



UNIONE EUROPEA
Fondo Sociale Europeo



Advances In Modelling, Health-Monitoring, Infrastructures, Geomatics,
Geotechnics, Hazards, Engineering Structures, Transportation
(AIM HIGHEST)

Curriculum: Infrastructure, Geomatics, and Transport Engineering
CYCLE 37th (2021-2024)

**Towards Equitable and Safe Urban Mobility: Methods and Models for
Analysing Pedestrian Safety and Accessibility**

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This work was co-financed by European Union – FSE-REACT EU, PON "Research and Innovation 2014–2020", Action
IV.5 – DM 1062/2021, CUP: B73D21008910006, Codice borsa e n. DOT1320558-3.

Acknowledgment

As I complete my PhD studies, I would like to express my sincere gratitude to the **Government of Italy** and the **University of Palermo** for providing me with this fully funded and prestigious opportunity to achieve my goal of earning a doctoral degree in my field of interest.

I am especially thankful to my supervisor, **Prof. Eng. Dr. Marco Migliore**, for his outstanding support, continuous guidance, and insightful mentorship throughout every stage of my research. His deep knowledge, patient supervision, and profound commitment to my academic growth have been crucial to the success of this work. I am truly honoured to have worked under his direction and supervision.

I also extend my deep thanks to my co-supervisor, **Dr. Gabriele D'Orso**, for his constant support, clear advice, and technical expertise. His constructive feedback, attention to detail, and encouragement at key points in my research journey have played an important role in shaping and strengthening this work. His dedication and responsiveness made a significant difference in my academic experience.

I am grateful to **Dr. Sjaan Koppel** and **Dr. David B. Logan** from **Monash University, Australia**, for giving me the opportunity to carry out part of my research at the **Monash University Accident Research Centre (MUARC)**. Their valuable input and support during my stay greatly improved the quality of my research.

I would also like to express my sincere thanks to **Eng. Angelo Mulone** for his kind cooperation and support during my industry training period with **GeoLab S.R.L.** His practical insights and professional guidance contributed meaningfully to my learning experience.

I would like to thank my **family**, who have always been a strong source of motivation and support. Their encouragement and belief in the importance of education have guided me from the beginning. I am truly thankful for their love, patience, and constant presence throughout this journey.

I also wish to thank my **colleagues** from the **University of Palermo** for their cooperation and encouragement during my studies. In addition, I am grateful to my **colleagues** and **friends** studying at various universities around the world for their support and guidance. I sincerely wish them all continued success in their academic and professional careers.

This PhD journey has been one of deep learning and personal growth. Completing this thesis is not only an academic achievement, but also a reflection of the support, love, and encouragement I have received from so many—**thank you**, from the bottom of my heart.

Abstract

Historic and evolving urban environments, such as Palermo, face persistent challenges including congestion, pollution, urban sprawl, social inequality, and environmental degradation. In response to these challenges, there is a growing consensus around promoting sustainable and inclusive modes of transport that can address these issues holistically. Among these, walking stands out as a cornerstone not only for being environmentally friendly and beneficial to health, but also for supporting social interaction and spatial equity. This has led to increased attention on the concept of walkability, which reflects how effectively the built environment supports safe, comfortable, and accessible walking for everyone.

However, walkability is not limited to urban design; it is closely tied to everyday experience, particularly the risks faced by pedestrians, who remain the most vulnerable road users in urban transport systems. This dissertation investigates pedestrian vulnerability by going beyond the traditional focus on safety to include the equally critical dimension of accessibility, especially for socially disadvantaged groups such as the elderly and people with disabilities. It demonstrates that a poorly designed pedestrian network and unsafe, low-quality infrastructure constitute a form of vulnerability that impacts both safety and access. The study takes Palermo, Italy, as a case study to evaluate pedestrian vulnerability through three key analytical components.

The first study evaluates the impact of real-world speed on the severity of vehicle-to-pedestrian crashes. The study uses percentile speed data from the TomTom speed database, together with pedestrian crash data acquired from local police, and applies a discrete outcome model to estimate the fatal and severe injury (FSI) risks. The study found a strong correlation between the higher range of percentiles of speed and increased FSI risks. The study further demonstrated the counterfactual analysis to examine the model's efficiency in examining the FSI risk while reducing the speed, and showed that modest speed reduction can significantly help in reducing the FSI injury risks. Based on this, the study recommends targeted speed reduction and management policies aimed at reducing FSI risk in the high pedestrian activity zones.

The second study focuses on the safety of pedestrians through the lens of investigating the factors contributing to pedestrian injury severity. The study uses a pedestrian crash dataset collected from the Palermo municipality police and applies a comprehensive machine learning framework to tackle missing data, injury severity class imbalance issues, while predicting the severity of pedestrian crashes. The study found several factors to be significant for their impact

on the increased severity of pedestrian crashes and suggested targeted evidence-based policies to counter their effect on the severity of pedestrian crashes and ultimately enhance pedestrian safety from the perspective of the achievements of the Vision Zero goals.

The third study addresses the pedestrian vulnerability in terms of risk of social exclusion by evaluating the walkability of catchment areas in the vicinity of railway stations located in Palermo. The study applies both meso-scale and micro-scale walkability assessments to examine how much the network connectivity and the quality of pedestrian infrastructure impact social equity and pedestrian accessibility to the railway stations. The study found significant spatial disparities between the railway stations located in the urban and peripheral zones. Particularly, the results showed that peripheral railway stations face challenges with poor connectivity, low walkable environments, and exclusion of some social groups. Based on this meso-scale walkability assessment, the study proposes targeted intervention policies regarding infrastructure investments, creation of pedestrian priority zones, and other planning strategies aligned with the concept of 15-minute cities and transit-oriented development models to improve pedestrian access and minimize spatial inequalities.

By combining safety and accessibility into a unified framework of pedestrian vulnerability, this thesis covers a more integrated understanding of the challenges faced by pedestrians in cities. It prioritizes inclusive urban planning that focuses on both protection and access for the most vulnerable road user group. The findings contribute valuable evidence for policymakers, urban planners, and researchers who aim to make cities safer, sustainable, and walkable for all.

Keywords: Pedestrian vulnerability; pedestrian safety; pedestrian accessibility; real-world speed; discrete outcome model; crash severity; machine learning; walkability; railway stations; network connectivity; pedestrian infrastructure; social equity; transport equity

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Chapter 1

Introduction

The first chapter outlines the main motivations that drive this research, further explored in Chapter 2. Then, the objective of this thesis and the research questions are defined, and the related research articles that form the main core of this thesis are presented. The last section describes the structure of this dissertation.

1.1 Problem statement

According to the United Nations (Revision of World Urbanization Prospects, 2018), more than half of the world's population (around 4.2 billion people) lives in cities today to aspire to a better quality of life and have easier access to amenities. Thus, metropolitans are facing various challenges in the form of congestion, pollution, and urban sprawl. These challenges will become more difficult in the near future. Indeed, according to the Revision of World Urbanization Prospects (UN, 2018), 68% of the global population is expected to live in cities by 2050, based on urbanization and population growth trends. Therefore, urban transportation systems across the globe are undergoing a critical phase to mitigate the negative consequences of the increase in urban population, trying to ensure sustainability, inclusivity, and safety (Farid et al. 2022).

Without proper land-use planning and the application of policies oriented to sustainable mobility, the increase in urban population will eventually lead to an increase in the motorization rate, making cities facing challenges of increased congestion and pollution (Lu et al. 2021). The increase in motorization rates will also create safety challenges (Khreis et al. 2016), as higher traffic volumes will lead to aggressive driving behaviours, more conflicts with other modes of transport, such as public transit and shared mobility services, and greater exposure for active transportation.

To address these issues, single countries and global organizations like the United Nations are working on policies and agendas to promote safe, sustainable, and inclusive transport systems. For instance, the Goal 11 of the United Nations' Agenda 2030 is to make cities inclusive, safe, and sustainable by promoting transport and social equity (Goal 11 | Department of Economic

and Social Affairs). Similarly, “Vision Zero,” a strategy first implemented in Sweden in the mid-1990s and then adopted in several countries worldwide, seeks to eliminate all traffic fatalities and severe injuries while ensuring safe, healthy, and equitable mobility for all (<https://visionzeronetwork.org/>). This strategy prioritizes human life and health above all else and encourages a shared responsibility among individual transport system users and “system designers” (the entities that shape the system, such as the automotive industry, lawmakers, and infrastructure owners) to establish a safe system approach (McCulloch et al. 2025).

In this context, promoting active mobility and its integration with other transport modes could be highly beneficial. Active travel refers to any transport of people and goods through non-motorized ways, which is based upon human-powered activity, such as walking, cycling, running, etc (Cook et al. 2022). Active mobility is quite beneficial in combating major mobility challenges such as congestion, pollution, promoting physical activity to have better health and fitness, and is quite helpful in urban planning due to being cost-effective while promoting inclusivity (Ferretto et al. 2021). Moreover, active mobility promotes liveability and sustainability since it is associated with more usage of public transit, creating least car-dependent neighbourhoods.

However, besides these enormous benefits, active mobility users are subjected to an elevated level of severe crash risk, which can be a deterrent to shift to active modes of transportation (Osama and Sayed 2019). Indeed, active mobility involves a category of road users that are defined as “vulnerable road users” (VRUs), such as pedestrians and cyclists.

VRUs are road users who, unlike vehicle occupants, lack the external protection that vehicle safety features provide, making them more susceptible to fatal and severe injuries when involved in a crash. Indeed, the word “vulnerability” comes from the Latin *vulnus*, which means “wound” and this explains why vulnerability is commonly used to refer to the possibility of being wounded. Moreover, the literature defines VRUs as road users outside the car, unprotected by an outside shield and most at risk in traffic, having a difference in mass, reduced visibility, and a difference in speed with other road users (OECD 2000).

Although progress has been made in recent years in traffic safety worldwide, there is evidence that the benefits are not shared equally by all the road users. Safety of vulnerable road users did not improve to the same extent as that of motorists, particularly in lower-income countries and in places where traffic laws are poorly enforced (Olszewski et al. 2019). Indeed, the traffic crashes involving vulnerable road users are a significant global health challenge, as according

to the World Health Organization's global status report on road safety (2023), the VRUs account for 56% of total road traffic deaths across the globe in 2021 (WHO 2023). Among VRUs, users of powered two- and three-wheelers, such as motor rickshaws, motorcycles, mopeds, and scooters, represent 30% of fatalities, even higher than four-wheel vehicle occupants who make up 25% of fatalities worldwide (WHO 2023). Similarly, road deaths involving pedestrians account for 21% and the ones involving cyclists for 5% of the total fatalities (WHO 2023). Although pedestrians, cyclists and riders of motorized two- and three-wheelers are more vulnerable as a result of being less protected than car occupants, the heavy burden of fatalities borne by these road users is also a reflection of the quality of the infrastructure and design of the built environment that prioritizes cars and other motorized transport. Thus, these statistics highlight the urgent need for road safety practitioners to evaluate contributing factors and design policies that prioritize crash mitigation measures for VRUs. Among VRUs, some social groups are more vulnerable than others, such as children, older people, and individuals with disabilities, facing greater risks due to their specific physical, cognitive, or sensory limitations (WHO 2018). Indeed, vulnerability to road crashes is also associated with physical vulnerability and the ability/skills to safely participate in traffic (European Commission 2011). For example, children may lack the experience and judgment needed to navigate traffic safely, demonstrating inadequate knowledge about road safety rules, inadequate attention and visual searching abilities, misperception of risks and perception of fear that can lead to errors in pedestrian decisions (Wang et al. 2021); older people often have reduced mobility and slower reaction times, resulting in a greater likelihood to wait for longer gaps between vehicles before attempting to cross the road (Tobey 1983), and to take longer to cross the road (Hoxie and Rubenstein 1994); individuals with disabilities might encounter additional challenges in perceiving or responding to road hazards (Schwartz et al. 2022).

Moreover, pedestrians represent the largest and most fundamental group among VRUs, as walking is an essential mode of transportation for all the segments of society and forms a key part of the trip chain for those using other transport modes, especially for completing the first- and last-mile journey when using public transport.

Although pedestrians are intrinsically vulnerable due to their physical characteristics, the vulnerability of pedestrians largely stems from the way the transport system is designed, with decision-making processes and practices that often favour motorised transport over walking. Thus, the needs of pedestrians - that can be well summarized by the hierarchy of walking needs pyramid (ITDP 2018) including the needs to have passable, accessible, safe, convenient,

comfortable, and enjoyable pedestrian environments - are often neglected by an automobile-oriented transport planning. As stated by (Khayesi 2020a), it would be better to talk about vulnerable transport planning rather than vulnerable road users to direct efforts for solutions strategically at tackling the root cause of vulnerability, since the real vulnerability lies within transport planning, which succumbs to influences that are more focused on the needs of motorized transport. Indeed, deficiencies in road design and transport policies are key factors in increasing risk for pedestrians. Therefore, it should not be underestimated how pedestrian vulnerability increases in environments that are not designed specifically for pedestrians but are oriented towards motorized vehicles. In this regard, walkability - defined as the extent to which walking is encouraged by the built environment within a neighbourhood (Wang and Yang 2019) – becomes a fundamental aspect to evaluate in road safety studies. A walkable neighbourhood not only is safer but also promotes public health as walkability is linked to cardiovascular fitness, reduces obesity risk, and enhances mental well-being (Pucher et al. 2010). Moreover, a walkable environment promotes walking, improving environmental sustainability by reducing car dependency, pollution, and congestion (Lee et al. 2017). Walkability also supports inclusivity and social equity which are vital component of sustainable urban development (Bridge 2025).

However, besides their numerous benefits, good levels of walkability remain unevenly distributed, particularly in car-dependent cities where infrastructure planning has historically prioritized motorized traffic over active mobility. Therefore, especially in rural, peri-urban and suburban areas, pedestrians face numerous challenges, including unsafe road conditions, poor infrastructure, and limited accessibility, which hinder the development of walkable and sustainable cities. These factors directly influence pedestrians' decisions to walk or not. Safety is surely a major concern, as unsafe environments discourage walking and encourage car dependency, leading to more congestion and pollution (Bernardo et al. 2021).

Thus, there is the urgency to re-evaluate transport planning practices to prioritize road safety and inclusivity, ensuring that transportation systems serve the needs of all road users equitably. Indeed, inclusivity is another aspect of vulnerability for pedestrians. They do not only are at most risk of suffering serious injuries in road crashes, but they can be at most risk of social exclusion due to a vulnerable car-oriented transport planning.

Indeed, accessibility is another critical issue for pedestrians, often compromised by poor infrastructure (Nieto-Combariza et al. 2025). Accessibility can be defined as the capacity and

ease of individuals to access activities, attractions, and amenities spread out across different locations (Gil Solá et al. 2018). The access is primarily affected by the topological features of the road network and the continuity of the pedestrian paths. However, also the design and the quality of the pedestrian environment, such as the absence of footpaths, poor lighting, high speeding, degraded pavements, absence of on-street amenities, unsafe crosswalks and intersections, etc., significantly impact pedestrians' accessibility and the choice of walking for any kind of trip generation (Stefanidis and Bartzokas-Tsiompras 2024; Liang et al. 2025). Thus, there is a close link between walkability and accessibility. Low walkable neighbourhoods due to poor quality of pedestrian infrastructure eventually discourages pedestrians from choosing walking to and from public transit as first- and last-mile journey solution (Liang et al. 2025). Moreover, the low quality of pedestrian infrastructure also significantly impacts inclusivity (Asiedu-Ampem et al. 2024). Among the community, some social groups solely rely on walking for any kind of trip purposes due to the unaffordability of private cars or the inability to use them. These social groups, in most cases, are also dependent on the usage of public transport, and therefore, poor and unsafe pedestrian infrastructure significantly affects their access to public transit. Such a situation led to social and transport equity challenges, which hinder inclusive and sustainable urban development.

Indeed, policymakers and local authorities must consider vulnerability in terms of lack of transport equity, trying to assure, through appropriate policies and pedestrian-oriented actions, fair and accessible transport options for all individuals disregarding of their income level, age, gender, and any other impairment of a different nature (Bruzzzone et al. 2023). This comprised assuring that public transport services and essential services are accessible for everyone, regardless of their geographic location, either central or peripheral. Therefore, ensuring road safety and accessibility for pedestrians is a cornerstone in urban planning as it directly influences the achievements of the United Nations' goal of building inclusive and sustainable cities and communities (Nieto-Combariza et al. 2025) as well as the Vision Zero goals.

In light of the above considerations, more in-depth analysis is needed to understand the key factors determining the risk to be involved in road crashes by pedestrians or the occurrence of pedestrian fatalities, taking into account not only crash-related variables, such as the vehicle speed, but also the role that transport planning and car-oriented design have in mitigating or enhancing these risks. Furthermore, the vulnerability of pedestrians compared to other road users in terms of being at most risk of social exclusion needs to be explored, developing methodologies for assessing inequalities in access to essential services and proposing best

practices in assessing the impacts of walkability on social and transport equity. This thesis therefore aims to create links between road safety, walkability and social equity, which are concepts often treated separately. This represents a gap that the thesis therefore aims to fill through case studies that offer the opportunity to facilitate evidence-based policy-making.

1.2 Research objectives

Taking into account the considerations made in the previous section, this research aims to achieve three main objectives (O) that are listed and described below.

O1: Exploring the concept of vulnerability of pedestrians as vulnerable road users

The thesis aims to investigate the main factors having an impact on the safety of pedestrians as vulnerable road users. In this regard, crash-related variables - such as human factors, vehicle characteristics, road features, and environmental conditions - must be thoroughly examined to determine which have the greatest impact on crash severity and the likelihood of being involved in a road accident, in order to develop effective mitigation strategies.

O2: Expanding the concept of vulnerability

Transport planning has direct effects on the vulnerability of pedestrians. An inadequate road design and car-oriented policies could lead not only to an increase in road accidents and road fatalities, but they can also make pedestrians more vulnerable compared to the other road users in terms of social exclusion. Including this aspect in the vulnerability concept is the second objective of this thesis.

O3: Investigating the link between road safety and walkability

Road safety is undoubtedly one of the key factors influencing walkability. The need for pedestrians to walk in a safe environment is a fundamental requirement, closely linked to both subjective perceptions and objective measures of safety. Although unsafe conditions may discourage walking and prompt people to use other modes of transport, many individuals who rely exclusively on walking are forced to navigate unsafe neighborhoods. Therefore, this thesis aims to investigate the integration of safety considerations into walkability assessments, with a focus on identifying appropriate safety indicators for sidewalks and crosswalks.

1.3 Research questions

Considering the gaps in the literature, the general objectives defined in Section 1.2 have been translated into five distinct research questions (RQs), which this thesis aims to answer,

providing context-sensitive results that can inform policy implications and delineate strategies and actions applicable to similar contexts. The RQs are listed below with a brief description of their nature.

RQ1: What is the impact of real-world speed on the risk of fatal and serious injuries after the involvement of pedestrians in road crashes, and how does speed reduction affect the severity of vehicle-to-pedestrian crashes?

Speed is the primary variable influencing the outcomes of road crashes, with higher speeds leading to more severe consequences. In particular, impact speed plays a crucial role in determining the severity of injuries resulting from a crash. However, estimating impact speed is challenging, as it requires a detailed and often complex reconstruction of crash dynamics. To address this limitation, percentile speed can be used as a proxy. By analyzing real-world data from vehicle-to-pedestrian crashes over a multi-year period, the relationship between percentile speed and injury outcomes can be investigated. Furthermore, through counterfactual analysis, the potential benefits of speed reduction in lowering the risk of fatal and serious injuries (FSI) for pedestrians can be explored.

RQ2: What are the main factors contributing to pedestrian accidents?

Pedestrians have been involved in accidents due to numerous factors. These factors, for example, include demographic, environmental, roadway, temporal, at-fault, and vehicle-related. Analysing the contribution of key factors to the pedestrian crash severity is important to understand the complex underlying crash mechanism and, consequently, to adopt targeted intervention safety policies.

RQ3: How accurately can machine learning algorithms investigate the severity of pedestrian crashes in real contexts?

To rigorously predict the crash severity, it is crucial to validate the performance of the analytical model. In this regard, crash datasets often face challenges with missing data and injury severity class imbalances, leading to complexities for conventional statistical models, which strictly rely on well-established data distribution and a pre-determined connection between dependent and independent variables. On the other hand, machine learning models are best suited to tackle these challenges and are prominent with prediction performance; however, they face constraints with model outcome interpretations. Therefore, by using comprehensive machine learning frameworks, the goal is to validate their performance in handling all the data and interpretation challenges while predicting the pedestrian crash severity.

RQ4: How accessibility and walkability impact on social equity?

The topological features and the quality of the pedestrian network have an impact on the access to essential services, leading to an increase or a decrease in the risk of social exclusion of some social groups. Although policies promoting walking such as the Transit Oriented Development and the 15-minute city model are nowadays applied in several cities worldwide, disparities in policy practice seem to exist between suburban areas and urban core in many European cities. A methodology is needed to assess whether spatial inequalities exist in the access to essential services or public transport services (e.g. railway stations) among different urban areas within a city. In this regard, to what extent micro-scale and macro-scale walkability indicators affect social equity needs to be explored.

RQ5: What safety indicators must be included in walkability assessments?

