

Infrastructural characteristics emerged as fundamental determinants of safety. Features like medians and bike lanes, typically considered safety enhancements, exhibited mixed effects. Inconsistent design or inadequate implementation can increase conflict points, especially in high-traffic areas. For instance, bike lanes that lack adequate separation or have interruptions for vehicle access can elevate risks for both cyclists and e-scooter riders. Conversely, intersections equipped with stop signs were

found to be significantly safer, as these signs encourage cautious driving behavior and reduce speeds. This finding highlights the importance of traffic-calming measures, particularly in areas with high vehicular and pedestrian activity.

The integration of micromobility, especially the growing use of e-scooters, into existing traffic systems remains a pressing concern. While e-scooters offer sustainable mobility options, their introduction has exposed significant gaps in current infrastructures and policies. Conflicts between e-scooters and other vulnerable road users, such as pedestrians and cyclists, continue to be a critical issue. These findings underscore the urgency of improving infrastructure design, providing better road-user education, and developing policies that address the unique needs of micromobility.

The predictive model analyzed both intersections and road segments, revealing that variables like the proportion of vehicular traffic on the main road of an intersection and e-scooter traffic significantly impact crash risks. An increase in the vehicular traffic, particularly on main roads, correlates with a higher crash risk. Similarly, a higher proportion of e-scooter traffic on secondary roads of an intersection highlights specific safety challenges for these vulnerable users. The influence of traffic on e-scooter crashes is in line with the existing literature, which identifies traffic volume as a critical determinant of crash frequency.

Another key finding relates to the design of cycling infrastructures. However, all the results from this study concerning this aspect and the related discussion, should be taken with caution, as regulations were recently updated to not allow e-scooters on bike paths.

The increasing penetration of e-scooters into urban daily traffic necessitates a comprehensive safety assessment to identify main issues and potential countermeasures. This study has shown that crash data analysis can inform practical interventions, ranging from infrastructure improvements to regulatory adjustments.

This study also highlights the need to address high-risk interactions between pedestrians and e-scooters at both infrastructural and regulatory levels. Measures such as using unfriendly road pavements for e-scooters in pedestrian areas or issuing fines

for violations can reduce conflicts. From a policy perspective, age restrictions and weight-control devices on e-scooters could help curb risky behaviors.

The increasing penetration of e-scooters in urban daily traffic implies that a safety assessment is needed to identify the main issues and think about possible countermeasures.

The methodological approaches and best practices identified can be generally applied to other similar urban contexts, providing a framework to address e-scooter safety challenges. Moreover, the findings generally align with previous literature, strengthening the idea of recurrent crash patterns for e-scooters, irrespective of the investigation site. A limitation of this study is the inability to develop crash frequency prediction models due to limited available temporal information. Additionally, the absence of traffic volume data on various road segments and the possible influence of the pandemic period on crash frequency contribute to this limitation. Future studies could address these gaps by collecting more comprehensive datasets and evaluating the long-term effects of interventions.

Ultimately, fostering a safer environment for e-scooter users requires a multifaceted approach, including infrastructure improvements, regulatory adjustments, and strategic urban planning. By aligning safety measures with local community needs, cities like Bari can create more sustainable and secure mobility systems.

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Embarking on this research journey has been a deeply enriching experience, and I am profoundly grateful to the individuals and organizations who have supported me throughout this endeavor. This work would not have been possible without the collaboration, expertise, and encouragement of those who believed in its value and potential.

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To all those who have contributed to this journey, directly or indirectly, I extend my sincerest gratitude. This thesis is a testament to the collaborative spirit and support I have received along the way.

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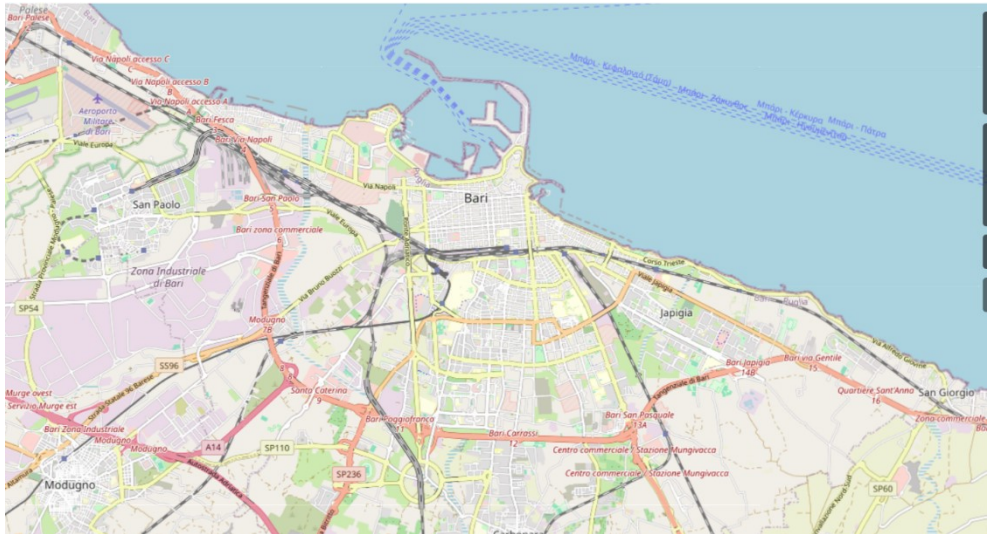


Fig. 1 - Map of the urban area of Bari, Italy, extracted from OpenStreetMap.