Being one of the basic needs of pedestrians, safety is also one of the key factors affecting walkability. However, walkability assessments often neglect this relevant aspect, focusing only on the topological features of the road network or proximity to amenities. Indeed, macro-scale or neighbourhood walkability assessments are often used to evaluate how much the built environment is friendly to pedestrians. However, as pedestrians interact directly with the street environment, neighborhood walkability indices often fail to consider human-scale characteristics, and, despite its importance to walkability research, street-level assessments are less common in the literature. Therefore, it is crucial to develop methodologies to assess walkability at the street level (micro scale), also including safety indicators in such kind of assessment. These indicators must be evaluated considering the street-level factors impacting pedestrian safety while acknowledging that sidewalks and pedestrians crossing may require distinct set of indicators.

1.4 Research outcomes

The main body of this thesis has resulted in three research articles (RA) of which one is published while the other two are under review in peer-reviewed and indexed journals. Thus, this thesis partially represents a compendium of scientific publications. In this regard, some coincidences may be present between the RAs and parts of this thesis. The following three RAs have been developed as outcome of this research:

RA1: Yasir, M., Logan, D. B., Migliore, M., D’Orso, G., Pervez, A., Koppel, S. **Evaluating the Role of Speed Reduction on the Severity of Vehicle-Pedestrian Crashes: A Case Study in Palermo, Italy.** Under Review.

RA2: Yasir, M., Ilyas, T., Migliore, M., Pervez, A. **Analysing Factors Influencing Pedestrian Injury Severity in Palermo Using Machine Learning Techniques.** Under Review.

RA3: D’Orso, G., Yasir, M., Migliore, M. (2025). **Combining Walkability Assessments at Different Scales in Measuring Spatial Inequalities in Access to Railway Stations.** Journal of Transport and Health, 44, 102081. <https://doi.org/10.1016/j.jth.2025.102081>. [2023 JCR Journal Impact Factor 3.2, Q1 Safety Research, Q2 Transportation]

The first study, *Evaluating the Role of Speed Reduction on the Severity of Vehicle-Pedestrian Crashes: A Case Study in Palermo, Italy*, examines the relationship between vehicle speed and the severity of pedestrian crashes. The study examines the influence of real-world vehicle speeds on the road segments where injury outcomes were reported by local police involving vehicle-to-pedestrian crashes in Palermo, Italy. The study utilizes the location of these crashes that were reported resulting in fatal and serious injury (FSI), to obtain speed data, which was acquired through the TomTom speed database. Particularly, percentile speed data was modelled to analyze the relationship between speed and injury risk and then estimate FSI risk through a discrete outcome.

Moreover, the study also evaluates the potential benefits of speed reduction strategies in reducing the risk of fatal and serious injuries (FSI) for pedestrians. A counterfactual analysis simulated the effects of reducing travel speeds by 3 km/h and 5 km/h to assess model efficiency and potential injury risk reductions. The study proposes evidence-based speed management policies to enhance pedestrian safety and mitigate the consequences of these crashes.

The second study, *Analysing Factors Influencing Pedestrian Injury Severity in Palermo Using Machine Learning Techniques*, employs a machine learning framework to analyze the factors contributing to the severity of pedestrian crashes. The study uses pedestrian crash data collected from the Palermo Municipality Police. The pedestrian crash data comprised eight years between 2015-2022, and the dataset provides detailed information about pedestrian-related crashes occurring within the municipality, with a focus on various crash attributes, pedestrian and driver characteristics, as well as environmental and traffic-related factors. However, the crash data collected presents notable challenges, including missing data and an imbalance in injury severity classes. Therefore, the study considered the crash injury severity analysis

through machine learning frameworks instead of traditional statistical models to first address the complexities with missing data, class imbalance, through machine learning techniques and then employed different machine learning models (Random Forest, XGBoost , GradientBoost and CatBoost) to predict the crash severity of pedestrians. The study aims to provide insights for practitioners and policymakers to design targeted measures for reducing pedestrian crash severity in the case study and similar places across the globe.

The third study, *Combining Walkability Assessments at Different Scales in Measuring Spatial Inequalities in Access to Railway Stations*, focuses on evaluating walkability at multiple scales to identify spatial disparities in access to railway stations in Palermo, Italy. By integrating micro-scale and macro-scale walkability assessments, this research aims to provide a comprehensive understanding of how urban design and infrastructure influence pedestrian accessibility to railway stations. These railway stations are scattered throughout the city in both urban and peripheral areas, connecting the main central station all the way to the city main airport. The railway in the city served as the main public transport that interconnects key points of interest such as educational institutes, public offices, recreational, touristic and historical places and therefore the study considers the assessment of the quality of the pedestrian infrastructure around these railway stations. For this assessment, the study proposes a set of indicators that are useful in evaluating the accessibility and quality of pedestrian's routes. Some of these indicators are linked to meso-scale walkability and network connectivity measures, such as road density, intersection density, and Pedestrian Catchment Area Ratio (also known as Ped-shed ratio). Whereas other indicators are linked to microscale walkability, specifically using a set of indicators measuring the quality of sidewalks and crosswalks. Indeed, the quality of pedestrian infrastructure was assessed based on the micro-scale assessment of practicability, pleasantness and safety indicators. The study also evaluates the road connectivity and the impacts it has on the access to railway stations for nearby residents and employees in order to assess social and transport equity. The study developed a GIS-based methodological approach to compare the walkability assessments at different scales and find spatial inequalities in access to railway stations; the findings will help policymakers and urban planners address inequalities in transport equity, ensuring that all communities have access to safe and efficient public transport options.

1.5 Thesis structure

The structure of this thesis is organized into the following chapters:

- **Chapter 1 (Introduction)** presents the problem statement, defining the research aim, the research questions, and the overall structure of the thesis.
- **Chapter 2 (Literature Review)** provides a comprehensive overview of the scientific literature on vulnerable road users, pedestrian safety and their links with walkability and accessibility, also identifying the research gaps, and highlighting the contribution of each of the three studies conducted.
- **Chapter 3 (RA1. Evaluating the Role of Speed Reduction on the Severity of Vehicle-Pedestrian Crashes: A Case Study in Palermo, Italy)** addresses the first research question regarding evaluating the impact of real-world percentile speeds and speed reduction on the severity of vehicle-to-pedestrian crashes. The chapter presents the data collection process, method, results, and discussion on the results that were conducted to address this specific research question (RQ1) and contribute to the achievement of the first research objective (O1).
- **Chapter 4 (RA2. Analysing Factors Influencing Pedestrian Injury Severity in Palermo Using Machine Learning Techniques)** responds to the second and third research questions, assessing the driving factors of injury severity in pedestrian crashes based on a machine learning framework. The chapter presents the data collection process, methodology, results, and discussion on results, which were conducted to achieve the first objective of the research (O1).
- **Chapter 5 (RA3. Combining walkability assessments at different scales in measuring spatial inequalities in access to railway stations)** addresses the fourth and fifth research questions, assessing spatial disparities in access to railway stations and exploring the link between road safety and walkability. The chapter interprets the study area, data collection, methodology, results, and discussion to results been developed and conducted to achieve the corresponding second (O2) and third (O3) objectives of the research.
- **Chapter 6 (Conclusion and policy recommendations)** presents the conclusion of the research conducted to address the research questions and informs about the fulfillment of the research objectives. This chapter also suggests some real-world policies derived from the case studies, discussing important implications for transport policy and planning, as well as useful insights for policymakers and local authorities aiming to create safer and more inclusive cities.

Chapter 2

Literature Review

This chapter provides a comprehensive overview of the state of the art on pedestrian safety and accessibility investigating the key factors affecting pedestrian vulnerability.

2.1 Pedestrian Safety

Walking is a vital part of urban transport systems, as every trip performed with the use of other transport modes begins and ends with walking. Thus, walking is especially relevant in the context of multimodal transport, where it is necessary to access public transit for any kind of trip purpose. Pedestrians form the foundation of urban mobility and play a key role in shaping city life through their movement along streets, sidewalks, and in public and recreational spaces (Jabbari et al. 2023). Cities naturally evolve around pedestrian activity—markets, offices, schools, and transit hubs all depend on the continuous movement of people on foot (Sevtsuk and Kalvo 2024). The role of walking in sustainable urban development is well recognized, especially as cities aim to reduce congestion, cut emissions, and promote healthier lifestyles (Elzeni et al. 2022). Despite their crucial role, however, pedestrian needs are often overlooked in urban design and transport planning (Thondoo et al. 2020) when compared to the needs of motorized transport users.

One of the most urgent issues pedestrians face is safety. Unlike motor vehicle occupants, pedestrians are vulnerable road users (Haque et al. 2025), and their safety is impacted by multiple factors (Khayesi 2020b). Streets remain unsafe for pedestrians in many parts of the world. A major concern is the growing number of pedestrian-involved traffic crashes. Globally, pedestrians account for 21% of all road traffic deaths, and 25% of such fatalities occurred within the European Union (WHO 2023). This is largely due to their lack of physical protection, which makes them more likely to suffer serious or fatal injuries in collisions (Levulyte et al. 2016). Furthermore, the fatality risk for pedestrians is nine times higher per kilometer traveled than it is for car occupants (Job 2020). For this reason, pedestrian safety is considered an important factor in evaluating the sustainability of urban environments (Alam and Powell 2017).

As in other European countries, the risk to pedestrians is also high in Italy, where historic and densely populated urban areas draw heavy pedestrian activity. According to the Italian National Institute of Statistics, pedestrians made up 49.3% of road fatalities in 2022 (ISTAT 2022). The data also shows that pedestrians face a mortality rate of 2.7 per 100 crashes, which is 4.4 times higher than the rate for car occupants, which is 0.6 (ISTAT 2022). Alarmingly, pedestrian deaths rose by 3.2% in 2022 compared to the previous year (ISTAT 2022). Urban areas are the primary sites for such accidents, with 34% of pedestrian-related fatalities occurring in cities, compared to just 9% in rural areas (ISTAT 2022; Rella Riccardi et al. 2023).

In response to these concerns, this research has specifically evaluated pedestrian safety using multisource data and different analytical approaches, focusing on Palermo, Italy as a case study. Indeed, the first part of the study examines how real-world vehicle speeds influence injury outcomes in vehicle-to-pedestrian crashes. The second part investigates the risk factors associated with pedestrian-involved crashes. In the following sections, a systematic review of progress in these studies is presented. Subsequently, the research gaps are identified to highlight their importance and to suggest how addressing them could potentially lead to improved pedestrian safety.

2.1.1 The impact of real-world speeds on pedestrian safety

Speed is defined as the rate at which a vehicle or object moves, typically measured in miles per hour (mph) or kilometres per hour (km/h). While posted speed limits are intended to set legal thresholds and control vehicle movement within safe boundaries, the actual speed at which vehicles travel—referred to as real-world speed—often exceeds these limits and raises serious safety concerns. This issue is especially common in urban areas and zones with high pedestrian activity, where enforcement of speed limits may be inconsistent. Therefore, distinguishing between posted speed limits and real-world speeds is essential for understanding their real impact on pedestrian safety.

For instance, in situations involving interactions between vehicles and pedestrians on urban streets, speed plays a critical role in determining both the likelihood and severity of crashes. When vehicles are driven at high speeds, drivers have less time to notice and react to unexpected pedestrian movement, which significantly increases the chance of a collision. In these cases, braking distances also increase sharply with speed, making it more difficult for vehicles to stop in time to avoid an accident. Moreover, the force of impact in a crash rises considerably as vehicle speed increases. Specifically, the impact force during a collision with

a pedestrian is directly proportional to the square of the vehicle's speed (Neal-Sturgess 2002). This makes speed a key factor when assessing and managing risks in traffic safety.

2.1.1.1 Prior Research

The relationship between speed and pedestrian injury risk has been extensively studied (Leaf and Preusser 1999; Davis 2001; Ballesteros et al. 2004; Gårder 2004; Rosén and Sander 2009; Kong and Yang 2010; Tefft 2013; Kröyer 2015; Sun et al. 2018; Karndacharuk and Mctiernan 2019; Bray Sharpin et al. 2021; Yannis and Michelaraki 2025). Among different speeds, impact speed has been widely recognized as the most direct and critical factor influencing pedestrian injury severity, often illustrated through the S-shaped fatality risk curve (Davis 2001; Rosén and Sander 2009; Kong and Yang 2010). The vehicle speed could be the same as the impact speed if no brakes or evasive action occurred before the vehicle hit pedestrians (Hussain et al. 2019). The impact speed can be estimated by analyzing the collision point and the vehicle's final position, in conjunction with the markings that indicate braking and trajectories between these points (Rosén and Sander 2009). However, despite its importance, real-world crash data often suffer from significant limitations, including biases toward severe and fatal injuries and inaccuracies in estimating actual impact speeds at crash sites (Rosén et al. 2011; Hussain et al. 2019). Earlier studies (Ashton 1980; E. Pasanen 1992) reported higher risk estimates for pedestrian injuries, likely due to biased data towards fatal and serious injuries, leading to a biased risk estimation. Later adjustments by (Davis 2001; Rosén and Sander 2009) corrected this bias by weighting injury severity data to align with national statistics, resulting in lower risk estimates. (Davis 2001) also found that pedestrians aged 60+ are more vulnerable to lower impact speeds than the other two age groups aged (0-14, 14-59). While pedestrian risk does rise with impact speed, (Rosén et al. 2011) emphasized that careful sampling is essential to balance the biased nature of data and prevent overestimating this relationship.

Similarly, (Kröyer 2015) stated that, although impact speed is the most direct factor influencing injury severity, incorporating this relationship into speed management policies is challenging. For example, if the mean travel speed at the crash site is higher, the vehicle will have a higher travel speed, leading to a higher impact speed. However, this does not eliminate the possibility that travel speed can be independent of mean travel speed, and the travel speed of the crash-involved vehicle might be low or vice versa at the crash site (Kröyer 2015). Therefore, difficulties in understanding the impact speed concept for their influence on speed management policies and in obtaining from the majority of studies outside of real-world crash investigations means that proxy speed measures have also been evaluated for their influence on injury

outcomes. For instance, studies such as (Leaf and Preusser 1999; Kröyer 2015) estimated the relationship between vehicle travel speed and the injury outcome based on mean travel speed rather than impact speed, finding that higher mean travel speeds are associated with increased fatality risks.

Similarly, the debate of safe speed limits and speed limits/zones impact on pedestrian safety has been explicitly discussed (Mueller et al. 1988; Leaf and Preusser 1999; Gårder 2004; Mitchell et al. 2015; Olszewski et al. 2015; Bray Sharpin et al. 2021; Yannis and Michelaraki 2025). This is particularly crucial because the impact speed discussed earlier from the vehicle while hitting a pedestrian varies across different speed limit zones. For example, a study by (Tefft 2013) found that the risk of fatality for pedestrians reaches 10% at an impact speed of 24.1 mph, 25% at 32.5 mph, 50% at 40.6 mph, 75% at 48.0 mph, and 90% at 54.6 mph. Similarly, (Hussain et al. 2019) found that pedestrian fatality risk at 30 km/h impact speed is 5% as compared to 40 km/h and 50 km/h where fatality risk increases significantly to 13% and 29%. In addition, studies have also explored the effect of 30 km/h and 50 km/h speed limits on pedestrian safety (Sun et al. 2018; Karndacharuk and Mctiernan 2019; Bray Sharpin et al. 2021; Yannis and Michelaraki 2025). According to (Bray Sharpin et al. 2021) the chance of a pedestrian dying due to being hit by a vehicle at 50 km/h is 40% as compared to 30 km/h where the chance of a pedestrian dying due to being hit by a vehicle is 13%. Similarly, (Karndacharuk and Mctiernan 2019) stated that there is a 90% chance for pedestrians to survive being hit by a vehicle at 30 km/h but less than 50% at 50 km/h or higher. In addition, a study by (Sun et al. 2018) in Edmonton, Canada explores the effect of reducing the speed limits from 50 km/h to 30 km/h and found that setting the speed limits to 30 km/h can significantly help in reducing vulnerable road users (cyclist, pedestrians) injuries to 55%.

2.1.1.2 Research Gaps and existing study contributions

While these single-dimensional speed indicators explicitly discussed above in existing research studies are positively associated with an increased risk and severity of pedestrian crashes, however they fail to fully capture the effect of speed variability across different speed ranges. This oversight neglects the influence of speed fluctuations, which can introduce unpredictable and hazardous conditions for pedestrians. For example, prior research by (Elvik 2019) has highlighted this limitation and argued that mean speed alone serves as a poor predictor of traffic injuries and that crash severity varies significantly depending on speed distribution.

To bridge this gap, speed distribution—particularly percentile speeds (e.g., 15th, 50th, and 85th percentiles)—has been proposed as a more effective metric for assessing pedestrian safety (Arias et al. 2021; Mahmoud et al. 2023). Unlike single-speed measures, percentile speeds capture variations in driver behaviour, offering deeper insights into the range of speeds at which pedestrians may be struck. Prior research (Arias et al. 2021; Mahmoud et al. 2023) has demonstrated that higher percentile speed ranges are associated with an increased frequency of pedestrian crashes compared to lower percentile ranges. This demonstrates that speed variability, especially at higher ranges, plays a critical role in crash risk. However, despite their potential, the relationship between percentile speeds and pedestrian injury severity remains largely underexplored, representing a significant gap in the existing literature.

Therefore, this study contributes to existing literature and seeks to address by investigating the relationship between vehicle speed, specifically percentile speeds, and pedestrian injury severity in the urban context of Palermo, Italy. To achieve this objective, the study used TomTom's Move percentiles speed data (15th, 50th, and 85th percentiles) as a proxy for travel speeds. The analysis evaluates how variations in speed, particularly in low-to-median and median-to-high ranges—impact the likelihood of fatal and serious injuries (FSI) in vehicle-to-pedestrian crashes.

2.1.2 Investigating risk factors associated with the severity of pedestrian crashes

Traffic crashes are a major global public health concern, imposing severe physical, economic, and societal burdens (WHO 2023). The Global Status Report on Road Safety revealed that road traffic crashes result in approximately 1.19 million fatalities annually (WHO 2023). Among various road user groups, vulnerable road users are particularly at risk, with pedestrians being disproportionately affected (Olszewski et al. 2015). A range of factors influence the severity of pedestrian crashes, including socio-demographic, environmental, roadway, temporal, and vehicle-related characteristics etc. Understanding the contributing factors to the severity of these crashes is vital for designing effective safety measures and developing targeted interventions to mitigate risks. Therefore, in this regard, crash severity analysis is considered an important and useful tool by traffic management agencies to better understand the circumstances contributing to the severity outcome of traffic crashes and the underlying mechanism (Shankar and Mannering 1996; Chen and Jovanis 2000; Tang et al. 2019; Yu et al. 2020). Similarly, a better understanding of these contributing factors involves developing models that efficiently interpret the effects of input variables on crash severity. Over time, the

analysis of pedestrian injury severity has evolved significantly, incorporating both traditional and advanced methodological approaches to better understand crash outcomes. In this regard, in the following sections, a detailed literature review will be conducted to understand the factors contributing to pedestrian crashes and to examine the importance of methodological approaches initiated for evaluating the contributing factors and their impact on the severity of pedestrian crashes.

2.1.2.1 Factors affecting pedestrian crashes

Pedestrian crash severity is influenced by various factors. Table 2-1 summarizes studies that have examined these factors and their impact on pedestrian crash outcomes across different locations. As shown in the Table 2-1, demographic characteristics, particularly pedestrian age, and gender, significantly affect the severity of pedestrian crashes (Toran Pour et al. 2018; Batouli et al. 2020; Tao et al. 2022; Rella Riccardi et al. 2023; Mahmuda Sultana Mimi 2024; Qingli Liu 2024; Khan et al. 2024). For instance, regarding age, prior studies (Yasmin et al. 2014; Haleem et al. 2015; Pour-Rouholamin and Zhou 2016; Li et al. 2021; Song, Fan, et al. 2021; Zamani et al. 2021) have concluded that both younger and older pedestrians face a higher likelihood of severe injuries in crashes. When considering gender, male pedestrians are generally found to be at a higher risk of severe crash outcomes (Tarko and Azam 2011; Abay 2013; Onieva-García et al. 2016; C. Wang et al. 2022). However, some research suggests that female pedestrians may be more vulnerable to severe injuries in pedestrian crashes (Forbes and Habib 2015; Noh et al. 2018). In addition to the above, driver age and gender also significantly influence pedestrian crash severity. Existing studies have found that younger (Abay 2013; Mohamed et al. 2013; Pour-Rouholamin and Zhou 2016) and older drivers (Forbes and Habib 2015; Song et al. 2020; Li et al. 2021; Alogaili and Mannering 2022; C. Wang et al. 2022) are more likely to be involved in severe pedestrian crashes. Regarding gender, male drivers are generally associated with a higher likelihood of involvement in severe pedestrian crashes (Forbes and Habib 2015; Song et al. 2020; C. Wang et al. 2022).

Regarding environmental attributes, various factors such as adverse weather conditions, lighting, and visibility have been found to significantly influence pedestrian crash severity (Siddiqui et al. 2006; Kim et al. 2010; D. Li et al. 2017; Sanders et al. 2022; Goswamy et al. 2023; Rella Riccardi et al. 2023). More specifically, adverse weather conditions, particularly rainy and cloudy weather, have increased the probability of severe pedestrian crash outcomes (Aziz et al. 2013; Zhai et al. 2019; Zamani et al. 2021). Similarly, dim lighting conditions, such

as dark, dusk, and dawn, result in low visibility and have been associated with a higher severity of pedestrian crashes (Behnood and Mannering 2016; Song et al. 2020; Zamani et al. 2021). In contrast, past studies (Fountas et al. 2020; Li et al. 2021) have also found that enhanced visibility and proper lighting conditions contribute to a lower risk of severe pedestrian crash outcomes.