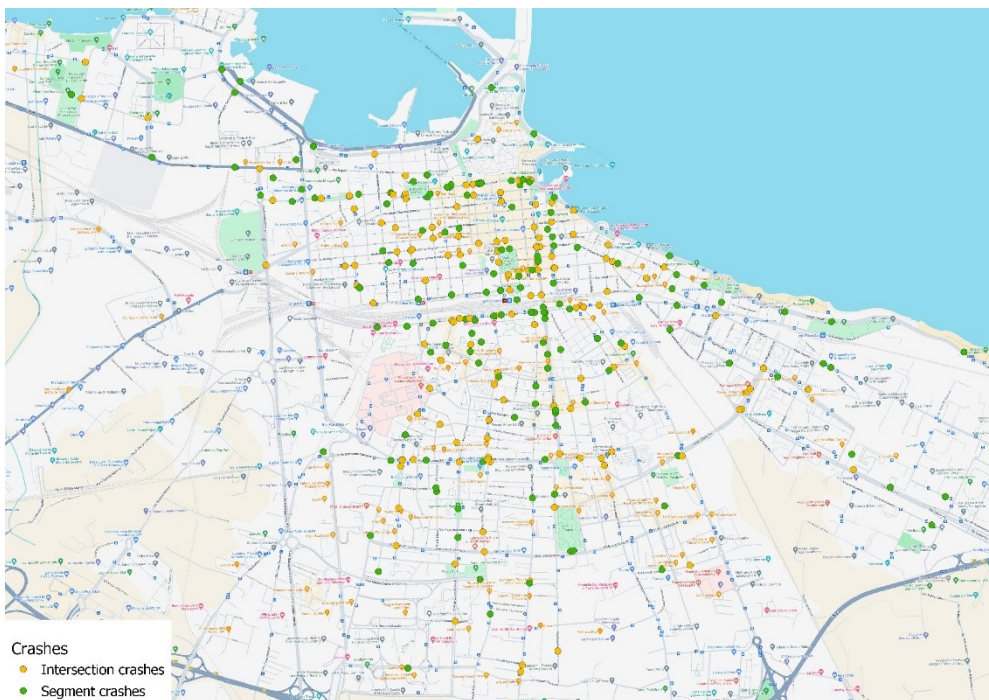


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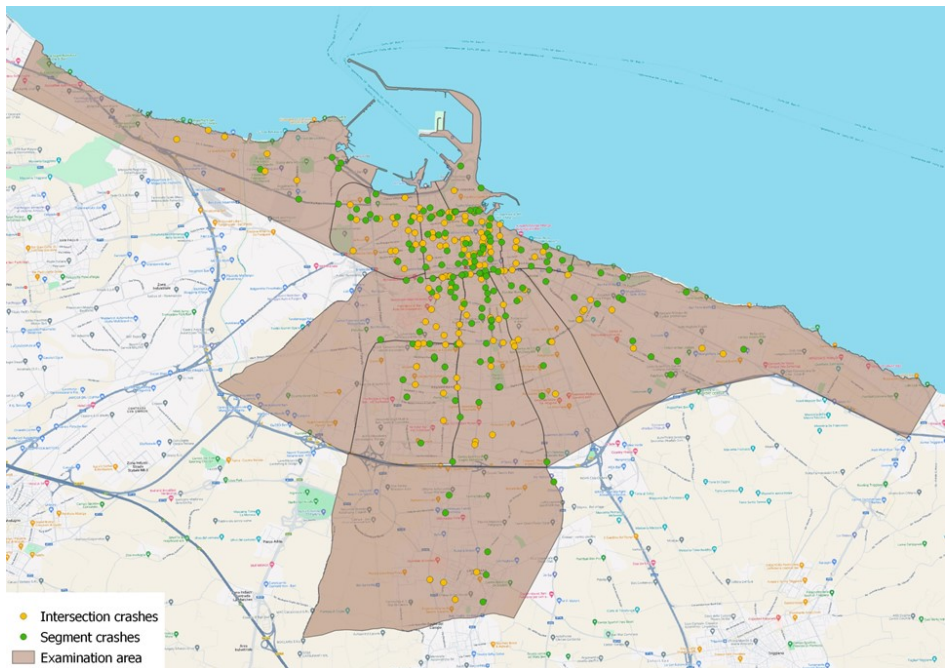


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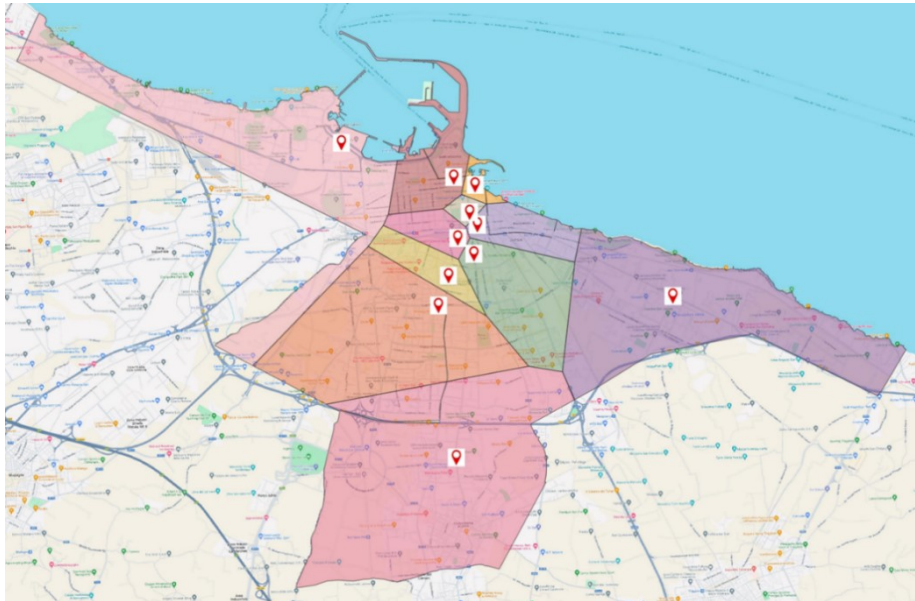