Various roadway characteristics, including the number of lanes, speed limits, roadway type, and roadway width, have been shown to significantly influence the severity of pedestrian crashes (Pulugurtha and Sambhara 2011; Ukkusuri et al. 2012; Tulu et al. 2015; Haleem et al. 2015; D. Li et al. 2017; Moradi et al. 2019; Rao et al. 2022; Khan et al. 2024). The roadway type with a single lane is less severe to pedestrian crash outcomes, than the roads with multi lanes (Aziz et al. 2013; Pour-Rouholamin and Zhou 2016). Similarly, roads with speed limits higher than 60 km/h tend to be more severe for pedestrian crash outcomes as studied by (Sasidharan et al. 2015). Additionally, median is found to be another roadway feature that impacts the severity of crashes involving pedestrians and vehicles. Studies such as (Xin et al. 2017) discovered that pedestrian crashes that happened at undivided roadways are associated with an enhanced likelihood of severe injuries, whereas in contrast, (Zafri et al. 2020) found that divider roads decrease the probability of fatal damages. Moreover, roadway control devices such as traffic signals and signs decrease the risk of pedestrian fatalities (Kim et al. 2008; Pour-Rouholamin and Zhou 2016), nevertheless their absence increases the risk of serious injuries (Xin et al. 2017). The intersections that are equipped with signals are less likely to be risky for pedestrians crossing (Behnood and Mannering 2016).

Temporal characteristics have also been found to influence the severity of pedestrian crash outcomes, such as day of week, time of day, and several studies focused on the occurrence of temporal shifts in pedestrian crashes through different times of day, day of week, seasons, and years (Li et al. 2021; Zamani et al. 2021; Alogaili and Mannering 2022; Natalia Barbour 2024). Prior studies on pedestrian injury severity analysis shown that pedestrian crashes occurring on weekends tend to result in more severe injuries compared to those occurring on weekdays (Alnawmasi and Mannering 2019). In addition, existing studies have found that crashes occurring during the early morning hours as well as those during the evening hours tend to increase the severity of pedestrian crashes (Wang et al. 2017; Alnawmasi and Mannering 2019; Song, Li, et al. 2021). Similarly, the season of the year has been identified as a factor influencing crash severity. Specifically, studies (Mohamed et al. 2013) reported that pedestrians are more likely to be involved in severe crashes during the winter season.

As reported in Table 2-1, Vehicle-related characteristics—such as vehicle design, speed, mass, size, and type—significantly contribute to the severity of pedestrian-vehicle crashes. These factors not only directly interact with pedestrians, leading to more severe injury outcomes, but also influence the crash dynamics themselves (Roudsari et al. 2004; Matsui et al. 2011; Han et al. 2012; Verzosa and Miles 2016; Liu et al. 2019). Specifically, large and heavy vehicles, such as buses, and trucks, have been shown to increase the severity of injuries in pedestrian-vehicle collisions (Kim et al. 2010; Tarko and Azam 2011; Mohamed et al. 2013; Sasidharan et al. 2015; Hamidun et al. 2017; Noh et al. 2018; Zafri et al. 2020; Zamani et al. 2021; Alogaili and Mannering 2022). On the other hand, with regard to vehicle design, sport utility vehicles (SUVs), often classified as sports-design vehicles, have been found to result in more severe pedestrian injuries compared to passenger cars (Kim et al. 2008). Although these larger and more powerful vehicles are commonly associated with increased severity of pedestrian crashes, motorcycles have been reported to result in less severe injury outcomes in similar incidents (Noh et al. 2018).

In addition to the factors previously discussed, other critical features, such as pedestrian behavior and the presence or absence of crosswalks, also play a significant role in influencing the outcomes of pedestrian-involved crashes. Previous studies have highlighted that pedestrians who are crossing a roadway are more likely to experience severe crashes compared to those who are not crossing (Tarko and Azam 2011). Conversely, pedestrians walking along a road, rather than crossing, are generally at a lower risk of sustaining severe injuries (Haleem et al. 2015). Similarly, the presence of crosswalks has been shown to reduce the likelihood of severe crashes for pedestrians crossing the road (Pour-Rouholamin and Zhou 2016). On the other hand, the absence of crosswalks significantly increases the probability of severe injuries, underscoring the importance of pedestrian-friendly infrastructure (Abay 2013).

2.1.2.2 Methodological approaches

Table 2-1 summarizes past studies focused on pedestrian injury severity, highlighting the methodologies with a broad range of statistical and machine learning models. Traditional statistical models, such as binary logistic regression (Sze and Wong 2007; Sasidharan et al. 2015; Zafri et al. 2020; A. Hossain, Sun, Das, et al. 2024; A. Hossain, Sun, Hasan, et al. 2024), multinomial regression (Tay et al. 2011; Chen and Fan 2019; Nasri et al. 2022; Agyemang et al. 2023), and ordered probit models (Forbes and Habib 2015; Chung 2018; Salehian et al. 2023; Fu and Tu 2024), have been widely used to identify factors influencing pedestrian injury

severity. However, these approaches often face challenges due to assumptions regarding data distribution and pre-defined connection between dependent and independent variables and violations of these assumptions can lead to biased and erroneous estimations (Santos et al. 2022).

To address the limitations of traditional models, machine learning models have gained prominence for their ability to handle complex and non-linear relationships among variables (Tang et al. 2019; Santos et al. 2022). These models have better prediction performance (Mokhtarimousavi et al. 2020; Ali et al. 2024) and are capable to tackle the missing data and injury severity class imbalance-related challenges (Deb and Liew 2016a; L. Li et al. 2017; Yahaya et al. 2019; Boo and Choi 2022). Acknowledging the importance of crash severity modeling, numerous studies such as (Mokhtarimousavi et al. 2020; Komol et al. 2021; Han Yue 2024) have employed machine learning methods to evaluate pedestrian crash severity outcomes. Among the machine learning methods, (Mokhtarimousavi et al. 2020) utilized Artificial Neural network, whereas (Komol et al. 2021) used K-Nearest Neighbour, Support Vector Machine, and Random Forest for evaluating the crash outcomes of crashes involving pedestrians. In addition, research (Han Yue 2024) applied XGboost algorithm to investigate the impact of streetscape environmental characteristics on the outcome of pedestrian crashes reported at intersections.

However, besides their superior predictive performance, the machine learning models struggle with the interpretation of crucial model outcomes such as the effects of predictor variables on the response variables (Wen, Xie, Jiang, et al. 2021; Ali et al. 2024). With the passage of time and a recent development, this major drawback of machine learning models has been tackled with explainable artificial intelligence methods (Ali et al. 2024). These explainable artificial intelligence methods include such as Local Interpretable Model-agnostic Explanations, Local Sensitivity Analysis (LSA), Partial Dependence Plots (PDP), Global Sensitivity Analysis (GSA), and SHapley Additive exPlanations (SHAP) (Wen et al. 2022; Ali et al. 2024). The effectiveness of these post-hoc techniques for their efficiency in explaining the machine learning models results in traffic safety research has been explicitly explained by (Wen et al. 2022). Among these techniques, LSA, PDP, and SHAP has been widely used in traffic safety studies for interpreting the machine learning models outcomes (Schlögl et al. 2019; Tang et al. 2019; Wang and Kim 2019; Parsa et al. 2020; Pu et al. 2020; Wen, Xie, Wu, et al. 2021). The values from SHAP can be interpreted through global and local analysis. The global analysis is

useful for interpreting the global feature importance. In such cases, the mean absolute SHAP values to each feature are assigned by a machine learning model to rank their importance in predicting crash severity which provides a detailed overall significance of each feature in the prediction process (Kashifi 2023). Whereas in local interpretability analyses, the effect of each feature has been individually investigated for their impact on the crash severity. In such a scenario, a three-dimensional tensor has been developed based on shapely values, which is beneficial in evaluating the impact of each feature on the output class for each individual observation (Kashifi 2023). This tensor structure can be further used for deeply evaluating the influence of the interaction of multiple factors on the crash severity with visual plotting such as dependency plots. Such interaction effects analysis of variables enables a comprehensive evaluation of each variable impact on the severity of crash outcomes. Particularly in the realm of pedestrian injury severity analysis, the SHAP technique has been found to be quite efficient in explaining machine learning model outcomes as used in many past studies (Guo et al. 2021; Goswamy et al. 2023; Kong et al. 2023; Han Yue 2024).

Table 2–1. Summary of past studies on pedestrian injury severity

Authors	Method	Study Area	Key findings
(Goswamy et al. 2023)	XGBoost & Random Parameter discrete outcome model (RPDOM)	Florida, USA	Factors contributing to fatality, property damage only, possible injury, Non-Incapacitating Injury, Incapacitating Injury: XGBoost: Temporal features (Year, month & hour), number of pedestrians, roadway features (Shoulder, Curb), Weather Conditions, Rectangular RAPID Flashing Beacons (RRFB) RPDOM: Paved shoulder, Nighttime, Number of Lanes, speed limit increase, number of persons or vehicles, roadway types, Male drivers, Rainy weather.
(Rella Riccardi et al. 2023)	Association Rules & Mixed Logit Model	Italy	Fatal pedestrian crash contributory factors: Mixed Logit: Nighttime, Motorways, slippery pavement, weekends, summer season, Cars and trucks, drivers psychophysical state, aged pedestrians, male pedestrians Association Rules: Rural area roadway, tangent, Nighttime, weekend, Truck, speeding, male driver, drivers age (18-24, 25-44, 45-54), aged pedestrians.
(D. Li et al. 2017)	Classification trees combination with Random Forest Model	Great Britain	Factors affecting fatality, serious injury, and slight injury: Aged pedestrians, Higher speed limits, Light conditions, Vehicle maneuver.
(Guo et al. 2021)	XGBoost & MNL Model	Colorado, USA	Factors affecting fatal severity identified by XGboost and MNL in common: Aged Pedestrians, Driver speed, Driver age, number of crashes people, older speed.

(Tao et al. 2022)	Bayesian Neural Network	Australia	Factors affecting fatal severity: Speed limit, Crash type, Pedestrian age, Time of day, Bus Involvement
(Rao et al. 2022)	Support Vector Machine, Random Forest, Decision tree	Great Britain	Factors affecting fatality: Vehicle Manoeuvres, Speed Limit, Pavement & day of week. Factors affecting Serious injury: Vehicle maneuvers, road type, no of vehicles present, weather.
(Khan et al. 2024)	Inception-v3 deep learning model	Louisiana, USA	Factors affecting fatality, injury, and no injury: Pedestrian gender, driver impairment, posted speed limit, alcohol involvement, pedestrian age, roadway light conditions, visibility problem, pedestrian and driver behavioral disturbance.
(Sun et al. 2023)	Random Forest based SHAP (RF-SHAP), Random Parameters Logit Model	Shenyang, China	Factors associated with fatal crashes: Age, truck-involved crashes, driving behaviour, crash type (head-on crashes, side collision and side-swipe), Autumn and Winter season
(Sun et al. 2022)	Random Parameter Logit (RPL), Bayesian Network	Shenyang, China	Factors associated with fatal crashes identified by RPL: Fall and winter season, functional zone (ZON), age of vulnerable group (AVG) and motor vehicle type (MVT). Factors associated with fatal crashes identified by Bayesian network: Functional Zone (ZON) (crashes in rural areas), Age of pedestrian, crash type, Truck
(Batouli et al. 2020)	Logistic Regression Model	Colorado, USA	Factors affecting the severity of fatal pedestrian crashes: Higher vehicle speed, Vehicle type (passenger cars/vans, sport utility vehicle (SUV), pickup truck/utility van, and larger trucks and buses), Older age, lighting conditions, intersection proximity
(Mahmuda Sultana Mimi 2024)	Association Rules Mining (ARM)	Texas, USA	Factors associated with fatal crashes for older pedestrians: High-speed limits, Nighttime, Pedestrians aged (74 or above)
(Bo Du 2024)	Random Parameters Negative Binomial (RPNB), Binary Logit Model	Australia	Factors associated with severity of pedestrian crashes: Crash type, early morning time, weekdays, non-signal intersection, suburb areas
(Chung 2018)	Ordered probit model	Incheon, South Korea	Factors affecting the injury severity: Crash speed, Crash Location Characteristics, Pedestrian Characteristics, Driver maneuverer
(Kim et al. 2010)	Mixed Logit Model	North Carolina, USA	Factors associated with pedestrians' fatal severity: Darkness with and without streetlights, Male pedestrians, trucks, Freeway, Speeding involved
(Haleem et al. 2015)	Mixed Logit Model	Florida, USA	Factors affecting the severity of pedestrian crashes at signalized intersections: higher AADT, speed limit, and percentage of trucks; very old pedestrians; at-fault pedestrians; rainy weather; and dark lighting Factors affecting the severity of pedestrian crashes at un-signalized intersections: Pedestrian walking along the roadway, middle and very old pedestrians, at-fault pedestrians, vans, dark lighting conditions, and higher speed limit

(Sasidharan et al. 2015)	Binary Logit Models	Switzerland	Variables associated with the severity of fatal and severe injuries crashes: national roads, high speed limits (≥ 60 kmph), alcohol, mid-block crossings, heavy vehicles, and pedestrian violation of rules
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2.1.3 Research Gaps and Existing Study Contributions

In response to growing concerns about pedestrian-related injury severity, several studies have investigated pedestrian safety at the national level (Alfonso Montella 2011; Meocci et al. 2021; Rella Riccardi et al. 2022). While these studies offer valuable insights, they often generalize findings across diverse geographic and urban contexts. As such, they may overlook critical micro-level variations in infrastructure quality, traffic behavior, and mobility patterns that can significantly influence crash frequency and severity (Zhu et al. 2022; Tanishita et al. 2023). The densely built and historically constrained city centers, in particular, present unique spatial and operational challenges, such as irregular road layouts, limited pedestrian zones, inconsistent enforcement of traffic rules, and competing demands between motorized and non-motorized road users that are not easily captured by nationwide analyses (De Oliveira et al. 2019). As a result, broad, national analyses may not fully address the factors contributing to pedestrian safety in unique urban environments, especially those with historical layouts or rapid urbanization.

To bridge these gaps, a growing body of literature has begun to explore pedestrian crash severity within localized, city-specific contexts. For instance, studies conducted in cities like Alghero and Rome (Congiu et al. 2019; Mauro D’Apuzzo 2024) have explored city-specific contexts, examining factors influencing pedestrian crash severity. These studies also emphasize the importance of localized analyses to capture the unique dynamics of pedestrian safety in specific urban environments. Despite these efforts, certain major urban areas remain underrepresented in the research. To the best of our knowledge, no study to date has focused exclusively on assessing pedestrian crash injury severity in Palermo, the capital city of Sicily, Italy. Palermo is a major tourist destination in southern Italy, however, the city also faces substantial mobility and safety challenges, largely due to high private car dependency, inadequate public transport, and the lack of sustainable urban mobility policies (Barbarossa 2020). The city’s road network, shaped by centuries of development, often lacks the infrastructure necessary to support safe pedestrian movement in the face of growing vehicular traffic (D’Orso et al. 2024). This is also evident because Palermo also experiences some of the worst traffic congestion in Europe. According to the TomTom Traffic Index Ranking, Palermo

ranked as the 77th most traffic-congested city globally in 2023, while INRIX identified it as the third most congested city in Europe in 2022 (INRIX 2023). The downtown streets of Palermo are heavily congested, with drivers spending the equivalent of five full days per year stuck in traffic (INRIX 2023). Moreover, data from the Palermo Municipality Police indicates that 1,999 pedestrian crashes were reported between 2015 and 2022. However, it is important to acknowledge that this figure underestimates the true number of incidents, as many minor crashes often go unreported. Given Palermo's complex urban structure and mobility challenges, a localized investigation into the determinants of pedestrian crash severity is both timely and essential.

2.2 Pedestrian accessibility

The second most pressing concern for pedestrians is accessibility in urban environments (Bivina et al. 2020a; D'Orso and Migliore 2020a; Jehle et al. 2022). Accessibility is a fundamental component of urban planning that directly influences how people move through and interact with their cities (Järv et al. 2018). Unlike other transport users, such as vehicle occupants and public transport passengers, pedestrian accessibility specifically addresses the ease, safety, and comfort with which individuals can navigate urban spaces on foot (Alfonzo 2005; Lin et al. 2015). A key element of pedestrians accessibility is road connectivity. Increased road connectivity due to grid-like networks, small blocks, and limited cul-de-sacs, encourages walking, reducing travel distances and providing a wide range of routes from which to choose. As highlighted by (Dill 2004), there is a wide range of measures of connectivity that can be used to assess how much the neighbourhood design is able to promote walking. The main network connectivity indicators used by transportation and urban planners are reported in Table 2-1.

Figure 2–1. Network connectivity indicators

Indicator	Definition	Impact
Road density	Total street length per 1 km ² area.	Higher road density means more roads are present in a given area, which can lead to better accessibility.
Intersection density	Number of road intersections per 1 km ² area, where intersections are the junctions at which three or more road segments intersect.	A high intersection density indicates a walking-friendly environment, allowing pedestrian to change direction frequently and reach destinations following a more direct route.
Connected node ratio (CNR)	Number of road intersections divided by the number of nodes (intersections plus cul-de-sacs).	The maximum value is 1.0. Higher numbers indicate that there are relatively few cul-de-sacs and dead ends, and presumably a higher level of connectivity. Values of 0.7 or higher are favored.

Link-node ratio (LNR)	Number of links divided by the number of nodes (intersections plus cul-de-sacs).	The link count represents the number of street segments between two nodes, and the node count is the sum of the number of intersections and the number of dead ends (cul-de-sacs). A perfect grid has a LNR of 2.5. A LNR of 1.4 or more is a desirable target.
Block length	Average block length for blocks within a defined area.	Shorter blocks mean more intersections and therefore a greater number of routes available.
Block size	It captures two dimensions of the block, rather than the individual length of each side. This can be measured by the area or the perimeter.	Small blocks mean more intersections and therefore a greater number of routes available. Block size could be used as a research tool or performance measure by calculating the share of blocks meeting a standard or the average value.
Block density	Number of blocks per km ² .	Increased block density is thought to represent increased connectivity: more blocks mean smaller blocks and more intersections.
Pedestrian Route Directness (PRD)	Ratio of route distance to straight-line distance for two selected points.	The lowest possible value is 1.00, where the route is the same distance as the "crow flies" distance. Values closer to 1.00 indicate a more direct route, theoretically representing a more connected network.
Alpha index	Ratio of the number of actual circuits to the maximum number of circuits and is equal to $(\# \text{ links} - \# \text{ nodes} + 1) / (2(\# \text{ nodes}) - 5)$.	Values for the alpha index range from 0 to 1, with higher values representing a more connected network. Trees and simple networks will have a value of 0. A value of 1 indicates a completely connected network.
Gamma index	Ratio of the number of links in the network to the maximum possible number of links between nodes. The maximum possible number of links is expressed as $3 * (\# \text{ nodes} - 2)$ because the network is abstracted as a planar graph.	Gamma index ranges from 0 to 1 and is often expressed as a percentage of connectivity, e.g. a gamma index of 0.54 means that the network is 54 percent connected.
Pedestrian Catchment Area ratio (PCA)	The ratio between the network-defined service area, considering a walkable network distance (for example, 500 m) from a fixed point, and the theoretical service area considering Euclidean distances (buffer with a radius of 500 m).	PCA ratio measures how well the road network covers the area around a specific key destination. Values of the ratio close to 1 indicate extremely walkable areas, while a score less than 0.30 would reflect an inaccessible walking environment. Although there has not been enough research to determine an optimal PCA score, it is suggested that a minimum score of 0.5-0.6 is a useful threshold (Schlossberg, 2006).

Other key elements of pedestrian accessibility include the quality of footpaths, safe crossings, intersection safety, and the presence of supportive amenities such as street lighting, pedestrian-specific signals, seating benches, shops, and recreational areas (Lo 2009; Ujang and Zakariya 2015). A pedestrian-friendly environment not only promotes sustainable mobility but also encourages social interaction, economic activity, and public health.

Indeed, pedestrian accessibility is closely related to both walkability and social equity (Alnaim et al. 2025). This perspective was emphasized by (Rebecchi et al. 2019; Garau et al. 2020), who proposed a multi-criteria framework to assess urban walkability based on dimensions such

as Density, Diversity, Usefulness, Safeness, Comfort, and Affordability. Their objective was to understand how built environments influence people's likelihood to walk for different purposes. The framework captures walkability across various spatial scales and offers design recommendations to help policymakers and urban designers develop healthier, more walkable cities. For example, safe and well-maintained footpaths equipped with streetlights and shade, along with clearly marked and secure crosswalks, contribute significantly to a safe and convenient walking experience that encourages pedestrian activity. In areas near public transit stations—such as bus, railway, metro, and tram stops—walkability becomes even more critical, as many individuals walk to and from these locations daily (Bivina et al. 2019; Kathuria et al. 2019; Sarker et al. 2020). If the pathways to transit stations are not walkable, fewer people may choose public transport, potentially increasing reliance on private vehicles and exacerbating urban challenges like traffic congestion and pollution. Therefore, pedestrian accessibility is intricately linked to the perceived quality of land use and transport systems (Vural Arslan et al. 2018; Gkavra et al. 2019; Ma and Cao 2019).