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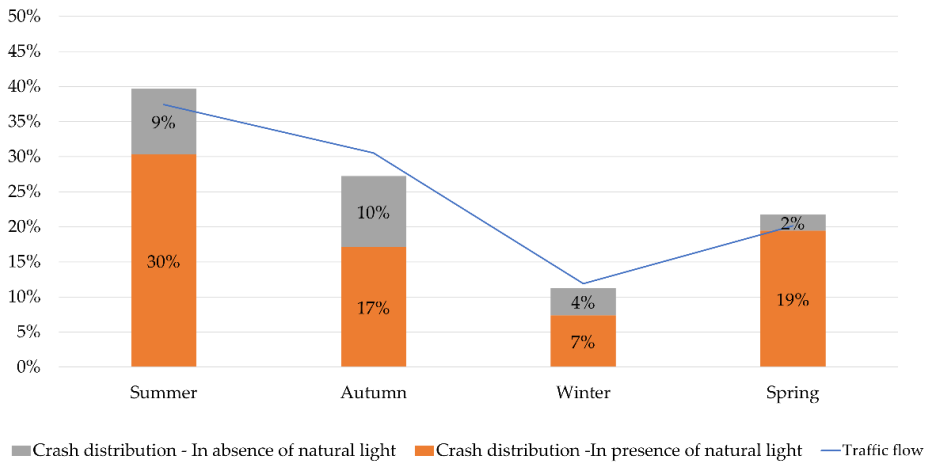


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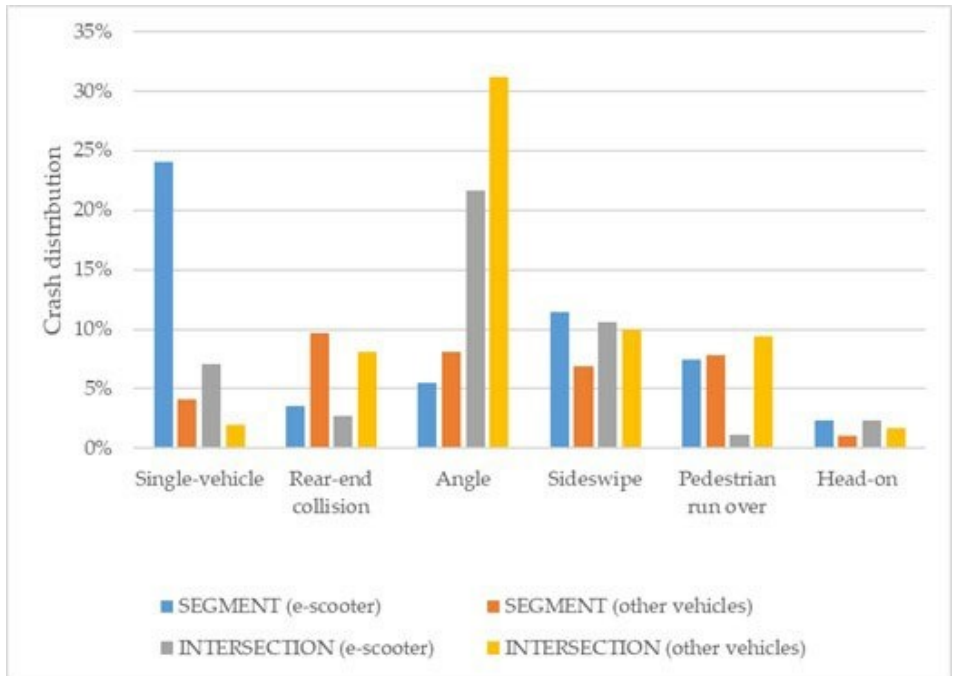


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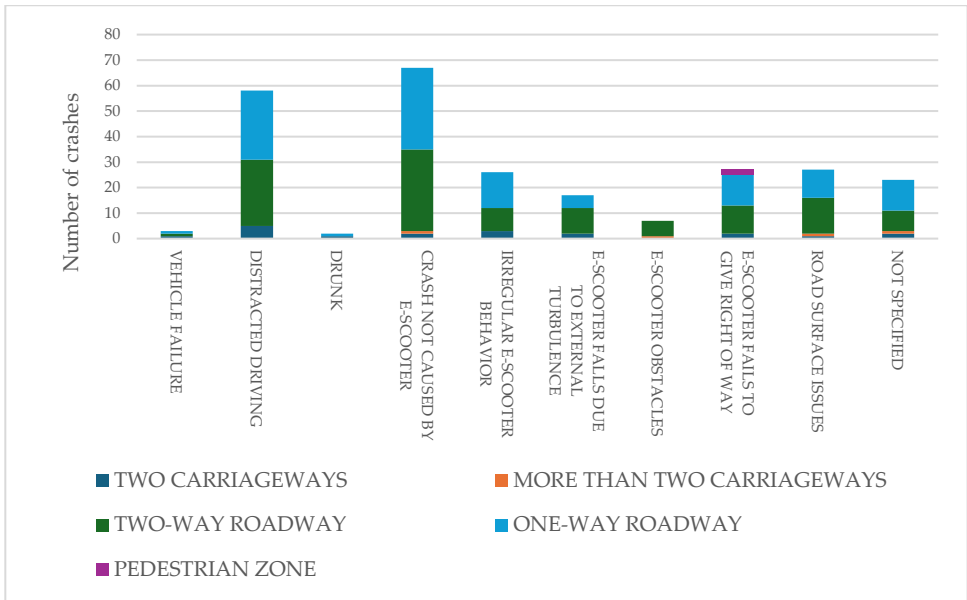