This issue is also fundamentally connected to transport equity (Y. Wang et al. 2022). As already stated in Chapter 1, transport equity refers to ensuring equal and fair access to public transport options for all individuals (Y. Wang et al. 2022). In many low-income urban areas, residents are especially reliant on walking and public transport for their daily mobility needs. However, certain suburban neighborhoods suffer from poor pedestrian infrastructure and safety conditions, leading to public transit stops. As a result, residents in these areas face limited mobility choices and additional barriers simply to reach public transit. Enhancing the quality of pedestrian infrastructure in such areas is crucial for improving pedestrian access and making public transport a viable and equitable mobility option for everyone.

In this context, improved pedestrian access to public transportation also supports broader goals of social equity. This means ensuring that all individuals—regardless of income level, age, or physical ability—have fair access to public transport services. Not everyone owns a private vehicle, and many people rely entirely on public transport for their mobility needs, including first and last mile connectivity. Inadequate, unsafe, or unpleasant walking environments compromise their access, freedom of movement, quality of life, and opportunity. Thus, ensuring walkable streets and pathways is not solely a transportation concern but also a matter of social justice.

To address these issues, this research evaluates pedestrian accessibility and walkability in relation to railway stations, specifically from the perspectives of transport and social equity. It provides a comprehensive walkability assessment framework that links the physical design of infrastructure to the social experience of vulnerability among pedestrians. The study uses Palermo as a case study, analyzing the quality of pedestrian infrastructure using mesoscale and microscale walkability indicators through a GIS-based approach across fourteen railway stations. A systematic review of the research progress in the aforementioned study is presented in the following sections. Subsequently, research gaps are identified to highlight their significance and the potential contributions of this study to improving pedestrian accessibility and walkability to railway stations.

2.2.1 Disparities in walkability and accessibility to railway stations

The role of walking in making a railway station more appealing is evident: the more individuals who can access a station quickly, the greater the concentration of activities and services that tend to develop in its surrounding area (Wenner et al. 2020). In addition, enhancing pedestrian infrastructure around the station could encourage more individuals to walk to and use the metro. Globally, it has been commonly observed that a majority of people continue to depend on their vehicles to reach metro stations. Introducing practical solutions that motivate more people to walk rather than drive to the station would significantly contribute to making the station areas more livable, while also promoting Transit-Oriented Development (TOD) (Bivina et al. 2020b). The term “transit-oriented development” or “TOD” became popular in the early 1990s, when Peter Calthorpe identifies the station area as a fundamental building block for transportation and land use integration. TOD is defined as “mix residential, retail, office, open space, and public uses in a walkable environment, making it convenient for residents and employees to travel by transit, bicycle, foot or car” (Calthorpe 2015). Calthorpe adds that a TOD is “a mixed-use community within an average 2000-foot (approximately 600 meters) walking distance of a transit stop and a core commercial area”.

In this regard, not all communities and social groups have equal opportunities or the same level of access to railway stations when it comes to walking. Poor walkability on local streets can influence an individual’s choice of transport, affecting how they travel for daily activities and whether they can reach a railway station within their catchment area (Ferrer and Ruiz 2018). In many cities, there are clear inequalities in walkability and access to railway stations. This issue is especially noticeable in aging cities that are already dealing with complex urbanization problems. These inequalities often stem from factors such as poor quality infrastructure, land

use limitations, and planning challenges rooted in the historical development of cities. As a result, people who depend most on walking and public transport are the ones most affected by these disparities.

Railway stations located in central or newly developed areas usually benefit from better pedestrian access, supported by well-maintained sidewalks and safer crossing points. However, stations in older neighborhoods, low-income communities, and peripheral areas often face major challenges. In these areas, damaged pavements, unsafe crosswalks, and barriers like high-speed roads or fences make it much harder for pedestrians to reach the station safely and comfortably. These issues directly affect people's ability to use the railway system for daily commuting.

When the walking environment around railway stations is poor, it makes the stations less useful, especially for people who rely solely on them, such as students, elderly individuals, and those without access to a car. In such cases, limited walkability leads to lower access to rail services, which can possibly restrict a person's ability to travel for work, education, or essential services. This situation creates transport and social equity challenges.

Past studies, in this regard, have explicitly examined the challenges faced by pedestrians concerning walkability and accessibility to railway/metro stations. In this regard, the literature has largely assessed accessibility considering it as both subjective and objective. The subjective accessibility refers to the assessment of accessibility based on perceived perception, which could be related to pedestrians' perception of ease in reaching a destination, whereas objective accessibility is usually referred to as the assessment of accessibility based on accessibility indicators which are based on physical elements and ground facility levels of surroundings environments (Jehle et al. 2022; Chen et al. 2024). For instance, (Jehle et al. 2022) studied the factors affecting perceived pedestrian accessibility to railway stations and found that perceived factors such as comfort, traffic safety, and security in terms of freedom from barriers, presence of crosswalks, and lighting significantly affect people's perception with regard to pedestrian accessibility to railway stations. Similarly, another study by (Otsuka et al. 2021) assessed walkability around railway stations from three European countries based on both objective and subjective measures, and revealed that several objective factors, such as unsafe crosswalks, traffic noise, speed, and air quality as well as subjective factors, such as aesthetics, fear of crime, and cleanliness, strongly impact the walkability to the railway stations. In addition, research conducted by (Halldórsdóttir et al. 2017) in the Copenhagen region, in assessing

different transport mode access to railway stations established that walkability, bikeability, bus service, and bicycle parking (especially at the activity end) significantly increase the likelihood of choosing sustainable access and egress modes to and from railway stations. Similarly, a study was conducted to analyze the pedestrians' perceived satisfaction in accessing the metro service stations in Delhi, India by (Bivina et al. 2020b). The study found that among microscale and mesoscale indicators, the microscale indicators, such as quality of sidewalks, width of sidewalks, encroachment on sidewalks, etc., significantly impact the pedestrians' perception of reachability to metro stations. (Ozawa et al. 2021) proposed a method to evaluate walkability around urban railway stations in Bangkok using the Analytic Hierarchy Process (AHP), which involved scoring and weighting various physical and structural components of the walking environment based on expert input and pedestrian surveys. The study identified critical factors affecting walkability including the presence of sidewalks, dangerous spots, sidewalk width, number of steps, and obstacles on roads, as well as pedestrian signals and crosswalk markings. In continuation, another study from Bangkok, by (Vichiensan et al. 2022) assessed walkability in the catchment areas of 25 urban rail transit stations by applying exploratory and confirmatory factor analyses along with structural equation modeling to understand both objective conditions and perceived user experiences. The study identified that greenery, which includes trees or plantings, security, safety, cleanliness, and convenience, highly impacts walkability to rail transit stations.

While these studies had explicitly focused on evaluating built environmental and perceived risk perception factors that significantly affect pedestrian accessibility and walkability to the railway stations, nonetheless, other studies in the literature also focused on understanding the pedestrian accessibility to the railway stations in the background of transit-oriented development (TOD). To counter the challenges like urban modernization, traffic pollution, and congestion, the concept of transit-oriented development can play a pivotal role. Emphasizing walkability around railway stations based on Transit-Oriented Development (TOD) principles, which integrate transport and urban planning for sustainable, transit-friendly urban communities and vibrant neighbourhoods, can reshape urban dynamics, reduce car dependency, and help uplift urban life. For example, (Schlossberg and Brown 2004) classified 11 TODs in Portland in terms of their walkability using 6 built environmental indicators (quantity of accessible paths, i.e. minor roads; quantity of impedance paths, i.e. arterial roads; PCA ratio; impeded PCA calculated excluding the high-volume, high-speed corridor; intersection density, and density of dead ends). Similarly, (Kamruzzaman et al. 2014) include

some indicators related to network connectivity in their six TOD indicators (employment density, residential density, land use diversity, intersection density, cul-de-sac density, and public transit accessibility) to classify 1734 census districts in Brisbane. (Jeffrey et al. 2019) further highlighted that walkability improves train station access and can be used for measuring TOD potential; with this perspective, the authors evaluated the potential of 230 train station areas in metropolitan Melbourne, Australia, to function as a TOD using 14 different walkability measures, including PCA ratio and CNR as indicators related to the network design. In addition, a study by (Lyu et al. 2020) employs a spatial error regression model (SERM) to analyze how transit-oriented development (TOD) components influence metro station area accessibility in Beijing, using metrics like transit performance, land use patterns, and walkability. The key factors impacting walkability include the length of paved footpaths (LFS) and Walk Scores (WSS), though their relative importance was found to be smaller compared to land use and transit components in enhancing accessibility. Moreover, another study by (Akbari et al. 2018) was conducted to identify rail station level characteristics and attributes of the surrounding environment with regard to their connection to walking access and egress to rail ridership. The research acknowledged that enhanced walkability, high frequency of rail service, and high-density residential developments with restricted levels of parking are positively linked to the trip generations that begin with walking to the rail station. Similarly, the railway stations in the cities of Singapore and Shanghai were evaluated by (Niu et al. 2021; Zhang et al. 2022) based on Transit-Oriented Development (TOD) Principles. Factor and cluster analysis from both studies highlighted the characteristics and typology of TOD around railway stations, facilitating urban planners to diagnose issues and design strategies in diverse urban contexts.

Since the quality of pedestrian infrastructure is not always at the same level in different areas of the city, eventually, it impacts societies and communities that have limited access to public transit for their mobility solutions. This creates transport and social equity challenges. Therefore, there is a need to consider the social and transport equity perspective when examining pedestrian accessibility to railway stations in urban and suburban areas (Behbahani et al. 2019). For instance, (Guo and Brakewood 2024) highlighted this perspective in their work and stated that evaluating the spatial inequalities in access to railway services and identifying accessibility issues having social impacts is critical, especially considering that low-density areas have limited public transport services that can fulfil people's fundamental needs, connecting them to essential services and job opportunities, which can create equity challenges. In this perspective, another study by (Adli et al. 2020) assesses walking access to

two Auckland rail stations using spatial and statistical methods within a social justice framework. The findings reveal that while neither station met minimum accessibility standards, the TOD station offered comparatively better access for low-income individuals. Therefore, they emphasize that social equity is important when planning access to public transport.

2.2.2 Research Gaps and existing study contribution

As stated above, numerous past studies have evaluated pedestrian accessibility to railway stations from various perspectives, considering the social context, the built environment, and individuals' perceived experiences. However, only a few studies have explored this issue within the context of the case study area (Palermo, Italy). For example, a study by (D'Orso and Migliore 2020a) developed a method to assess the pedestrian environment around selected railway station catchment areas in Palermo. Their findings revealed that the quality of pedestrian infrastructure around these stations is unsatisfactory. As discussed earlier, poor walkability has a strong negative impact on pedestrian accessibility to railway stations and influences the travel mode choices of various social groups for different types of trips. This often results in lower usage of public transport options, such as the railway, and encourages greater reliance on private vehicles for mobility and commuting. Over time, this can further aggravate traffic congestion and environmental pollution in cities like Palermo.

When assessing pedestrian accessibility and walkability to railway stations, it is also important to consider the perspectives of transport and social equity. For example, if a railway station is not equally accessible to all individuals—regardless of income, age, gender, or background—then the availability of public transport becomes less efficient and equitable. In this context, clear differences exist between railway stations in suburban areas and those in urban centers. Additionally, while it is commonly stated that slightly more than half of the world's population now lives in cities (United Nations, 2014), a significant portion still resides in suburban, exurban, or rural areas. This raises an important question: how can planning concepts that aim to create equitable and walkable neighborhoods—such as Transit-Oriented Development (TOD) or the 15-minute city—be effectively applied beyond urban areas? Traditional transport planning often relies on utilitarian principles, which may overlook how the outcomes of infrastructure projects are distributed. This approach can sometimes worsen inequalities rather than reduce them (Freiberg et al. 2024). Furthermore, the public benefits of transport investments—such as the placement of railway stations—are not always shared equally among different population groups (Foth et al. 2013).

Through a review of existing literature from a transport and social equity standpoint, we found that, to the best of our knowledge, no previous study has comprehensively evaluated pedestrian accessibility and walkability while also examining their impact on transport and social equity. To address this gap, the present study conducts an in-depth assessment of pedestrian accessibility and its relationship with transport and social equity, focusing on fourteen railway stations in Palermo, Italy. The study developed a detailed Geographic Information Systems (GIS)-based methodology to analyze spatial inequalities using both mesoscale and microscale walkability indicators. Findings revealed disparities in pedestrian accessibility between stations located in urban cores and those in suburban areas. These differences were shown to impact various individuals living within the catchment areas of each station. Based on these insights, the study proposes several solutions to address existing challenges and improve accessibility for all users. The recommendations aim to transform these areas following Transit-Oriented Development principles, enhancing both access and the overall livability of neighborhoods.

Chapter 3

Evaluating the Role of Speed Reduction on the Severity of Vehicle-Pedestrian Crashes: A Case Study in Palermo, Italy

Urban environments are facing challenges due to the demand to accommodate vehicular mobility with pedestrian safety, especially in the historical layout, which already faces constraints with advanced urbanization. To this end, vehicle speed has long been recognized as a critical factor influencing both the likelihood and severity of pedestrian crashes. However, there is still a gap in better quantifying how real-world vehicle speeds can impact injury outcomes and how speed reduction strategies can enhance pedestrian safety, while taking into account the historical urban structure of the case study.

This chapter, presenting the study referred to as RA1, examines the influence of real-world vehicle speeds at the locations of injury outcomes in police-reported vehicle-to-pedestrian crashes in Palermo, Italy. Recognizing that even small reductions in travel speed could have a meaningful impact, the research specifically explores how minor decreases in vehicle speeds, particularly in low-speed urban environments, can significantly reduce the risk of pedestrian fatalities and serious injuries. Furthermore, the study aims to evaluate the effectiveness of speed management strategies and propose actionable policies that could mitigate the consequences of such crashes.

To achieve these objectives, pedestrian crash data from the Palermo Municipality Police were used to identify crashes reported in fatal and serious (FSI) injuries, particularly involving vehicles and pedestrians. These crash locations were then utilized to identify road segments and obtain speed data through a speed database. Speed data was acquired from a TomTom Move speed database, represented by specific percentiles (15th, 50th, and 85th), which served as proxies for vehicle impact speeds to estimate the risk of fatal and serious injuries (FSI). A discrete outcome model was employed to analyze the relationship between speed and injury risk. Additionally, a counterfactual analysis was conducted to estimate model efficiency in potential risk reduction by simulating the effects of reducing travel speeds by 3 km/h and 5 km/h on pedestrian injury risk.

The results revealed a strong association between higher vehicle speeds and an increased likelihood of fatal and serious injuries. The counterfactual analysis demonstrated that a 3 km/h and 5 km/h reduction in the 15th, 50th, and 85th percentile speeds could significantly reduce the risk of fatal and severe injuries. The findings underscore the importance of speed management policies in urban settings, where pedestrian activity is high and crash risks are elevated. They further suggest that even modest reductions in vehicle speed can substantially improve pedestrian safety. Consequently, strategies such as implementing appropriate speed limits, enhancing pedestrian infrastructure, and adopting traffic calming measures are critical interventions to reduce the incidence and severity of pedestrian injuries.

3.1 Data description

The study is based on two separate datasets. The pedestrian crash dataset was obtained from the Palermo Municipality Police, and real-world speed data were sourced from TomTom Move, which provides traffic analytics and mobility data derived from vehicle-based GPS data collected anonymously from a range of devices.

3.1.1 Crash data

The crash data used in this study were provided by the Palermo Municipal Police and spans an eight-year period from 2015 to 2022. The dataset provides detailed information about pedestrian-related crashes occurring within the municipality, focusing on various crash attributes, pedestrian and driver characteristics, and environmental and traffic-related factors. These attributes include crash severity, crash locations, temporal factors (e.g., time of day, day of the week, seasonal variations), demographic characteristics of both pedestrians and drivers (e.g., age, gender), environmental conditions (e.g., weather, visibility), traffic conditions (e.g., traffic congestion), and roadway features (e.g., road type, pedestrian crossings, lighting, road conditions). In addition, vehicle-related variables such as vehicle type and crash at fault (e.g., driver at-fault, pedestrian at fault) were also recorded. It is crucial to state that the dataset does not include detailed crash reconstructions, such as the exact mechanisms of the crash or the relative positions of the vehicles and pedestrians involved. Consequently, the probable crash causes reported by the police are based on their initial assessments and should not be treated as definitive explanations of the events leading to the crashes.

In this study, each crash in the dataset was categorized based on the severity of the injuries sustained by the pedestrian. Injury severity was classified into four categories: “Died”, “Seriously Injured”, “Injured”, and “Not Injured.” This classification provided a clear

framework for analyzing the relationship between crash characteristics and injury severity. It is worth mentioning that to ensure the focus of the analysis on pedestrian crashes involving direct impact by a moving vehicle, crashes attributed to other factors were excluded. Therefore, only variables such as crash severity, temporal, and roadway features were considered for analysis, as shown in Table 3-1. These excluded factors were the cases where pedestrians were struck by vehicles in reverse, fell due to other reasons, or were involved in crashes outside of regular traffic settings (such as non-traffic-related incidents). As a result, a final sample of 54 fatal crashes and 87 serious injury crashes was extracted for detailed analysis, providing a comprehensive dataset of pedestrian injury crashes with fatal and severe injury outcomes. Moreover, it is important to mention that the crash data were used solely to obtain crash locations and some variables, as shown in Table 3-1, relevant to the context of the study. These crash locations were then used in the speed database to identify particular road segments where these crashes happened, and then the speed data was obtained. Eventually, the crash data was not directly used to estimate FSI risk.

Table 3–1. Descriptive statistics of crash data

Variable	Attributes	Frequency	Percentage(%)
Injury severity	Fatal	54	38.30
	Serious Injury	87	61.70
Year	2015	14	9.93
	2016	18	12.77
	2017	19	13.48
	2018	27	19.15
	2019	25	17.73
	2020	12	8.51
	2021	14	9.93
	2022	12	8.51
Road type	One way	53	37.59
	Two way	78	55.32
	Dual carriageway	8	5.67
	Single or dual carriageway with service road	2	1.42

3.1.2 Speed data

To assess the relationship between travel speed and FSI in pedestrian crashes, crash locations provided in the crash datasets were used to obtain speed profiles for each crash location from the TomTom Move speed database. The TomTom Move "Traffic Stat" tool was employed to

generate comprehensive speed reports for each crash site at a particular road segment. These reports covered one month, assessment of the crash site road segment considering 24 hours a day, and across all days of the week, which provides detailed data on vehicle speeds at the crash locations. The crash sites were identified using the tool's search function, which enabled precise selection of the relevant road segments within the roadway network corresponding to each crash location.

The analysis considered various road types as shown in Tables 3-2 and 3-3 to ensure an accurate representation of traffic flow conditions at each crash site. For one-way streets, speed profiles were collected specifically for the direction of travel where the crash occurred. On two-way roads, speed profiles were collected for both directions of travel to account for potential variations in vehicle speed depending on the direction of movement. After that, the average speed data were taken for both directions of vehicle speed on two-way roads as reported in Tables 3-2 and 3-3. Particular attention was given to crashes occurring at each roadway intersection. In these cases, the leg of the intersection where the crash occurred was determined based on the statements provided by the individuals involved in the incident, as recorded in the police reports in the dataset. When crashes occurred during turning movements, the relevant intersection leg on a roadway type was identified as the direction from which the vehicle entered the turn, ensuring the speed data reflected the specific road conditions and turning behavior at the time of the crash.

The speed data collected for each fatal and severe injury crash location are shown in Tables 3-2 and 3-3. Since, the study aimed to estimate fatal and severe injury risk based on percentile speed as a proxy for impact speed, and therefore Tables 3-2 and 3-3 display a range of percentile speed data together with the speed limits. The 15th percentile speed means that 15% of vehicles at a particular road segment travel at the reported speed or below this threshold. In other words, 85% of vehicles travel faster than this speed. The same is the concept for the 50th and 85th percentiles of speed reported in Tables 3-2 and 3-3. It is worth noting that for the few cases where speed data is the same across a range of percentile speeds in Tables 3-2 and 3-3, the route sample size collected by the TomTom speed database was quite low, and therefore, it was not able to capture the differences in speed percentiles across different ranges. Moreover, considering the speed limits for different road segments, FSI crash locations displayed in Tables 3-2 and 3-3, 50 km/h is set as the standard; however, only 13% of FSI crash locations have speed limits of 30 km/h and 40 km/h. The speed limit of 50 km/h being set as standard could be high for some road segments where the pedestrian flow is high due to being in the historical

city center zone. For example, one such location is “Via Roma”. This roadway, located in the historic city centre, is 1.8 km long, giving access to many historical buildings, tourist locations, and commercial activities of the city. However, being located in a no-traffic zone, this roadway is still open for traffic with a 50 km/h speed limit, creating a hazardous situation for pedestrians in their interactions with traffic, while being reported as a fatal and serious injury location in Tables 3-2 and 3-3. In addition, we can also note in Tables 3-2 and 3-3 and Figures 3-1 and 3-2 that for 24% of the total fatal and severe injury crash locations, the 85th percentile speed exceeds the speed limits. Thus, this means in 24% of the cases, crashes occur in locations where at least 15% of vehicles travel beyond the speed limit, showing that speeding and poor compliance of vehicular traffic regarding speed limits eventually put pedestrians at risk for severe crashes. Moreover, considering the 15th percentile speed, Table 3-2, 3-3 shows that this percentile speed is beyond the speed limits for 5 FSI crash locations, depicting that more than 85% of vehicles, almost the total of vehicles travelling on those roads, exceed the speed limits.