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Fig. 13- Cycling lane on Corso Vittorio Emanuele II in Bari, source: Google Street View.



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Fig. 15 - Bicycle crossing at Corso Vittorio Emanuele and Via Marchese di Montrone, Bari, source: Google Street View.

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Table 1 - Distribution of crashes in the period July 2020–November 2022

Year	Number of Crashes
2020 (from July to December)	41
2021 (from January to December)	118
2022 (from January to November)	98
Total	257

Table 24 – Variables of road segments database

traffic_range	Categorical variable indicating the range of average daily traffic (ADT) based on quartiles: - 25th Percentile: 2,807 vehicles/day - 50th Percentile: 6,154 vehicles/day - 75th Percentile: 10,630 vehicles/day - Maximum Value: 44,921 vehicles/day.
num_lanes	Number of lanes on the segment.
adt_per_lane	Average daily traffic per lane, calculated as vehicular_traffic divided by num_lanes (vehicles/day).
one_way	Presence of a one-way direction on the segment.
median_pre- sence	Presence of a median on the segment.
side_access	Presence of side access points.
parking_avai- lability	Availability of parking along the segment.
bike_lanes	Presence of a bicycle lane along the segment. The variable was not further categorized based on the type of bicycle lane (e.g.,

	segregated bike path or painted bike lane), as the number of sites with bicycle lanes was limited. This decision ensured simplicity in the model while maintaining its robustness.
pref_lanes	Presence of reserved lanes, such as those for public transport.
segment_length	Length of the segment in meters.
e_scooter_traffic	Average daily traffic of e-scooters.

Table 25 – Variables of intersections database

Variable Name	Description
rangeadt1	Categorical variable indicating the range of ADT on the main intersecting street based on quartiles: - 25th Percentile: 5,915 vehicles/day - 50th Percentile: 9,508 vehicles/day - 75th Percentile: 15,690 vehicles/day - Maximum Value: 44,921 vehicles/day.
ADT2	Vehicular traffic on the secondary intersecting street.
rangeadt2	Categorical variable indicating the range of ADT on the secondary street based on quartiles: - 25th Percentile: 1,838 vehicles/day - 50th Percentile: 3,749 vehicles/day - 75th Percentile: 6,693 vehicles/day - Maximum Value: 22,338 vehicles/day.
adtvehtot	Total vehicular traffic, calculated as the sum of ADT1 and ADT2.
rangeadttot	Categorical variable indicating the range of total ADT at the intersection based on quartiles:

Variable Name	Description
	<ul style="list-style-type: none"> - 25th Percentile: 8,690 vehicles/day - 50th Percentile: 13,597 vehicles/day - 75th Percentile: 22,724 vehicles/day - Maximum Value: 55,833 vehicles/day.
intersec- tion_type	Type of intersection (e.g., three- or four-legged).
turning_lanes	Presence of turning lanes at the intersection.
signage	Type of signage at the intersection: <ul style="list-style-type: none"> - Presence of Yield Sign (or Roundabout) - Presence of Traffic Signal - Presence of Stop Sign.
bike_crossing	Presence of bicycle crossings at the intersection.
adtmon1	Average daily traffic of e-scooters on the main street.
rangeadt- mono1	Categorical variable indicating the range of e-scooter traffic on the main street based on quartiles: <ul style="list-style-type: none"> - 25th Percentile: 98 e-scooters/day - 50th Percentile: 264 e-scooters/day - 75th Percentile: 508 e-scooters/day - Maximum Value: 1,648 e-scooters/day.
adtmon2	Average daily traffic of e-scooters on the secondary street.
rangeadt- mono2	Categorical variable indicating the range of e-scooter traffic on the secondary street based on quartiles: <ul style="list-style-type: none"> - 25th Percentile: 39 e-scooters/day - 50th Percentile: 129 e-scooters/day - 75th Percentile: 296 e-scooters/day - Maximum Value: 1,406 e-scooters/day.

Variable Name	Description
adtmonotot	Total daily e-scooter traffic, calculated as the sum of ADTmono1 and ADTmono2.
rangeadtmonotot	Categorical variable indicating the range of total e-scooter traffic at the intersection based on quartiles: - 25th Percentile: 166 e-scooters/day - 50th Percentile: 499 e-scooters/day - 75th Percentile: 773 e-scooters/day - Maximum Value: 2,234 e-scooters/day.

Table 26 - Descriptive statistics of the e-scooter crash dataset (Severity).

Crash-Related Variable	Number	Percentage
Severity		
Fatal	0	0%
With injuries to involved users	181	70%
No injuries	76	30%

Table 27 - Descriptive statistics of the e-scooter crash dataset (Severity).