For instance, a fatal crash location is reported on a roadway named “Via Crispi Francesco,” as shown in Table 3-2 and Figure 3-1. This roadway has a speed limit of 40 km/h; however, the 50th and 85th percentile speeds reported in Table 3-2 exceed this limit. Since the percentile speed encompasses vehicular traffic speeds from low to medium and medium to high ranges, this indicates that the roadway does not comply with speed limits at different times of the day. In this scenario, the higher speed could reduce driver reaction time and could increase the impact speed, potentially leading to a severe injury crash in a possible unprecedented interaction between a vehicle and pedestrians. Similarly, the situation is the same for other fatal and severe injury locations marked with a red dot in Figures 3-1 and 3-2, where vehicular traffic exceeds speed limits, thereby posing significant risks for pedestrians.

The percentile speed data collected in Tables 3-2 and 3-3 for the FSI crash locations allowed for the development of a model aimed at forecasting FSI risks. The analysis aimed to assess the impact of different percentile speed distributions on pedestrian FSI risks and to explore potential interventions, such as speed reductions, that could mitigate the severity of pedestrian injuries at the FSI crash locations in the study area.

Table 3–2. Percentiles speed data for fatal crash location

Fatal Crash Location	Road Type	Speed Limit	15 th	50 th	85 th
			Percentile Speeds (Km/h)	Percentile Speeds (Km/h)	Percentile Speeds (Km/h)

VIA HAZON AZOLINO , 57	One way road-way	50	13.6	13.6	13.6
VIA ROMA (spec.) via stabile	One way road-way	50	17	27.66	37.41
VIA CIRINCIONE GIUSEPPE , 105/b	One way road-way	50	18	25.1	33.6
VIA DELLA LIBERTÀ , 100/b	One way road-way	40	12	20.87	31.98
VIA CAPPUCCINI Intersezione con VIA QUARTO DEI MILLE	One way road-way	50	16.07	30.58	43.435
VIA PITRE' GIUSEPPE , 31	Two way road-way	50	22	36.5	48
VIA CRISPI FRANCESCO , 258	One way road-way	40	32	42	52
VIA BRUNELLESCHI FILIPPO , 64	One way road-way	50	20.5	27.5	36.5
VIA GALLETTI , 2c	Two way road-way	30	12.5	23.5	36
VIA GIBILROSSA , 35	Two way road-way	30	50.5	54.5	55
PIAZZA DEL SACRO CUORE , 1	One way road-way	50	34	41	51
VIA MESSINA MARINE , 344	Two way road-way	50	34	46	61.5
VIALE AMEDEO D'AOSTA , 82	One way road-way	50	16	26	35
VIA ROMA , 447	Two way road-way	50	15.2	24.1	32.3
PASSAGGIO MARINUZZI GINO , 8/a	Two way road-way	50	11	33	44
VIA RIZZO AMMIRAGLIO Intersezione con VIA THAON DE REVEL PAOLO AMM.	Two way road-way	50	13	22.5	31.5
VIA RESUTTANA , 518	Two way road-way	50	19	26	36
VIALE REGIONE SICILIANA Nord Ovest Intersezione con VIA MANGO	One way road-way	50	39	48	57
VIALE REGIONE SICILIANA Nord Ovest Intersezione con VIA PERPIGNANO	single or dual carriageway with service road	50	14	39	53
VIA AQUILEIA , 32	Two way road-way	50	11	21	33

VIA FICHIDINDIA , 45/A	One way road-way	30	33	44	63
VIA DEI CANTIERI , 26	Two way road-way	50	8.5	18.5	31.5
VIA DELLA LIBERTÀ , 31	One way road-way	50	11	20	35
VIALE ERCOLE In prossimità di via case rocca	One way road-way	50	49	57	67
VIA ROMA intersezione PIAZZA S.DOMENICO	One way road-way	50	21.5	31.5	47
VIA MADONIA VINCENZO S.N.C.	Two way road-way	50	17	25	32.5
VIA PALLAVICINO , 15/17	One way road-way	30	24	33	41
VIA CASTELLANA , 90	Two way road-way	50	19	37	49
VIA DANTE Intersezione VIA LATINI BRUNETTO	One way road-way	50	6	10	21
VIA DEI NEBRODI , 75	Two way road-way	50	13.5	25.5	37
VIALE CROCE ROSSA , 33	One way road-way	50	32	44	53
PIAZZA DON BOSCO , 1/b	One way road-way	50	16	26	35
VIA PITRE' GIUSEPPE , 174/b	Two way road-way	50	19	36	45
VIA TERRASANTA , 82	One way road-way	50	22	29	38
VIA PONTE DI MARE , 67	Two way road-way	50	13	24	33
VIA BASILE ERNESTO Altezza Civico 55	One way road-way	50	35	47	64
VIALE REGIONE SICILIANA N.O. Altezza VIA PERPIGNANO	single or dual carriageway with service road	50	31	49	69
VIA GALLETTI 21	Two way road-way	50	10.5	22	33.5
VIA JUVARA FILIPPO 18	Two way road-way	50	18.5	27	36.5
VIA MESSINA MARINE Intersezione con VIA SAETTA ANTONINO	Two way road-way	50	36	45	55.5

VIA EUGENIO L'EMIRO Intersezione con VIA ARISTIPPO ENRICO	Two way road- way	50	24.5	39.5	47
VIA SACCO E VANZETTI 48	Two way road- way	50	21	39	55.5
VIA SACCO E VANZETTI , 36	Two way road- way	50	13.5	16	31.5
VIALE DE GASPERI ALCIDE , 185	Two way road- way	50	6	11	24
VIA CUSMANO GIACOMO , 67	One way road- way	50	13	21	31
VIA DELLA LIBERTÀ Intersezione con VIA DUCA DELLA VERDURA	Dual Carriageway	40	4	9	23
VIA MAQUEDA , 42	Two way road- way	30	8	15	17
VIA GIOTTO intersezione VIA LO VERDE GIACOMO	Two way road- way	50	19	28.5	37.5
VIA BELGIO Intersezione VIALE STRASBURGO	One way road- way	40	14	23	33
VIA TERRANOVA CESARE , 65	Two way road- way	50	27	41	53.5
VIA BRIGATA AOSTA Intersezione VIA COSTANZO AURELIO	One way road- way	50	9.5	17	23.5
VIALE ERCOLE A mt. 160 case rocca	One way road- way	50	52	70	92
VIA DELLA LIBERTÀ Intersezione con VIALE LAZIO	One way road- way	40	9	15	29
VIA IMPERATORE FEDERICO , 26a	Two way road	50	10	21.5	34

Table 3–3. Percentiles speed data for severe injury crash location

Severe Injury Crash Location	Road Type	Speet Limit	15th Percentile Speeds (Km/h)	50th Percentile Speeds (Km/h)	85th Percentile Speeds (Km/h)
VIA MESSINA MARINE , 319	Two-way road-way	50	36.5	52.5	67
FORO UMBERTO I (spec.) VIA LINCOLN	Dual Carriageway	50	31	43	57
VIALE STRASBURGO , 185	Two way road-way	50	17	27.5	42

PIAZZA S.LORENZO , 21	Two way road-way	50	38	50	63.5
VIA CRISPI FRANCESCO Intersezione con VIA S.SEBASTIANO	One way road-way	50	9	31	47
VIA BRUNELLESCHI FILIPPO , 42	Two way road-way	50	10	22	35.5
CORSO CALATAFIMI Di fronte 916/a	Two way road-way	50	16	29.5	41.5
PIAZZA DEL SACRO CUORE (spec.) 6	One way road-way	50	31	37	44
VIALE CROCE ROSSA , 10	Two way road-way	50	13	20	28
VIA DEI QUARTIERI , 66	Two way road-way	50	13.5	24	36.5
PIAZZA VERDI GIUSEPPE , 60	Two way road-way	50	12	20.5	30
VIA DELL'ORSA MINORE , 13	Two way road-way	50	14.5	25.5	35
VIALE REGIONE SICILIANA In prossimità di soprap. Emiri	One way road-way	50	29	45	58
VIALE LAZIO Intersezione con VIA TEVERE	One way road-way	50	11	25	36
PIAZZA DEL SACRO CUORE , 6	One way road-way	50	28	36	43
VIALE DE GASPERI ALCIDE (spec.) VIA	Two way road-way	50	9	15	30
VIALE STRASBURGO , 163	Two way road-way	50	35.5	47.5	61.5
VIA TOMMASO NATALE intersezione VIA LIMONE	Two way road-way	50	16	28.5	41
VIA RAMPOLLA MARIANO CARD. , 10/c	Two way road-way	40	32.5	44	55.5
VIA BASILE ERNESTO , 22	One way road-way	50	9	17	29
VIA CAPPUCCINI , 145	Two way road-way	50	28	36.5	45
VIALE CALTAGIRONE (spec.) via demma	One way road-way	50	30.5	31	31
VIALE MARGHERITA DI SAVOIA In prossimità di Cancel. Giusino	Dual Carriageway	50	44	49	59.5
VIALE CAMPANIA , 18	One way road-way	50	22	33	42
PIAZZA SETT'ANGELI , 3	One way road-way	50	7	9	16

VIA ORETO , 385	Two way road-way	50	16	21	32
VIALE DE GASPERI ALCIDE , 183	Two way road-way	50	6	11	24
VIA PRINCIPE DI PATERNO' Intersezione con VIALE GIULIANO BORIS	One way road-way	50	5	14	32
VIALE REGIONE SICILIANA Sud Est , 2097	Two way road-way	70	29	36	43
VIA TRICOMI ERNESTO , 16	Two way road-way	50	20.5	26.5	37.5
VIALE STRASBURGO Di fronte Bar Pecora Nera	Two way road-way	50	6	10	25
CORSO CALATAFIMI , 1075	Two way road-way	50	20	32.5	41.5
PIAZZA ORLANDO VITTORIO EMANUELE Intersezione CORSO FINOCCHIARO APRILE CAMILLO	Two way road-way	50	8.5	20	29.5
PIAZZA PRINCIPE DI CAMPOREALE , 6	One way road-way	50	22	29	36
VIA DELL'ARTIGLIERE , 22	One way road-way	50	9	15	24
PIAZZA GIULIO CESARE Intersezione PIAZZA CUPANI FRANCESCO	One way road-way	50	14	22	31
VIA MESSINA MARINE , 613	Two way road-way	50	9.5	15.5	23.5
VIA NOCE , 72	Two way road-way	50	20	27.5	35.5
VIA GIAFAR EMIRO , 10	Two way road-way	50	10	15.5	25.5
Via S.Lorenzo Altezza (Inters.) Via S. Eugenio De Mazenod	One way road-way	50	15	35	35
VIA NEBRODI(DEI) 73	Two way road-way	50	21	30	46
VIA PERPIGNANO 199	One way road-way	50	22	28	39
VIA LANZA DI SCALEA GIUSEPPE Di fronte al civico 1513	One way road-way	50	43	50	58
VIALE STRASBURGO , 134	Two way road-way	50	6	13	29
VIA DEI CANTIERI , 65/a	Two way road-way	50	24.5	37.5	47.5
VIALE DEL FANTE A mt. 50 p.za Salerno	Two way road-way	40	44	62	80.5

VIALE LAZIO , 14	One way road-way	50	13	28	38
VIA CAVOUR CAMILLO , 59	Two way road-way	50	26.5	38.5	50
VIA BELGIO In direzione di VIA DEI NEBRODI reg. siciliana	Dual Carriageway	40	20	34	48
VIA PITRE' GIUSEPPE , 176/C	Two way road-way	50	43.5	56	72.5
PIAZZA GIULIO CESARE , 19	One way road-way	50	11	17	23
VIA DEI QUARTIERI , 19/C	Two way road-way	50	11.5	22	32.5
VIA LA VALLE RAFFAELE Intersezione PASSAGGIO MARINUZZI GINO	Two way road-way	50	4	24	29.5
Foro Umberto I Intersezione Con Via Lincoln	One way road-way	50	27	40	55
VIA RESTIVO EMPEDOCLE , 10/a	One way road-way	50	12	23	34
VIALE DEI PICCIOTTI , 7	Two way road-way	50	22	32	43
VIA VITTORIO EMANUELE , 125	Two way road-way	50	6	16	22
VIA MONTEPELLEGRINO , 45	Dual Carriageway	50	25	32	40
VIALE REGIONE SICILIANA Nord Ovest Carr. centrale dir.tp	One way road-way	50	27	38	49
VIA MATTARELLA PIERSANTI , 2	One way road-way	50	6	10	23
VIA CARTAGINE , 3A	Two way road-way	50	26	32.5	41
VIA IMERA Intersezione con VIA ANTINORI ORAZIO	Two way road-way	50	18.5	24	32.5
CORSO TUKORY , 187	One way road-way	50	12	18	27
VIA BUONRIPOSO (spec.) galleria ferrov	Two way road-way	50	18	28.5	40
VIA NOCE , 25	Two way road-way	50	26	33.5	42.5
VIA TRINACRIA , 28	Two way road-way	50	26.5	34.5	45
VIALE REGIONE SICILIANA Sud Est , 4251	Two way road-way	50	34.5	45	58

VIALE DE GASPERI ALCIDE , 42	Two way road-way	40	14.5	22	34.5
VIA PADRE GIUSEPPE PUGLISI Intersezione con VIA ALAGNA GIACOMO	One way road-way	50	3	14	27
VIA ROMA , 245	Two way road-way	50	12	22	32.5
VIALE CROCE ROSSA , 63 A	Two way road-way	50	15	25	35
Viale Regione Siciliana N.O. Altezza Del Civico 2278	One way road-way	50	22	34	44
VIA OLIO DI LINO , 4/E	Two way road-way	30	44	53	65
CORSO CALATAFIMI In prossimità di via C. Onorato	Two way road-way	50	24.5	35	46.5
VIA JUVARA FILIPPO Intersezione VIA RE FEDERICO	Dual Carriageway	50	9	14	18
VIA MONTEPELLEGRINO (spec.) ingr. mercato	Dual Carriageway	40	31	42	56
VIA BUONRIPOSO , D.F. 62	Two way road-way	50	24	35	43
VIA GALLETTI , 136/I	Two way road-way	30	27	37	47
VIA MONTALBO , 233	One way road-way	50	21	29	37
VIA ORETO (spec.) VIA LA COLLA	Two way road-way	50	7	14	24
VIALE CROCE ROSSA , 171	Dual Carriageway	50	15	24	32
VIA PATTI Altezza CHIESA S.FNERI Civico 17	Two way road-way	30	22	29.5	36
VIALE MARCHESE DI VILLABIANCA Intersezione con VIA GARGALLO TOMMASO	One way road-way	50	6	18	31
CORSO CALATAFIMI S.N.C	Two way road-way	50	18	32	47.5
VIA PEREZ FRANCESCO PAOLO , 141	One way road-way	50	20	27	35
VIALE REGIONE SICILIANA Sud Est , 3995	Two way road-way	50	35	43.5	51
VIA CAVOUR CAMILLO , 25	Two way road-way	50	19	28	39

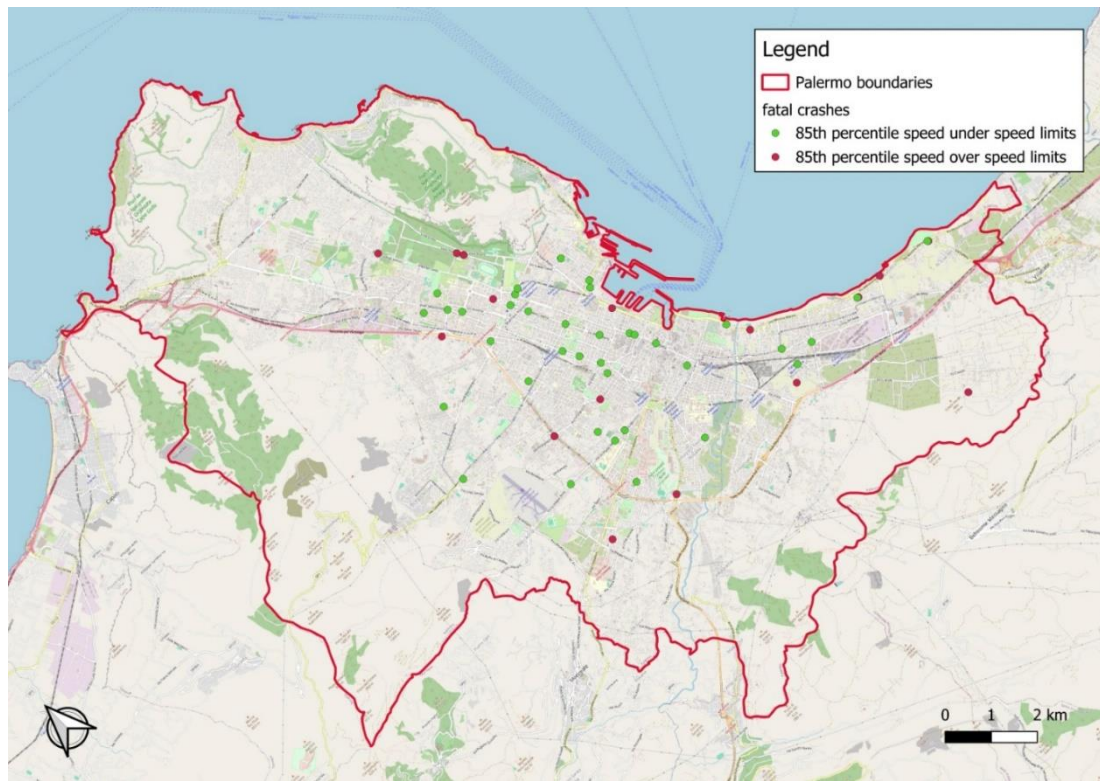


Figure 3–1. Fatal crash locations with 85th percentile speed under and over speed limits

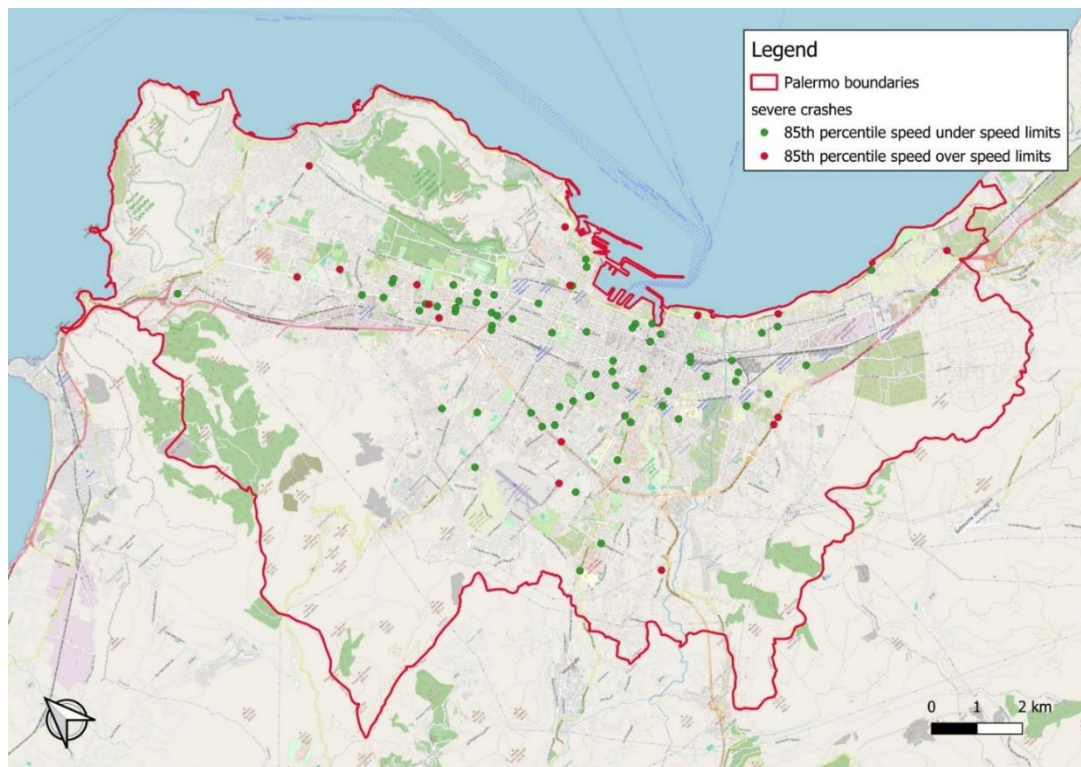


Figure 3–2. Severe injury crash locations with 85th percentile speed under and over speed limits

3.1.3 Hotspot areas identification

To identify the hotspot areas and the roads where there was a high density of road crashes, a heat map was created (Figure 3-3). Indeed, representing the road accident locations on a map allows for understanding if there is any pattern behind them or any routes with an anomalous concentration of accidents. Figure 3-3 shows that most of the accidents involving pedestrians occurred within the denser core of the city, while few accidents occurred in suburban areas. This is strictly correlated to the greater pedestrian activity in the city center, where most of the services and amenities are concentrated; it demonstrates that, despite the pedestrian volume, the pedestrian infrastructure is not safe enough to support it.

Thus, the heatmap was useful for identifying the most dangerous roads for pedestrians.

One roadway that is a black spot from the perspective of pedestrian safety is Via Roma, a two-way collector road located in the city center, within a restricted traffic area, as stated before, having a particularly high accident density (with peaks of 45 accidents per km). This road is characterized by intersections mostly without traffic lights; indeed, there are 35 zebra crossings - resulting in an average distance between crosswalks of 58 meters - but only two of them are signalized with traffic lights. Pedestrian crossings are poorly maintained, and there are no pedestrian crossings in one or more legs of several intersections. This frequently induces pedestrians to jaywalk in order not to lengthen their path, following their desired lines (i.e., the shortest paths). The absence of traffic lights and stop signs, and the road width, allows drivers to drive their vehicles at high speeds, making crossing the street risky.

Another black spot is Via Libertà, another collector road characterized by high vehicle flows, having two one-way service roads (one per direction) running parallel to the main one-way road. Most of the accidents occurred on the service roads, which have a small width but high traffic volumes. In many intersections, there are no pedestrian crossings, and the visibility of pedestrians crossing the street is limited by obstacles such as legally or illegally parked cars.

In addition, Viale Strasburgo represents another dangerous road for pedestrians. It is a two-way collector road, having a service road on one side, and it is characterised by a great pedestrian activity due to the presence of several commercial activities. The density of the pedestrian crossings is very high, having an average distance between them of about 50 m. They are mostly not traffic lighted.

Finally, Corso Calatafimi is the last black spot that can be clearly identified. Also in this case, this road is a two-way collector road, playing the role of connecting several neighborhoods to the city center.

Thus, it can be noted that the type of road seems to have an impact on the occurrence of road crashes involving pedestrians. Up to 60% of the road accidents occurred on roads classified as “interquartiere” roads (collector roads) by the General Urban Traffic Plan of Palermo. These roads are the ones connecting distant sectors and neighborhoods of the city with a speed limit of 50 km/h. In those streets, all traffic components are allowed, excluding the movement of animal-drawn vehicles. They are mainly two-way roads characterized by at least two traffic lanes and present sidewalks along the sides. They are usually characterized by intense vehicle traffic, absorbing most of the road traffic within the city. Thus, the combination of high speed, high traffic volumes, and high road width can have a significant negative impact on pedestrian safety.

However, if another collector road - Via Notarbartolo - is considered, it can be seen a low concentration of accidents involving pedestrians along this road. Via Notarbartolo is a commercial road with several amenities and facilities, linking the city center to the city's beltway, the Notarbartolo train station, and the tram lines' terminal. It is a two-way road with one line per direction and parking lots and sidewalks on both sides. Therefore, this street shares with the roads mentioned above a lot of similarities in terms of the role it plays in the city, while they are very different in terms of pedestrian safety. Indeed, Via Notarbartolo is characterized by 17 mainly signalized zebra crosswalks with most of them placed in correspondence to intersections, with an average crosswalk every 58 meters. The sidewalks are separated from the vehicle traffic by the parking lots and they are wider in correspondence to the crossings (sidewalk extensions). Where the parking lot is missing, a barrier prevents pedestrians from jaywalking. The design solutions applied in Via Notarbartolo are a good way to deter both drivers and pedestrians from adopting risky behaviours. Thus, this analysis also highlights that the reduction of road crashes is deeply linked to the presence of signalized intersections, pedestrian-oriented design, and traffic calming tools.

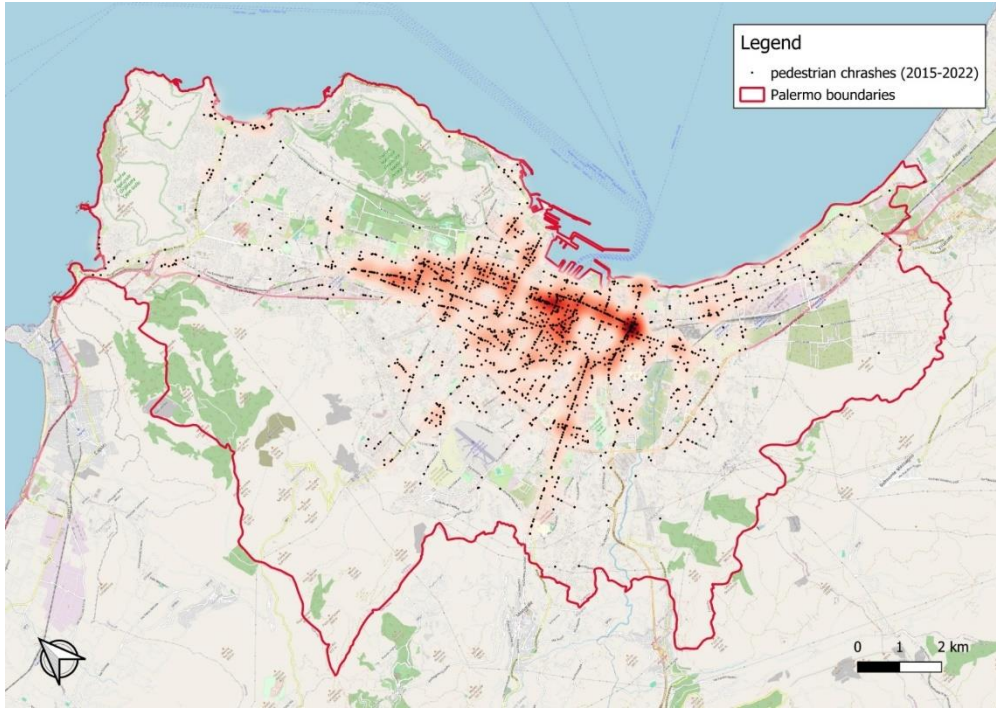


Figure 3–3. Heat map of roads with a high density of crashes

3.2 Method

3.2.1 Estimation of fatal and serious injury risk

The representative percentile speeds (15th, 50th, and 85th) at the crash locations were applied to estimate fatality and serious injury risks using the risk equations (Davis 2001), as shown below:

Fatal risk estimation

$$Fatality_Risk = 1 - \frac{\exp(a_2 - bx)}{1 + \exp(a_2 - bx)} \quad (1)$$

- $a_2 = 8.866, b = 0.127, x = \text{Impact Speed}$

Serious injury risk estimation

$$Serious\ Injury_Risk = \frac{\exp(a_2 - bx)}{1 + \exp(a_2 - bx)} - \frac{\exp(a_1 - bx)}{1 + \exp(a_1 - bx)} \quad (2)$$

- $a_2 = 8.866, b = 0.127, a_1 = 4.970, x = \text{Impact Speed}$

These equations were originally designed to estimate FSI risks across different age groups based on impact speed, using data from pedestrian crashes. (Davis 2001) refined the injury risk

curve, providing a more accurate model compared to earlier works by (Ashton 1980) and (E. Pasanen 1992). Specifically, (Davis 2001) estimated model parameters for three distinct age groups: 60+, 15-59, and 0-14 years. However, since pedestrian age data with a different range of ages was not available in the acquired crash dataset, the parameter estimates for the 15-59 age group were used in both Eq. (1) and Eq. (2) for risk calculations. Subsequently, the FSI risk for each pedestrian crash was calculated at each of the speed percentiles (15th, 50th, and 85th).

Table 3–4. Parameter estimates for the logit model

Model Parameter	Age (years)
	15-59
a_1	4.970
a_2	8.866
b	0.127

3.2.2 Speed reduction scenarios

In this study, two sample speed reductions were investigated for the counterfactual analysis based on (Davis 2001) to explore the potential benefits to pedestrian FSI risk of reduced speeds in vehicle-to-pedestrian crash scenarios. The percentile speeds (15th, 50th, and 85th) profiles for each crash were reduced by 3 and 5 km/h based on a trial-and-error method, and the resultant FSI risks were estimated using Eqs. (1-2) as before. After that, the ratio of risk reduction between before and after FSI risk was examined through log scale plotting to understand the impact of reduced speed on the FSI risk reduction.

3.3 Results

3.3.1 Speed and risk

The analysis investigates the impact of speed reductions on pedestrian injury severity, focusing on FSI. The results are presented in Tables 3-5 and 3-6, which summarize the mean speed and associated risks before and after speed reductions across three different percentile speed categories: 15th, 50th, and 85th percentiles. Both Tables 3-5 and 3-6 provide quantitative evidence of the relationship between travel speed distribution and FSI risk in vehicle-to-pedestrian crashes. The "mean speed" for each percentile category represents the average speed observed within that specific percentile range for all FSI crashes, while the "mean risk" reflects the average risk of fatal and serious injuries (FSI), as calculated using Eqs. (1) and (2) for each crash.

The data presented in Tables 3-5 and 3-6 reveal a consistent and clear trend: as the percentile speed increases, both the mean speed and associated risks also increase. Specifically, the difference in mean speed and risk between lower and higher percentiles becomes more pronounced, with the gap between the 15th and 50th percentiles being relatively small, compared to the larger difference observed between the 50th and 85th percentiles. This trend strongly suggests that higher vehicle speeds are directly linked to an increased risk of severe pedestrian injury outcomes in FSI crashes, particularly in the context of pedestrian vulnerability.

Table 3–5. FSI crash risk estimation (speed reduction: 3km/h)

Crash Outcomes	Speed Profile (Percentile)	Mean Speed (Km/h)	Mean Risk (%)	Mean Speed after Reduction (Km/h)	Mean Risk after Reduction (%)	Average Speed Reduction (%)	Average Risk Reduction (%)
Fatal	15 th	20.1	0.7	17.1	0.5	14.9	30.5
	50 th	30.5	2.6	27.5	2.0	9.8	26.1
	85 th	41.5	8.2	38.5	6.5	7.23	21.1
Serious	15 th	19.8	13.0	16.8	10.0	15.2	23.0
	50 th	29.4	26.8	26.4	22.1	10.2	17.5
	85 th	40.0	43.6	37.0	38.5	7.5	11.6

Table 3–6. FSI crash risk estimation (speed reduction: 5km/h)

Crashes	Speed Profile (Percentile)	Mean Speed (Km/h)	Mean Risk (%)	Mean Speed after Reduction (Km/h)	Mean Risk after Reduction (%)	Average Speed Reduction (%)	Average Risk Reduction (%)
Fatal	15 th	20.1	0.7	15.1	0.4	24.9	45.6
	50 th	30.5	2.6	25.5	1.6	16.4	40.0
	85 th	41.5	8.2	36.5	5.5	12.1	32.6
Serious Injury	15 th	19.8	13.0	14.8	8.3	25.3	36.0
	50 th	29.4	26.8	24.4	19.3	17.0	28.1
	85 th	40.0	43.6	35.0	35.1	12.5	19.4

3.3.2 Counterfactual Analysis

To evaluate the impact of speed reductions on crash risks, a counterfactual analysis was conducted. Specifically, speed reductions were applied to each percentile speed category for FSI crashes, as detailed in Tables 3-5 and 3-6. The analysis focused on estimating the effects of these reductions on both the mean speed and the associated risk of fatal and serious injuries. The choice of 3 km/h and 5 km/h speed reductions was based on trial-and-error methods designed to assess their efficacy in reducing both speed and injury risk. As shown in Table 3-5 and 3-6, the speed reduction of 3 km/h and 5 km/h have significantly resulted in average speed and risk reduction across each percentile speed range.

Figures 3-4 - 3-9 display the distribution of FSI risk for the percentiles of speed at all fatal and serious injury crash locations. The FSI risk estimated at the estimated speed percentile and after speed reductions can visibly differentiate a decrease in FSI risk due to speed reduction as the distribution moves to the left, indicating the risk reduction. Particularly, Figures 3-4 and 3-7 show the FSI risk distribution at the 15th percentile speed, which represents the lower speed range. The risk distribution likely reflects scenarios where vehicles are traveling at or below this speed threshold. Since lower speeds generally result in less severe crashes, the FSI risk might be relatively lower in this distribution compared to higher percentile speeds. Whereas Figures 3-5 and 3-8 display the FSI risk at the 50th percentile speed, which is considered as median speed. At this speed, the risk distribution is likely more balanced, reflecting typical driving conditions. The FSI risk shown at this percentile speed would be higher than the 15th percentile but lower than at the 85th percentile speed. Figures 3-5 and 3-8 provide insight into the baseline risk under normal driving conditions and serve as a reference point for comparing the effects of speed reduction. Similarly, Figures 3-6 and 3-9 display the FSI risk distribution at the 85th percentile speed, which represents the maximum range of travel speed distribution. At this speed, the risk is higher compared to other percentile speeds as it covers higher speeds, which could generally lead to more severe crashes. This has also been reported in Tables 3-6 and 3-7, which show that for the 85th percentile speed, the FSI risk estimated is higher compared to the 15th and 50th percentile speeds. Overall, these figures collectively display how FSI risk varies across percentiles speed with effectively displaying the FSI risk distribution with respect to travel speed distribution from low to high range. Moreover, the FSI risk distributions after speed reductions in all figures clearly show that even a small reduction in speed can significantly help in reducing the FSI risk.

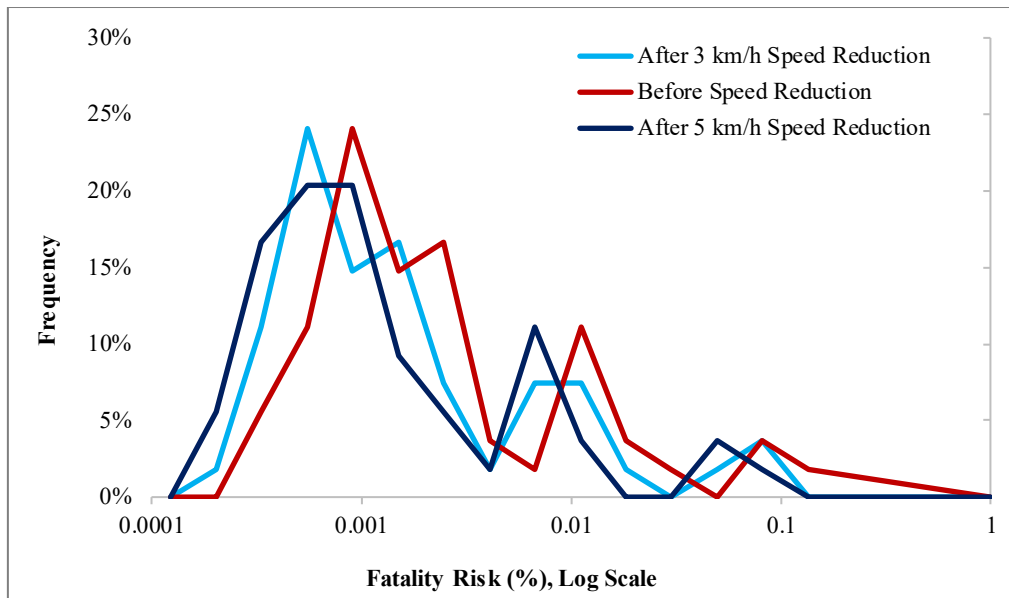


Figure 3–4. Fatality risk distribution by 15th percentile speed (n=54 fatalities)

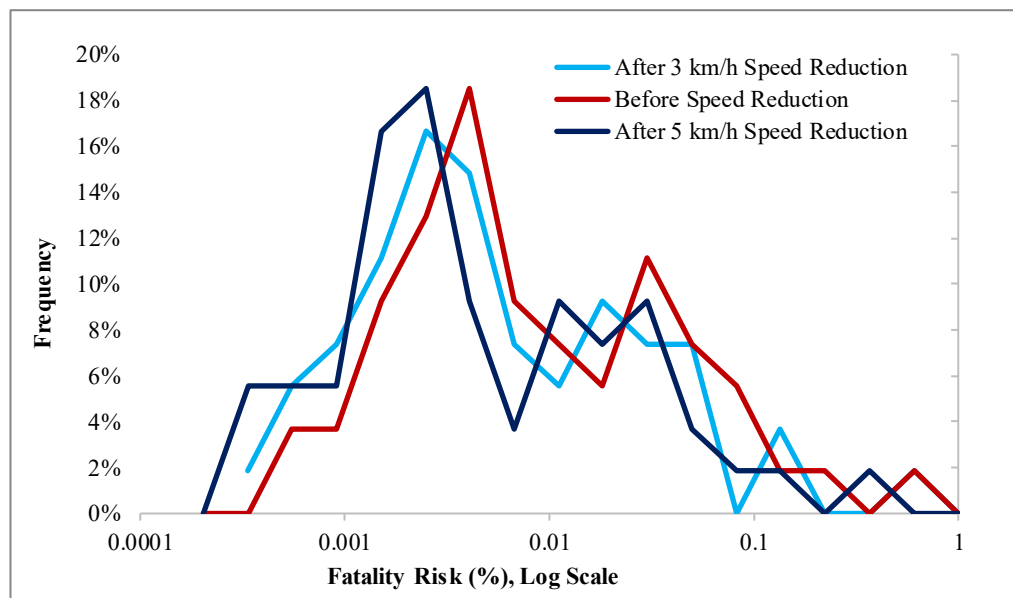


Figure 3–5. Fatality risk distribution by 50th percentile speed (n=54 fatalities)

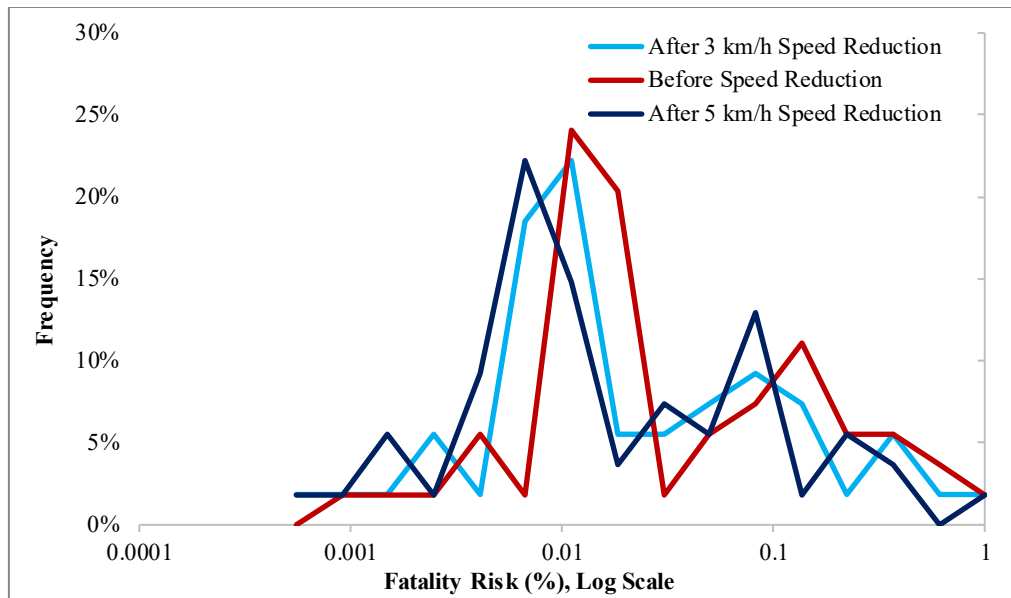


Figure 3–6. Fatality risk distribution by 85th percentile speed (n=54 fatalities)

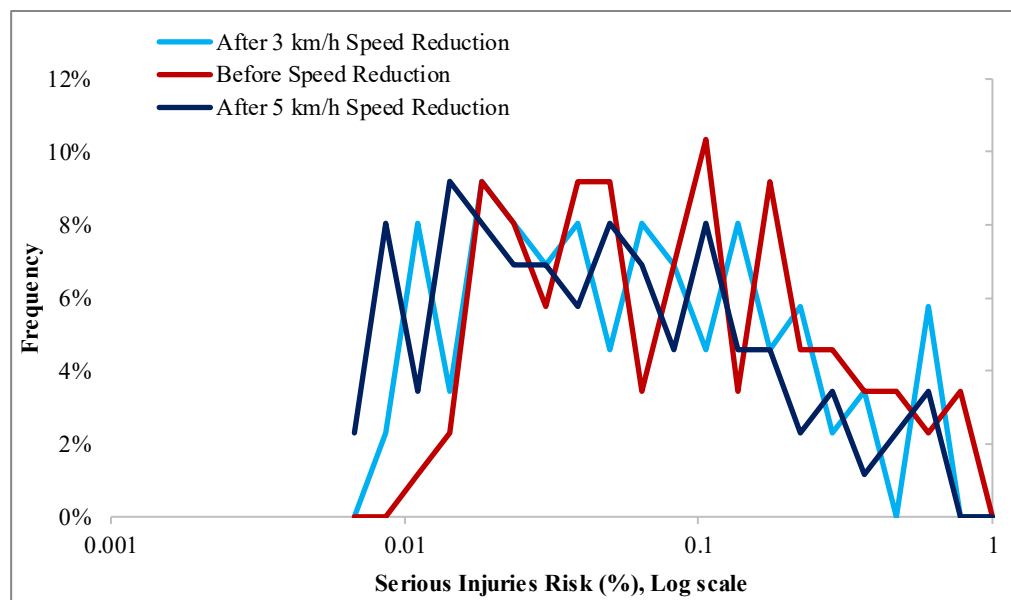


Figure 3–7. Serious injuries risk distribution by 15th percentile speed (n=87 serious injuries)