Crash-Related Variable	Number	Percentage
Road type		
Undivided one-way	115	45%
<i>Undivided one-way with cycle path</i>	9	4%
<i>Undivided one-way w/o cycle path</i>	106	41%
Undivided two-way	117	45%
<i>Undivided two-way with cycle path</i>	28	11%
<i>Undivided two-way w/o cycle path</i>	89	34%
Divided multi-lane	19	7%
<i>Divided multi-lane with cycle path</i>	5	2%

Crash-Related Variable	Number	Percentage
<i>Divided multi-lane w/o cycle path</i>	14	5%
Three+ Carriageways	4	2%
<i>Three+ Carriageways with cycle path</i>	1	0%
<i>Three+ Carriageways without cycle path</i>	3	1%
Pedestrian zone	2	1%

Table 28 - Descriptive statistics of the e-scooter crash dataset (Motor-vehicle traffic conditions).

Crash-Related Variable	Number	Percentage
Motor-vehicle traffic conditions		
Peak hours (7 a.m.–9 a.m., 1 p.m.–3 p.m.)	48	19%
Night hours (10 p.m.–6 a.m.)	26	10%
Other calm hours	183	71%

Table 29 - Descriptive statistics of the e-scooter crash dataset (Season, Lighting conditions, road elements).

Season		
Summer	102	40%
Autumn	70	27%
Winter	29	11%
Spring	56	22%
Lighting conditions		
In presence of natural light	191	74%
In absence of light	66	26%
Road elements		
Signalized intersection	27	11%

Unsignalized intersection	80	31%
Curve	2	1%
Segment (incl. bridges, tunnels)	135	52%
Roundabout	9	4%
Bridge	4	2%

Table 30 - Descriptive statistics of the e-scooter crash dataset (crash type).

Crash-Related Variable	Number	Percentage
Crash type		
Single-vehicle	82	31%
Rear-end	16	6%
Angle	69	27%
Sideswipe	56	22%
Pedestrian hit	22	9%
Head-on	12	5%

Table 31 - Descriptive statistics of the e-scooter crash dataset (pavement conditions, e-scooter driver age, sex, private or shared e-scooter, causes).

Crash-Related Variable	Number	Percentage
Pavement conditions		
Dry	246	96%
Wet/Slippery	11	4%
E-scooter driver age		
< 18	24	9%
18–30	96	37%
31–40	42	16%
> 40	49	19%

Crash-Related Variable	Number	Percentage
Unspecified	46	18%
E-scooter driver sex		
Man	154	60%
Woman	57	22%
Unspecified	46	18%
Passenger on board		
Yes	12	5%
No	245	95%
Private or shared		
Shared	71	28%
Private	158	72%
Unspecified	28	11%
Crash causes		
Not caused by e-scooter	67	26%
E-scooter failure	3	1%
Distracted driving	58	23%
Drunk driving	2	1%
Irregular behavior	26	10%
External turbulence	17	7%
Parked e-scooter obstructing	7	3%
Failure to yield	27	11%
Road surface issues	27	11%
Unspecified	23	9%

Table 32 - Descriptive statistics of the e-scooter crash dataset (cyclo path).

Crash-Related Variable	Number	Percentage
Cycle path		
Crash on cycle path	25	10%
No cycle path	232	90%
<i>Cycle path present</i>	22	9%
<i>No cycle paths</i>	210	81%

Table 11 - Results of the logistic regression model for injury severity.

Explanatory Variable	Coeff. Estimate	Std. Error	z Value	p-Value
Day hour: peak hour (ref.: calm hour)	0.617	0.758	1.51	0.131
Day hour: night hours (ref.: calm hour)	1.451	2.639	2.35	0.019
Crash type: angle (ref.: single-vehicle)	-0.607	0.256	-1.29	0.196
Crash type: sideswipe (ref.: single-vehicle)	-0.384	0.324	-0.81	0.420
Crash type: pedestrian hit (ref.: single-vehicle)	2.141	7.572	2.40	0.016
<i>Crash type: other (ref.: single-vehicle)</i>	<i>-1.001</i>	<i>0.210</i>	<i>-1.76</i>	<i>0.079</i>
Age: <18 (ref.: 18-30)	0.936	1.503	1.59	0.113
Age: 31-40 (ref.: 18-30)	0.593	0.845	1.27	0.205
Age: >40 (ref.: 18-30)	0.350	0.622	0.80	0.424
Age: Unspecified (ref.: 18-30)	-0.069	0.070	-3.17	0.002
Sharing: sharing (ref.: private)	-0.235	0.290	-0.64	0.522

Explanatory Variable	Coeff. Estimate	Std. Error	z Value	p-Value
Sharing: Unspecified (ref.: private)	2.247	8.452	2.52	0.012
Dynamics: irregular e-scooter behavior (ref.: Crash not caused by the e-scooter)	0.143	0.445	0.37	0.711
Dynamics: other (ref.: Crash not caused by the e-scooter)	0.848	1.781	1.11	0.266
<i>Dynamics: Road surface issues (ref.: Crash not caused by the e-scooter)</i>	<i>1.601</i>	<i>4.334</i>	<i>1.83</i>	<i>0.067</i>

Likelihood ratio test (reference: null model): $\chi^2(15) = 43.22, p < 0.001, R^2 = 0.1385$.

Note: Estimated coefficients associated with a p-value < 0.05 are highlighted in bold, while estimated coefficients with a p-value < 0.10 are reported in italics.

Table 12 - Results of the multinomial logistic regression model for crash types.

Explanatory Variable – Crash Type	Coeff. Estimate	Std. Error	z Value	p-Value
Crash type: angle (base outcome: single-vehicle)				
<i>Road type (ref.: undivided two-way)</i>				
<i>Undivided one-way</i>	<i>0.717</i>	<i>0.409</i>	<i>1.75</i>	<i>0.080</i>
Divided multi-lane	0.619	0.771	0.02	0.981
Pedestrian zone	1.136	88,084.55	0.00	1.000
Day hour (ref.: calm hour)				
Peak hours	-0.146	0.499	-0.29	0.769

Explanatory Variable – Crash Type	Coeff. Estimate	Std. Error	z Value	p-Value
Night hours	-0.566	0.617	-0.92	0.359
Road geometry (ref.: segment)				
Unsignalized intersection	2.793	0.473	5.90	<0.001
Signalized intersection	2.626	0.687	3.82	<0.001
Roundabout	<i>2.106</i>	0.960	<i>2.19</i>	<i>0.028</i>
Age (ref.: 18–30)				
<18	1.153	0.905	1.27	0.203
31–40	0.271	0.538	0.50	0.614
>40	-0.563	0.551	-1.02	0.307
Unspecified	-0.562	0.587	-0.96	0.338
Crash type: sideswipe (base outcome: single-vehicle)				
Undivided one-way	0.297	0.391	0.76	0.447
Divided multi-lane	0.274	0.696	0.39	0.693
Pedestrian zone	-0.133	89,385.11	0.00	1.000
Day hour (ref.: calm hour)				
Peak hours	-0.160	0.484	-0.33	0.741
Night hours	-1.301	0.731	-1.78	0.075
Road geometry (ref.: segment)				
<i>Unsignalized intersection</i>	1.222	0.470	2.60	0.009
<i>Signalized intersection</i>	1.318	0.684	1.93	0.054
<i>Roundabout</i>	0.649	1.054	0.62	0.538
Age (ref.: 18–30)				

Explanatory Variable – Crash Type	Coeff. Estimate	Std. Error	z Value	p-Value
<18	1.357	0.900	1.51	0.132
31–40	-0.166	0.518	-0.32	0.748
>40	-0.363	0.499	-0.73	0.466
Unspecified	-0.543	0.578	-0.94	0.347
Crash type: pedestrian hit (base outcome: single-vehicle)				
Road (ref.: undivided two-way)				
Undivided one-way	0.038	0.580	0.07	0.947
Divided multi-lane	0.511	1.011	0.51	0.613
Pedestrian zone	22.995	60,640.19	0.00	1.000
Day hour (ref.: calm hour)				
Peak hours	-0.485	0.766	-0.63	0.527
Night hours	-14.041	638.874	-0.02	0.982
Road geometry (ref.: segment)				
Unsignalized intersection	-0.080	0.777	-0.10	0.918
Signalized intersection	-13.587	509.270	-0.03	0.979
Roundabout	-13.521	938.137	-0.01	0.989
Age (ref.: 18–30)				
<18	1.107	1.369	0.81	0.419
31–40	-1.371	1.118	-1.23	0.220
>40	-1.528	1.121	-1.36	0.173
Unspecified	1.300	0.626	2.08	0.038
Crash type: other (base outcome: single-vehicle)				

Explanatory Variable – Crash Type	Coeff. Estimate	Std. Error	z Value	p-Value
Road (ref.: undivided two-way)				
Undivided one-way	-0.700	0.544	-1.29	0.198
Divided multi-lane	0.448	0.730	0.61	0.540
Pedestrian zone	-0.400	118,229.3	0.00	1.000
Day hour (ref.: calm hour)				
Peak hours	0.457	0.571	0.80	0.423
Night hours	0.262	0.717	0.37	0.714
Road geometry (ref.: segment)				
Unsignalized intersection	0.871	0.587	1.49	0.138
<i>Signalized intersection</i>	1.330	0.778	1.71	0.087
Roundabout	0.717	1.294	0.55	0.579
Age (ref.: 18–30)				
<18	1.251	1.004	1.25	0.213
31–40	-0.636	0.739	-0.86	0.389
>40	0.161	0.595	0.27	0.787
Unspecified	-0.830	0.800	-1.04	0.299

Likelihood ratio test (reference: null model): $\chi^2(48) = 123.43$, $p < 0.001$, $R^2 = 0.1599$

Note: estimated coefficients associated with a p-value < 0.05 are highlighted in bold, while estimated coefficients with a p-value < 0.10 are reported in italics.

Table 13 - Descriptive statistics for categorical variables (segments)