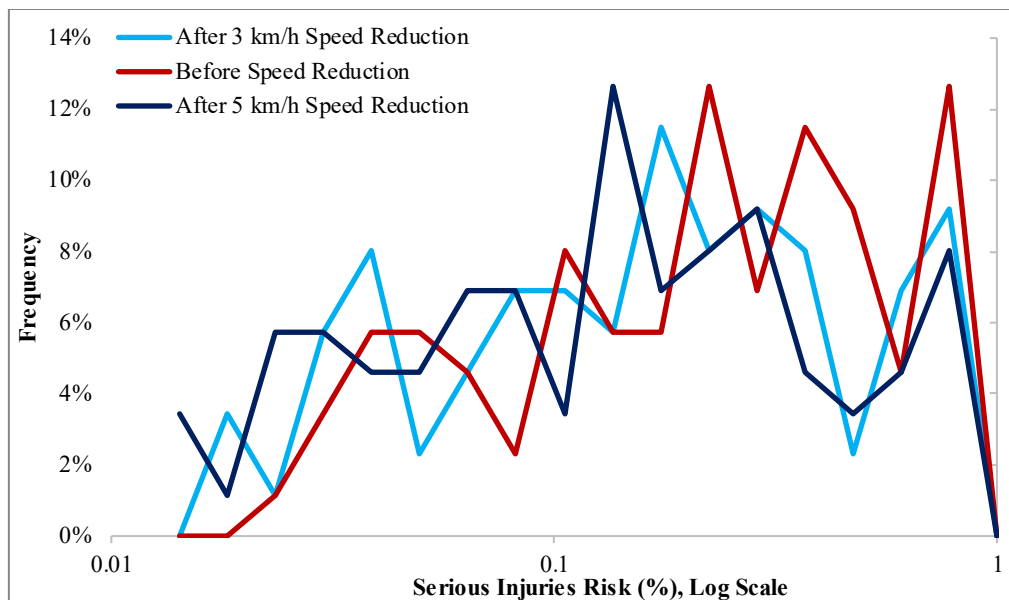


Figure 3–8. Serious injuries risk distribution by 50th percentile speed (n=87 serious injuries)

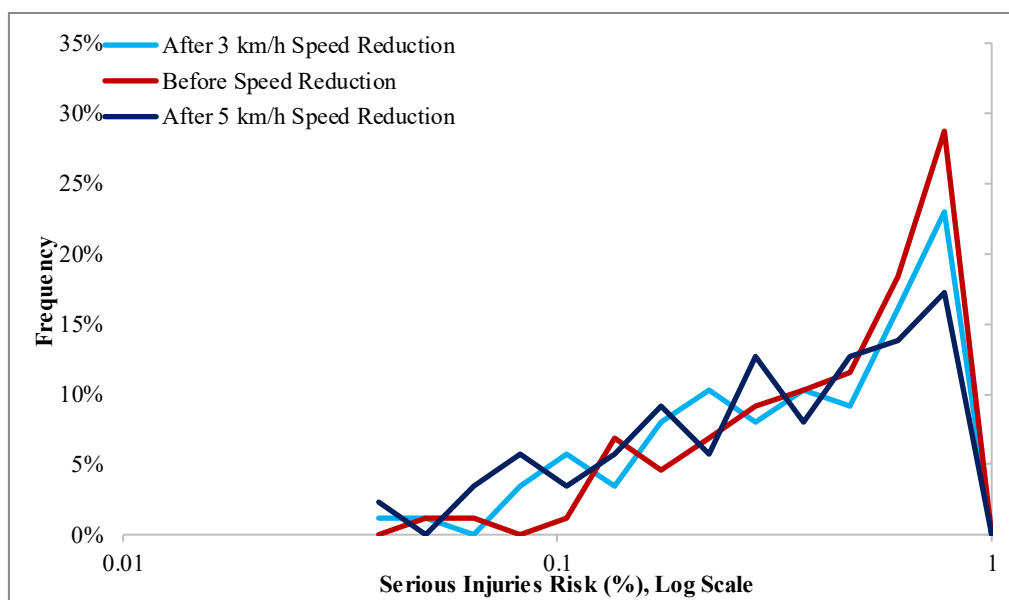


Figure 3–9. Serious injuries risk distribution by 85th percentile speed (n=87 serious injuries)

3.4 Discussion

Pedestrians are among the most vulnerable road users, and understanding the factors influencing crash severity is critical for improving road safety. Traditional speed measures, such as impact speed, mean travel speed, and speed limits, offer useful insights but often fail to account for the variability in travel speed distributions, which significantly affects crash

outcomes. Travel speed at the time of a collision depends on factors like braking response, driver reaction time, and vehicle control, making it essential to analyze how speed changes, from low to high impact crash severity. Although impact speed directly measures the collision force (Pitt et al. 1990), its variability across crashes limits its utility in shaping speed management policies (Kröyer 2015).

To overcome these limitations, percentile speeds have emerged as a reliable proxy for capturing the full spectrum of travel speed distributions. Unlike one-dimensional speed measures, percentile speeds provide a comprehensive view of speed ranges, such as low to median (15th–50th percentile) and median to high (50th–85th percentile). The results of this study also demonstrate that variability in travel speed significantly affects vehicle-to-pedestrian crash outcomes, as crash risk increases with an increment in percentile speed. Specifically, the median to high (50th–85th percentile) speed range is associated with an increased FSI crash severity compared to the low to median (15th–50th percentile) range, as shown in Tables 3-5 and 3-6 and Figures 3-4 – 3-9. For fatal crashes, the estimated crash risk at 15th, 50th, and 85th percentiles speed is 0.7%, 2.6%, and 8.2%, whereas for severe injury across each percentiles speed the estimated crash risk is 13%, 26.8%, and 43.6%, respectively as reported in Table 3-5 and 3-6. This shows that across the upper range of percentile speeds (50th–85th) the FSI crash risk increases as compared to the lower range (15th–50th). This is likely because drivers may struggle to adjust rapidly to sudden changes in traffic conditions, resulting in higher impact collisions. This finding is supported by recent studies (Arias et al. 2021; Mahmoud et al. 2023), which demonstrated significant influences of travel speed distributions on crash outcomes and indicated that the upper range of percentile speeds is associated with increased pedestrian crash frequency.

The current study further demonstrates that even modest speed reductions of 3–5 km/h can measurably decrease the risk of pedestrian FSI and support model efficiency (Davis 2001) as reported in Table 3-5 and 3-6. While a 3–5 km/h reduction might appear minimal when considered on an individual roadway basis, implementing such reductions across a broader network can lead to substantial improvements in pedestrian safety. This finding is particularly relevant in urban areas and zones with high pedestrian activity, where the likelihood of pedestrian-vehicle interactions is greatest. One practical approach to achieving these speed reductions is through adjustments to existing speed limits. Effective speed limit adjustments require a nuanced understanding of traffic dynamics and roadway design including factors such as traffic volume, number of lanes, roadway type, and the extent of pedestrian exposure.

Research indicates that targeted speed limit reductions can lead to significant decreases in both travel speeds (Heydari et al. 2014; Islam et al. 2014) and severity of crashes (Cairns et al. 2015; Islam and El-Basyouny 2015; Bornioli et al. 2020; Fridman et al. 2020; Hu and Cicchino 2024).

For example, an analysis of TomTom Move speed datasets shows that most urban roadways in Palermo maintain a standard speed limit of 50 km/h, which is typical for built-up areas in Italy. However, Palermo's unique characteristics, its historical urban layout, high pedestrian density, and significant tourist attractions—suggest that a 50 km/h limit may be too high in certain contexts. In zones such as the historic city center, residential areas, and school districts, where pedestrian volumes are particularly high, a lower speed limit may be more appropriate. Moreover, Palermo's cultural heritage sites and popular tourist attractions further increase pedestrian density, thereby increasing the risk. In this regard, the speed perspective was taken into consideration by (D'Orso and Migliore 2020a) through the quality of the pedestrian infrastructure assessment model in the Palermo context, where they emphasize that 30 km/h is considered safe for pedestrians as compared to 50 km/h. They further found in their results that high speeds of vehicles can significantly impact the pedestrian perception of safety.

In light of these observations, the appropriateness of a 50 km/h speed limit should be evaluated in the context of localized traffic conditions, pedestrian density, and urban design. In high-risk areas identified through crash data, reducing speed limits to 40 or 30 km/h could be a viable strategy, warranting further evaluation of its impact on travel speeds, crash severity, and crash frequency. Supporting this approach, a case study in Seattle demonstrated that a reduction of 5 mph (approximately 8 km/h) in speed limits led to a 17.2% decrease in crash severity and a 19.9% reduction in crash frequency (Hu and Cicchino 2024). These findings highlight the potential benefits of targeted speed limit adjustments in urban environments.

In addition, at one illustrative case, the fatal crash site on "Viale Ercole" in Palermo shown in Table 3-2, where the designated speed limit is 50 km/h, recorded 15th, 50th, and 85th percentile speeds of 52 km/h, 70 km/h, and 92 km/h, respectively, during a one-month sample period. These findings indicate frequent speed limit violations and highlight the risks associated with higher driving speeds. To counter such behaviours, our study supports the installation of intelligent transport tools, such as speed cameras, which can effectively enforce compliance with reduced speed limits and reduce reliance on constant police monitoring.

Furthermore, the application of "Movement & Place" framework (VicRoads 2016) offers a promising approach to urban planning that can encourage pedestrian-friendly speeds. This

framework integrates mobility needs ("Movement") with social, commercial, and community functions ("Place"), allowing streets to be classified and redesigned based on their primary function. In areas that prioritize "Place" functions—such as city centers, tourist areas, and cultural or historical sites—speed limits can be lowered to enhance pedestrian safety and overall urban amenity. Conversely, streets that predominantly support high traffic volumes ("Movement") may require tailored speed-reduction strategies to balance mobility with safety. In the historic city center of Palermo, for example, applying the Movement & Place framework could guide the redesign of streets and neighbourhoods to prioritize pedestrian safety over vehicle mobility.

However, this study is not without limitations. The absence of pedestrian age data in the crash dataset posed a significant constraint. To address this, the study utilized model parameter estimates for the 15–59 age group, which, while covering a broad demographic range, may not accurately reflect the FSI risks for younger or older pedestrians. Future research could address this limitation by incorporating more comprehensive datasets and exploring the differential impacts of speed on vulnerable age groups. In addition, although significant relationships have been found between percentiles' speed and the risk of FSI, the risk equations developed by (Davis 2001) were formulated for impact speed, whereas this study used different percentiles' speed instead. This was due to the fact that the impact speed is difficult to know, and it's not usually reported by police in their crash reports, while the percentiles' speed is easy to collect from the speed data platforms like TomTom.

Chapter 4

Analysing Factors Influencing Pedestrian Injury Severity in Palermo Using Machine Learning Techniques

Pedestrians are vulnerable road users being unprotected and involved in traffic crashes worldwide. Their safety remains a critical concern in urban areas, particularly in densely populated and historically constrained cities like Palermo, Italy. To improve pedestrian safety, it is essential to identify the risk factors that influence the severity of crashes involving pedestrians. Several studies in this field have explicitly investigated the risk factors associated with pedestrian crashes, however, gaps remain in analysing those factors that are found in unique, densely historical urban layouts. To do so, this chapter, presenting the study referred to as RA2, investigates the severity of pedestrian crashes by analysing eight years of police-reported crash data collected from Palermo, Italy.

However, the pedestrian crash dataset obtained from the Palermo Municipality Police is characterized by class imbalance in injury severity levels, as well as a non-negligible amount of missing and incomplete entries. These data issues can severely affect the analytical analyses and particularly validity and reliability of traditional statistical models, leading to biased results or poor generalizability. To overcome these challenges, the application of machine learning techniques offers a compelling alternative. Unlike traditional models, machine learning approaches are capable of capturing complex, nonlinear interactions without relying on prior assumptions about the data structure. They are well-suited to handle high-dimensional data, imbalanced class distributions, missing values, and outliers—common features in crash datasets (Tang et al. 2019; Wen et al. 2021; Santos et al. 2022; Ali et al. 2024). Therefore, the study employed a comprehensive machine learning framework to address the missing and class imbalance data challenges and evaluated four machine learning models (Random Forest, XGBoost, GradientBoost and CatBoost) to predict the crash severity of pedestrians in Palermo, Italy.

The study aims to explore how a range of factors—including temporal variables, environmental conditions, demographic attributes, vehicle and traffic characteristics, pedestrian infrastructure, and roadway features—contribute to varying levels of injury severity in the unique urban

context of Palermo. In addition to fully understanding the machine learning model outcomes regarding pedestrian crash severity analyses, the study utilized interpretable machine learning tools such as SHAP to identify key risk factors and their impact on the severity of pedestrian crashes. These include the Global, Local, and Interaction effects SHAP analysis. The global, local, and Interaction effects analysis by SHAP revealed several key factors, including pedestrian and driver gender, day of the week, time of day, pedestrian behaviours, roadway type, and features, as well as crash-at-fault reasons, which have a high impact on the severity of pedestrian crashes in the context of case study. Based on these risk factor evaluations, the study proposes several recommendations to enhance the safety of pedestrians in the unique historic urban context of the case study, potentially to align with achieving Vision Zero goals.

4.1 Data collection

4.1.1 Study area

The study is conducted in the Mediterranean city of Palermo, located on the island of Sicily in southern Italy. Palermo is a historic city covering approximately 158.9 km² and is divided into 25 districts. As the capital of Sicily, it had a population of 632,499 in 2022, according to the Italian National Institute of Statistics (ISTAT). Palermo attracts a large number of tourists throughout the year, with peak seasons from April to October. The city experiences a Mediterranean climate characterized by hot summers—with about 2,500 hours of sunshine annually and average temperatures around 26°C during July and August—and mild winters with concentrated rainfall and average temperatures between 10°C and 14°C from December to February.

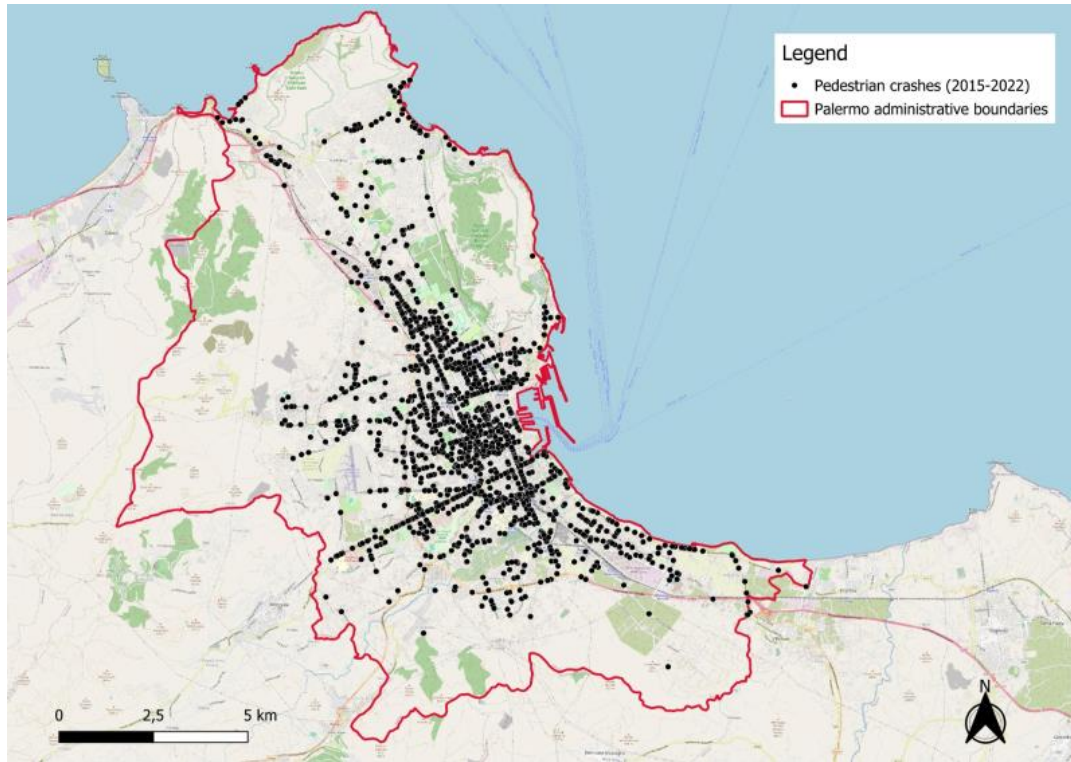


Figure 4–1. City of Palermo

4.1.2 Data description

This study utilizes a pedestrian crash dataset acquired from the Municipality Police of Palermo for eight years between 2015-2022. The dataset was provided in an Excel spreadsheet containing comprehensive information collected through a reconstruction approach for each pedestrian crash during the specified period.

In the crash dataset, pedestrian crash outcomes were categorized into four levels: fatal, major injury, minor injury, and no injury. The dataset comprised a total of 1,999 reported crashes across all severity levels. Among these, 55 crashes (2.75%) resulted in fatalities, while 91 crashes (4.55%) led to major injuries. The majority of crashes fell into the "minor injury" category, accounting for 1,782 cases (89.14%) of the total. In contrast, the "no injury" category had only 71 recorded cases (3.55%). For this study, due to the relatively small number of fatal and major injury cases, these two categories were combined into a single "severe injury" category. Similarly, minor injury and no injury cases were grouped into a "non-severe injury" category. As a result, the "severe injury" category comprised 146 crashes (7.30%), while the "non-severe injury" category contained 1,853 crashes (92.70%), as shown in Table 4-1.

The independent variables consist of temporal, demographic, roadway characteristics, and environmental based on their respective attributes. Among temporal variables most of the

crashes occurred in the winter season (28.66%), followed by autumn (27.51%) which shows the difference in season impact on the occurrence of pedestrian crashes. From a yearly perspective, most pedestrian crashes occurred in 2017 (16.71%), whereas 2020 has faced a low number of pedestrian crashes (8.70%) due to the Covid lockdown imposed by the Italian government to minimize the social gathering and expected spread of coronavirus. Additionally large number of crashes occurred on weekdays (81.24%) as compared to weekends (18.76%) showing that weekdays activities such as commuting to offices, industrial zones, and educational institutes increased the occurrence of pedestrian crashes.

Similarly, from a sociodemographic variable's perspective, female pedestrians are the most victims (43.82%) as compared to male pedestrians (36.02%) showing their high vulnerability in involvement to pedestrian crashes in a locality. Whereas male drivers (60.73%) lead in involvement in pedestrian crashes showing their unresponsive and aggressive driving habits. Most of the pedestrian crashes occurred when pedestrians were crossing the road (71.29%) on a straight section of road (68.98%) and at the intersection (22.81%) showing unsafe pedestrian crossing facilities and crosswalks. Among vehicles involved, cars are leading (55.38%) followed by two-wheeler vehicles which contribute to 22.66% of pedestrian crashes. Additionally, from a crash dynamics perspective, most of the crashes were reported with drivers (28.91%) being the main culprit followed by pedestrians (11.91%). Moreover, most of the crashes occurred on a two-way roadway (44.82), a slightly higher percentage as compared to one-way roadway (44.17%) showing that both types of roadways are not quite safe for pedestrians in the locality.