<i>Category*</i>	0	1	2	3	Total
num_lanes					

<i>Category*</i>	0	1	2	3	Total
Total	0 (0%)	434 (50%)	331 (38%)	110 (13%)	875 (100%)
Crashed	0 (0%)	66 (48%)	44 (32%)	27 (20%)	137 (100%)
Not Crashed	0 (0%)	368 (50%)	287 (39%)	83 (11%)	738 (100%)
one_way					
Total	358 (41%)	517 (59%)	0 (0%)	0 (0%)	875 (100%)
Crashed	77 (56%)	60 (44%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	281 (38%)	457 (62%)	0 (0%)	0 (0%)	738 (100%)
median_presence					
Total	802 (92%)	73 (8%)	0 (0%)	0 (0%)	875 (100%)
Crashed	116 (85%)	21 (15%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	686 (93%)	52 (7%)	0 (0%)	0 (0%)	738 (100%)
side_access					
Total	437 (50%)	438 (50%)	0 (0%)	0 (0%)	875 (100%)
Crashed	99 (72%)	38 (28%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	338 (46%)	400 (54%)	0 (0%)	0 (0%)	738 (100%)
parking_availability					
Total	173 (20%)	194 (22%)	508 (58%)	0 (0%)	875 (100%)
Crashed	38 (28%)	32 (23%)	67 (49%)	0 (0%)	137 (100%)
Not Crashed	135 (18%)	162 (22%)	441 (60%)	0 (0%)	738 (100%)
bike_lanes					
Total	815 (93%)	60 (7%)	0 (0%)	0 (0%)	875 (100%)
Crashed	116 (85%)	21 (15%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	699 (95%)	39 (5%)	0 (0%)	0 (0%)	738 (100%)
pref_lanes					
Total	827 (95%)	48 (5%)	0 (0%)	0 (0%)	875 (100%)
Crashed	120 (88%)	17 (12%)	0 (0%)	0 (0%)	137 (100%)
Not Crashed	707 (96%)	31 (4%)	0 (0%)	0 (0%)	738 (100%)

*num_lanes: 1=1 lane, 2 = 2 lanes, 3=more than 2 lanes;

one_way: 0=Two-way traffic, 1= one way;

median_presence: 0=Absent, 1=Present;
 side_access: 0=Absent, 1=Present;
 parking_availability: 0=Absent, 1=Present on one side only, 2=Present on both sides;
 bike_lanes: 0=Absent, 1=Present;
 pref_lanes: 0=Absent, 1=Present.

Table 33 - Descriptive statistics for numerical variables

	vehicular_traffic	adt_per_lane	segment_length	e_scooter_traffic
Mean	8146	4956	157	274
<i>Mean crashed</i>	9595	6199	212	335
<i>Mean not crashed</i>	7878	4725	146	263
Standard deviation	7353	4214	201	274
<i>Standard deviation Crashed</i>	8080	6496	328	320
<i>Standard deviation Not crashed</i>	7184	3596	165	264

Table 15 - E-scooter crash likelihood prediction model for road segments

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-2,14E+03	2,03E+02	-10.525	< 2e-16 ***
adt_per_lane	5,86E-02	2,10E-02	2.783	0.005381 **
median_presence1	9,81E+02	3,03E+02	3.240	0.001197 **
bike_lane1	8,05E+02	3,18E+02	2.532	0.011355 *
side_access1	-1,29E+03	2,19E+02	-5.904	3.54e-09 ***
segment_length	1,57E+00	4,43E-01	3.552	0.000383 ***
e_scooter_traffic	6,98E-01	3,30E-01	2.117	0.034279 *

Table 16 - Alternative model 1 (segments)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-1,80E+03	1,95E+02	-9.199	<2e-16 ***
adt	1,41E-02	1,40E-02	1.010	0.312695
median_presence1	9,54E+02	3,62E+02	2.637	0.008357 **

bike_lane1	8,93E+02	3,23E+02	2.764	0.005710 **
side_access1	-1,30E+03	2,19E+02	-5.938	2.89e-09 ***
segment_length	1,73E+00	4,65E-01	3.721	0.000199 ***
e_scooter_traffic	8,52E-01	3,44E-01	2.477	0.013245 *
n_lanes2	-4,93E+02	2,38E+02	-2.072	0.038233 *
n_lanes3	-3,20E+02	3,56E+02	-0.899	0.368506

Table 17 - Descriptive statistics for categorical variables (intersections)

Category*	0	1	2	3	4	Total
intersestion_type						
Total	0 (0%)	0 (0%)	0 (0%)	168 (42%)	233 (58%)	401
Crashed	0 (0%)	0 (0%)	0 (0%)	57 (44%)	74 (56%)	131
Not Crashed	0 (0%)	0 (0%)	0 (0%)	111 (41%)	159 (59%)	270
turning_lanes						
Total	363 (91%)	38 (9%)	0 (0%)	0 (0%)	0 (0%)	401
Crashed	113 (86%)	18 (14%)	0 (0%)	0 (0%)	0 (0%)	131
Not Crashed	250 (93%)	20 (7%)	0 (0%)	0 (0%)	0 (0%)	270
signage						
Total	180 (45%)	39 (10%)	110 (27%)	72 (18%)	0 (0%)	401
Crashed	76 (58%)	11 (8%)	34 (26%)	10 (8%)	0 (0%)	131
Not Crashed	104 (39%)	28 (10%)	76 (28%)	62 (23%)	0 (0%)	270
bike_crossing						
Total	378 (94%)	23 (6%)	0 (0%)	0 (0%)	0 (0%)	401
Crashed	117 (89%)	14 (11%)	0 (0%)	0 (0%)	0 (0%)	131
Not Crashed	261 (97%)	9 (3%)	0 (0%)	0 (0%)	0 (0%)	270

*intersection_type: 3 three-legged, 4 = four-legged;

turning_lanes: 0=Absent, 1=Present

signage: 0=Absent, 1 = Yield Sign (or Roundabout), 2=Traffic Signal, 3=Stop;

bike_crossing: 0=Absent, 1=Present.

Table 18 - Descriptive statistics for numerical variables (intersections)

	ADT1	ADT2	adtvehtot	adtmon1	adtmon2	adtmonotot
Mean	11576	4974	16550	332	194	526
<i>Mean crashed</i>	11960	5017	16977	362	215	575
<i>Mean not crashed</i>	11390	4953	16342	317	185	502
Standard deviation	8267	4275	11062	308	206	416
<i>Standard deviation crashed</i>	8437	4607	11739	317	227	421
<i>Standard deviation not crashed</i>	8193	4113	10734	304	194	413

Table 19 - E-scooter crash likelihood prediction model for road intersections

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-51.163	21.956	-2.330	0.01979 *
signage1	-0.9405	0.4207	-2.235	0.02540 *
signage2	-0.6103	0.2761	-2.210	0.02707 *
signage3	-16.257	0.3839	-4.235	2.28e-05 ***
bike_crossing1	14.809	0.4750	3.118	0.00182 **
prop_adt1	26.985	11.874	2.273	0.02305 *
prop_adt_escooter2	10.220	0.5492	1.861	0.06278 .
log_ADT2	0.2848	0.1731	1.646	0.09986 .
ratio_e_scooter_vehicles_1	41.942	24.329	1.724	0.08471 .

Table 34 - Alternative model 1 (intersections)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-38.415	20.296	-1.893	0.05839 .
signage1	-0.9454	0.4195	-2.254	0.02422 *

signage2	-0.6199	0.2755	-2.250	0.02447 *
signage3	-16.389	0.3833	-4.275	1.91e-05 ***
bike_crossing 1	14.788	0.4743	3.118	0.00182 **
prop_adt1	25.607	11.775	2.175	0.02965 *
prop_adt_escooter1	-0.9259	0.5449	-1.699	0.08924 .
log_ADT2	0.2620	0.1713	1.529	0.12627
ratio_e_scooter_vehicles_1	38.324	24.177	1.585	0.11294

Table 35 - Alternative model 2 (intersections)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-29.762	16.231	-1.834	0.06671 .
signage1	-0.9470	0.4192	-2.259	0.02386 *
signage2	-0.6084	0.2748	-2.214	0.02685 *
signage3	-16.395	0.3839	-4.271	1.95e-05 ***
bike_crossing 1	14.815	0.4734	3.130	0.00175 **
prop_adt1	0.9895	0.8518	1.162	0.24537
prop_adt_escooter1	-0.9383	0.5492	-1.708	0.08755 .
log_ADT1	0.2598	0.1864	1.394	0.16324
ratio_e_scooter_vehicles_1	37.515	24.583	1.526	0.12699

Table 36 - Alternative model 3 (intersections)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-32.330	16.393	-1.972	0.04859 *
signage1	-0.9247	0.4211	-2.196	0.02809 *
signage2	-0.5937	0.2760	-2.151	0.03146 *
signage3	-16.453	0.3855	-4.268	1.97e-05 ***
bike_crossing 1	14.649	0.4759	3.078	0.00208 **
prop_adt1	14.347	10.004	1.434	0.15154
prop_adt_escooter1	-12.490	0.6029	-2.072	0.03829 *

log_ADT1	0.2725	0.1896	1.437	0.15062
ratio_e_scooter_vehicles_1	53.328	28.015	1.904	0.05697 .
ratio_e_scooter_vehicles_2	-0.6211	0.7125	-0.872	0.38333

Table 23 - Alternative model 4 (intersections)

Variable	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-36.786	21.769	-1.690	0.09107 .
signage1	-0.9258	0.4216	-2.196	0.02808 *
signage2	-0.6006	0.2770	-2.168	0.03016 *
signage3	-16.424	0.3852	-4.263	2.01e-05 ***
bike_crossing 1	14.657	0.4762	3.078	0.00209 **
prop_adt1	22.070	26.646	0.828	0.40752
prop_adt_escooter1	-12.160	0.6119	-1.987	0.04688 *
log_ADT2	0.1377	0.4404	0.313	0.75462
ratio_e_scooter_vehicles_1	52.246	28.238	1.850	0.06429 .
log_ADT1	0.1372	0.4724	0.290	0.77150
ratio_e_scooter_vehicles_2	-0.5465	0.7523	-0.726	0.46761

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CURRICULUM



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Born in Taranto on July 31, 1996, with a background in civil engineering, the academic journey includes a Bachelor's and Master's degree in Civil Engineering from the Politecnico di Bari, both completed with top marks (110/110). The academic focus has been on transportation systems and infrastructure, leading to enrollment in a Ph.D. program at the Politecnico di Bari. The doctoral research centers on risk analysis of crashes involving micromobility, specifically electric scooters.

Participation in international conferences, such as the "Living and Walking in Cities," and advanced training programs, including the International PhD Summer School at Université Gustave Eiffel in Paris, has enriched the academic experience. The research output includes several publications: "Analysis of E-Scooter Crashes in the City of Bari" (2024) published in *Infrastructures*, 9(3), 63; "Analysis of e-scooter crashes in the city of Bari," presented at the XXVI International Conference on Living and Walking in Cities, 2023, Brescia; "Last mile food delivery logistic system: sharing vehicles and time windows approach to reduce social and environmental impacts,"

presented at the XXVIII Summer School “Francesco Turco”; "Interactions between Automated Shuttle, Vulnerable Road Users and Regular Vehicles: a Case Study in Bari, Italy," published by Springer in 2022; and "Exploratory analysis of electric scooter crashes in the city of Bari," featured in *Sustainable Pavements and Road Materials: Proceedings of the 7th SIIV Arena, Naples, 2022*.

The research aims to contribute to safer and more sustainable urban mobility through advancements in transportation systems and infrastructure.