Table 4–1. Descriptive statistics of pedestrian crash data

Variable	Variable Category	Attributes	Frequency	Percentage (%)
Severity	Injury Severity Classes	Severe Crashes	146	7.30
		Non-Severe Crashes	1853	92.70
Temporal Characteristic	Season	Winter	573	28.66
		Spring	461	23.06
		Summer	415	20.76
		Autumn	550	27.51
		2015	262	13.11
		2016	277	13.86
		2017	334	16.71
	Year	2018	295	14.76
		2019	276	13.81
		2020	174	8.70
		2021	193	9.65

Demographic Characteristics	Day of Week	2022	188	9.40	
		Weekday	1624	81.24	
		Weekends	375	18.76	
	Time of Day	Daytime	1502	75.14	
		Nighttime	497	24.86	
	Pedestrian Age	< 18	1575	78.79	
		>18	79	3.95	
		Unknown	345	17.26	
	Pedestrian Gender	Male	720	36.02	
		Female	876	43.82	
		Male/Female ¹	58	2.90	
	Driver Age	Unknown	345	17.26	
		<18	1569	78.49	
		>18	11	0.55	
	Driver Gender	Unknown	419	20.96	
		Male	1214	60.73	
		Female	359	17.96	
	Vehicle-related Characteristics	Vehicle Involved	Unknown	426	21.31
			Car	1107	55.38
			Two-Wheeler	453	22.66
Heavy Vehicles		54	2.70		
		Accident that did not involve other vehicles	62	3.10	
		Tram	6	0.30	
Road Features		Unknown	317	15.86	
		Curved section of road	33	1.65	
		Intersection	456	22.81	
		Roundabout	30	1.50	
	Straight section of road	1379	68.98		
	Traffic light-controlled intersection	101	5.05		
	Asphalt	1881	94.10		
Road Surface	Paved with cobblestone	23	1.15		
	Unpaved Road	74	3.70		
	Unknown	21	1.05		
Roadway Characteristics	Road Type	One way	883	44.17	
		Two ways	896	44.82	
		Dual Carriageway	126	6.30	
Roadway Characteristics	Single or dual carriageway with service road	51	2.55		
		Unknown	43	2.15	
		Dry	1699	84.99	
	Road Surface Condition	Wet	235	11.76	
		Unknown	65	3.25	
	Traffic Lights	Functional	98	4.90	
		Not present	1901	95.10	
Environmental Characteristics	Weather Condition	Clear	1515	75.79	
		Cloudy	268	13.41	

Other Characteristics	Visibility Condition	Rainy	181	9.05
		Unknown	35	1.75
		Good	1882	94.15
		Insufficient	71	3.55
	Lighting	Unknown	46	2.30
		Sufficient	1913	95.70
	Crosswalks	Insufficient	86	4.30
		Crash at the crosswalk	374	18.71
		Not at the Crosswalk	552	27.61
		Crash at a crosswalk with a crosswalk equipped with traffic signs/signals	397	19.86
		Unknown	676	33.82
	Traffic Condition	Normal	1690	84.54
		Intense	141	7.05
		Unknown	168	8.40
	No. of Pedestrian involved	1	1551	77.59
		≥ 2	139	6.95
		Unknown	309	15.46
	Pedestrian Behaviour	Crossing the Street	1425	71.29
		At the road	156	7.80
		At the sidewalk	75	3.75
		At the bus Entry/Exit	7	0.35
		Entering Car	2	0.10
		Unknown	334	16.71
		Driver hit the Pedestrian	1505	75.29
		Driver hit the Pedestrian while driving backside	57	2.85
Other Characteristics	Nature of Incidents	Pedestrian fell down	62	3.10
		Pedestrians involved in another accident	57	2.85
		Unknown	318	15.91
		Driver	578	28.91
	Accident Dynamics	Pedestrian	238	11.91
		Driver / Pedestrian	175	8.75
		Driver / Infrastructural	15	0.75
		Environmental	26	1.30
		Infrastructural	119	5.95
		Unknown	848	42.42

¹Represent frequency and percentage where more than 1 pedestrians were involved in a crash and the gender of them was reported as males and females

4.2 Methodology

4.2.1 Data preparation

Following data collection, the dataset underwent several preprocessing steps to ensure its suitability for machine learning analysis. These steps were essential to improve the quality, interpretability, and performance of the models used in this study.

4.2.1.1 Encoding categorical variables

As the majority of variables in the dataset were categorical, it was necessary to transform them into a numerical format suitable for machine learning algorithms. Initially, one-hot encoding was applied, which converts each category into a separate binary variable. However, this approach led to high dimensionality due to the creation of numerous dummy variables, which in turn increased computational complexity and risked overfitting. To address these challenges, label encoding was later employed. This technique assigns a unique numerical value to each category, thus reducing dimensionality while preserving the categorical information. The use of label encoding proved more efficient in terms of both memory and computational resource utilization, particularly for tree-based algorithms that are capable of handling ordinal categorical values effectively.

4.2.1.2 Handling missing values

A significant challenge in the dataset was the presence of missing values for different variables, labelled as “Unknown”, as shown in Table 4-1. The incomplete crash dataset, being underreported with missing values, is a well-known problem in traffic safety research (Imprialou and Quddus 2019). The crash datasets are usually underreported due to human faults, equipment malfunction, and incorrect data transfer (Li et al. 2020). In this regard, (Afghari et al. 2019) further emphasized that missing data is the inability to collect all of the information being used for the study, and that some spatial and behavioural information might be difficult to collect. The elimination of variables or their underreporting due to missing values in the crash dataset could increase the unobserved heterogeneity in the data and could lead to biased estimation of the model outcome (Mitra and Washington 2012; Deb and Liew 2016a). The crash data, considering the missing data mechanism, has usually been identified as missing in the following three patterns: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR) (Jha et al. 2021a). Among these MCAR refers to a type of missingness that occurs randomly, where the likelihood of a value being missing is unrelated to any other data in the dataset. MAR is a structured form of missingness in which the chance of a value being absent can be accounted for by other observed variables in the

dataset. It is entirely non-random, and the missing entries may be associated with and anticipated from existing data. In addition, MNAR is the category where the missing value in a variable is directly linked to the value itself.

Consequently, different analytical approaches have been used in safety literature to deal with these missing crash data patterns. Since the missing data for different variables (continuous, categorical, binary) could be missing in different patterns, and therefore, another challenge to deal with missing data is to choose a suitable imputation technique (Li et al. 2020). For instance, the most common method for dealing with missing data is the case-wise deletion method (Afghari et al. 2019). In this approach, the crashes with missing data are simply removed, which could result in a significant reduction in the data sample, which can impact the model with a biased outcome (Lord 2006; Lord and Miranda-Moreno 2008; L. Li et al. 2017). Mean imputation, also referred to as simple imputation, is the most straightforward approach, which works by replacing missing values with the most frequent value (mode) for categorical features or (mean) for continuous features (Bhat 1994). This method is easy to implement and has been applied in traffic safety research (Ding et al. 2019), however, it might ignore the connection between variables and affect their performance (Li et al. 2020). The k-nearest neighbour (KNN) imputation identifies missing values by referencing the most similar instances in the dataset (Batista and Monard 2003). For example, for categorical data, the missing value is imputed with the most frequent category among the k-nearest neighbors (Zhang 2012). This method has also been used for data imputation in traffic safety (Ding et al. 2019; Jha et al. 2021b), however (Gao et al. 2025) pointed out that KNN might show limitations due to their dependence on established correlations and strong sensitivity to data distribution patterns, particularly when applied to unfamiliar datasets. In addition, decision tree-based imputation (DSMI) is another imputation approach that was introduced by (Deb and Liew 2016b) for inputting data into truck crash datasets. This method got high accuracy for imputing data when compared with other imputation techniques such as Deep Missing Data Imputation (DMI) and KNN, however (Deb and Liew 2016b) also noticed a limitation when this technique has been applied to small data sets with few variables, and larger datasets.

Moreover, the multivariate imputation by chained equations (MICE) (Graham 2009) or iterative imputation technique predicts missing values for each feature as a function of other variables, iteratively refining the estimates. This round-robin process continues until convergence, making it particularly suitable for datasets with complex dependencies among variables. Its strength lies in capturing multivariate relationships effectively, though

computationally more demanding and sensitive to the correctness of the underlying model assumptions. The MICE technique is also capable of imputing data with missing at random in multiple variables (continuous, categorical, binary) with the assistance of each variable imputation model (Linear regression, Logistic regression, multinomial logistic regression model) in a dataset, and therefore has been used frequently for traffic crash data imputation due to its enhanced flexibility and proficiency in adapting to diverse variable types (L. Li et al. 2017; Li et al. 2020; Gao et al. 2025). Therefore, it can be observed that the efficiency of different imputation techniques for imputing data in crash datasets varies across different studies, identifying their relevance and limitations, considering their application for different datasets containing different variables and percentages of missing data.

Considering this, in this study, a multifaceted data imputation framework was carried out for imputing data into different variables, as shown in Table 4-1. Before imputation, it is important to mention that some variables such as temporal (Time of day, Season, Day of week, Time of day, Year), road features, traffic lights, and lighting, are fully observed in dataset as shown in Table 4-1 while do not contain missing data and therefore do not require imputation. Also, the dependent variable (crash severity) is fully observed in the dataset as shown in Table 1, and therefore, only the independent variables with missing data were imputed. Therefore, to impute data for the rest of the variables in Table 4-1, at first, a case-wise deletion method was applied to the dataset. In this approach, all the crashes with unknown values were deleted, resulting in a significant amount of data sample reduction. Consequently, data sample reduction can impact the model with a biased parameter estimation, increasing the errors, and therefore, this method was not chosen for imputation purposes. After that, different machine learning based imputation methods were applied. Among these are Simple, K-Nearest Neighbors, and iterative imputations were included. These imputation methods were chosen for their robustness in tackling missing data, considering different types of variables in a pedestrian crash dataset.

4.2.1.3 Selection of data imputation method

To determine the most effective imputation technique, each method was evaluated based on key performance metrics: F1-score (both micro and macro) and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These metrics are particularly suitable for imbalanced binary classification tasks.

- *F1-Micro* calculates the metric globally by aggregating total true positives, false negatives, and false positives, and is useful when dealing with class imbalance.

- *F1-Macro* averages the metric independently for each class, providing a balanced perspective across all classes.
- *AUC-ROC* evaluates the model's ability to discriminate between classes across all thresholds by plotting the true positive rate against the false positive rate.

4.2.1.4 Validation of data imputation methods

In traffic safety modelling, validating that the imputation does not skew the original data is important. Traffic crash datasets are dominated by categorical factors, and improper handling of missing data can misrepresent these factors' relationships with crash outcomes (Deb and Liew 2016a). As noted in a recent review, traditional imputation methods (like KNN or MICE) are commonly applied in crash data for data imputation; however, they may not capture complex dependencies (Gao et al. 2025). Therefore, the purpose of validating data imputation methods is to ensure that the selected imputation methods (Simple, KNN, Iterative) do not introduce any bias to the imputed dataset. In this regard, by using distribution-comparison metrics (such as Jensen-Shannon Distance (JSD) and Hellinger) and visualizations, it can be demonstrated in a rigorous, peer-review-ready manner that the imputed data "looks like" the original. For example, (Gao et al. 2025) showed that a successful imputation approach preserved key variable importance and data structures in crash records. Therefore, the goal is to make sure that the imputation procedures did not significantly alter the underlying distribution of categorical features, so that the nature of the data (and the relationships between factors and severity) remains intact.

In this study, to validate the data imputation for the variables with missing data, two quantitative metrics, the Jensen-Shannon divergence (JSD) and chi-square, were applied to the imputed dataset to evaluate the distribution of data between the imputed and original pedestrian crash dataset. JSD is a symmetric and bounded measure quantifying divergence between original and imputed categorical distributions. In such a case, a lower JSD value indicates greater similarity and thus minimal distributional distortion. Whereas the Chi-square test assesses whether observed (imputed) distributions significantly differ from expected (original) distributions. In this regard, a higher p-value (>0.05) suggests no statistically significant distortion due to imputation. Moreover, to further visualize the distributional divergence between the imputed and original pedestrian crash dataset, a JSD heat map was adopted. The JSD heat map comparing original versus imputed category frequencies visually confirms quantitative metrics. They enable intuitive assessment of any shifts, supplementing numeric divergence measures. Together, these techniques provide complementary evidence, crucially

confirming whether imputation methods preserve data integrity, a fundamental requirement for reliable downstream analysis in crash severity modeling.

4.2.1.5 Data balancing

Initially, crash severity was recorded across multiple levels; however, for analytical clarity and model effectiveness, these were consolidated into two broad categories: “Severe” and “Non-Severe.” Following this categorization, only 146 out of the total 1,999 crashes were classified as severe, while the remaining 1,853 were categorized as non-severe. This notable imbalance presented a significant challenge for machine learning applications, as it risked producing biased models that could disproportionately favour the majority class (Ali et al. 2024).

To mitigate the strong imbalance between “Severe” and “Non-Severe” crashes in our training data, we applied the Synthetic Minority Over-sampling Technique (SMOTE) from the imblearn package (Chawla et al. 2002). SMOTE generates new minority-class samples by interpolating between each minority instance and its k nearest neighbors in feature space. In our implementation, we used the default sampling strategy (i.e., balance to a 1:1 ratio) with $k = 5$ and a fixed random seed (`random_state = 42`) to ensure reproducibility. SMOTE was applied only to the training split—after the 80/20 train–test partition—to avoid any leakage of synthetic data into model evaluation. The resulting balanced training set enabled our CatBoost (and other) classifiers to learn equally from both classes, reducing bias toward the majority class and improving generalization performance.

4.2.2 Machine learning models

In this study, to predict injury severity, four machine learning models were employed, each selected for their strengths in handling categorical data, managing complexity, and delivering high predictive performance.

Random Forest, introduced by (Breiman 2001), is an ensemble learning method that constructs multiple decision trees during training and outputs either the mode for classification tasks or the mean prediction for regression tasks. It employs two main techniques: Bootstrap Aggregation (Bagging), which randomly samples the data with replacement to build each decision tree, and Feature Randomness, which selects a random subset of features at each node, encouraging diversity among the trees. These characteristics reduce the risk of overfitting and enhance predictive accuracy. Random Forest has been widely applied in traffic safety studies, particularly for crash prediction, hotspot identification, and severity analysis (Santos et al.

2022; Ali et al. 2024). For example, (Gan and Weng 2020) demonstrated that Random Forest outperforms multinomial logit models in predicting driver injury severity.

Categorical Boosting (CatBoost), developed by Yandex, is a gradient-boosting algorithm designed to efficiently handle categorical features without the need for extensive preprocessing (Dorogush et al. 2018). Its Ordered Boosting method minimizes the risk of prediction shift caused by target leakage by processing data in a manner that avoids using future information during training. Additionally, CatBoost excels in handling categorical data through permutation-driven encoding, which converts categorical variables into numerical representations. CatBoost has demonstrated strong performance in datasets with significant categorical variables and has been applied in many traffic safety studies. For instance, (Zahid et al. 2024) used Catboost together with SHapley Additive exPlanations (SHAP) to analyze motorcycle crash data and identify key factors affecting injury severity.

Extreme Gradient Boosting (XGBoost) is an optimized gradient boosting library known for its efficiency and scalability (Chen and Guestrin 2016). XGBoost incorporates regularization, using L1 and L2 penalties to control overfitting, and Parallel Processing to accelerate training through parallel computations. Additionally, it includes internal methods for handling missing data, making it particularly robust for datasets with incomplete information. XGBoost has been widely adopted in traffic safety studies, including (Goswamy et al. 2023), where it was used to assess the impact of Rectangular Rapid Flashing Beacons on pedestrian crashes, achieving a high accuracy rate of 97%.

Gradient Boosting (GradientBoost), first formalized by (Friedman 2001), construct an additive model by sequentially fitting new decision trees to the residual errors of the ensemble built so far. At each iteration m , a tree $h_m(x)$ is trained to approximate the negative gradient of the loss function $L(y, F_{m-1}(x))$, updating the model as:

$$F_m(x) = F_{m-1}(x) + v h_m(x)$$

where v is the learning rate controlling shrinkage. Key hyperparameters include the number of trees, tree depth, and learning rate. This iterative, loss-driven approach allows GBM to capture complex, non-linear relationships without strong parametric assumptions.

In traffic safety applications, GBM has proven highly effective for modelling both crash frequency and injury severity. It consistently outperforms traditional statistical models and exhibits robustness to missing data and outliers (Bridgelall and Tolliver 2021; Ali et al. 2024). For example, (Rahman 2018) demonstrated that GBM achieved higher predictive accuracy than bagging and random forest methods when forecasting pedestrian and bicycle crash counts at a macroscopic level. These improvements enable more precise identification of high-risk locations and the critical factors contributing to severe pedestrian crashes, thereby supporting targeted, data-driven safety interventions.

4.2.3 Models' validation

Model validation is an essential process to assess the generalizability and reliability of the predictive models. To ensure a comprehensive evaluation, several validation techniques and performance metrics were employed, as discussed earlier. These included the F1-score (both micro and macro), which balances precision and recall, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), which evaluates the model's ability to distinguish between classes (Vafeiadis et al. 2015; Naidu et al. 2023). The validation process was further strengthened through the application of k-fold cross-validation (Gorriz et al. 2024). This technique allowed the dataset to be divided into multiple subsets, enabling the models to be trained and tested on different combinations of data. This approach reduced the risk of overfitting and provided a more robust estimate of each model's predictive capability on unseen data. In addition, confusion matrix analysis was conducted to gain a deeper understanding of model performance by examining the distribution of true positives, false positives, true negatives, and false negatives. This helped identify specific areas where models were performing well or struggling, especially in cases of class imbalance (Naidu et al. 2023). Finally, a comparative analysis of four ensemble models—Random Forest, CatBoost, XGBoost, and GradientBoost—was carried out to identify the best-performing algorithm.

4.2.4 Model interpretation with SHAP

The SHAP technique, introduced by (Lundberg and Lee 2017) is based on game theory and local interpretability principles that interpret a machine learning model by adopting each feature's partial contribution to model prediction by estimating SHAP values. In the context of this study, SHAP was employed to analyze the Catboost model which involved several steps:

Computing SHAP values: SHAP values were calculated for each feature across the test dataset, providing a detailed breakdown of the impact each variable had on the model's predictions.

Visualizing Feature Importance: Summary plots were generated to visualize the magnitude and direction of the effects of key features on injury severity. This allowed to pinpoint which factors consistently drove the model’s predictions. *Exploring Individual Predictions:* Specific cases were examined to understand how feature values contributed to the predicted injury severity for individual crashes. *Interaction Effects:* To evaluate the complex interactions among several features, interaction effects between significant variables were examined with SHAP interaction dependency plots, further assisting in understanding their intricate impact on pedestrian crash severity.

The mean SHAP value across all samples can be explained as the average importance of feature j as shown in equation below:

$$Importance_j = \frac{1}{K} \sum_{i=1}^K |\phi_{i,j}|$$

Where $\phi_{i,j}$ denotes the SHAP value for sample i for feature j , and K is the number of samples that can be used for model interpretation analysis.

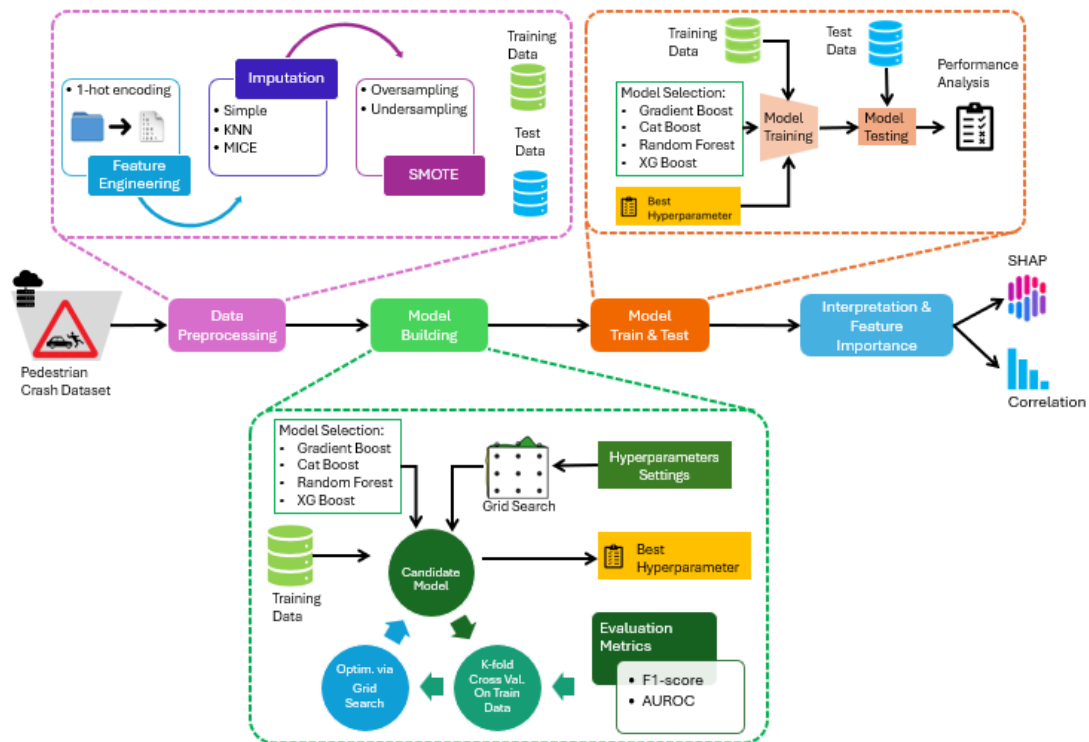


Figure 4–2. Methodological framework of the study

4.3 Results

4.3.1 Imputation methods performance

Table 4-2 below summarizes the performance of the applied imputation methods. The comparison model of different imputation techniques was adopted as being followed in the studies (Deb and Liew 2016a; L. Li et al. 2017; Li et al. 2020; Gao et al. 2025) to identify the effectiveness of each imputation method, considering the imputation accuracy and its performance. Among the applied imputation techniques, the iterative imputation (MICE) demonstrated the highest scores across all evaluation metrics.

Table 4–2. Evaluation metrics score of imputation methods

Imputation Methods	Evaluation Metrics		
	F1-Micro ($\pm$ std)	F1-Macro ($\pm$ std)	AUC ($\pm$ std)
Simple Imputation	89.07 $\pm$ 0.82	58.54 $\pm$ 1.10	64.15 $\pm$ 0.95
K-Nearest Neighbours Imputation	90.37 $\pm$ 0.65	61.75 $\pm$ 0.88	64.44 $\pm$ 0.72
Iterative Imputation (MICE)	94.33 $\pm$ 0.35	75.72 $\pm$ 0.57	75.19 $\pm$ 0.44

4.3.2 Validation of imputation methods

To rigorously validate the performance of imputation methods, ensuring minimal distortion in the original feature distributions, in this study, a Jensen-Shannon Distance (JSD) and a Chi-square test were applied to the imputed pedestrian crash dataset. In this regard, Table 3 shows the JSD and Chi-square p-values for each imputed variable. It can be observed that for the variables where the data was fully observed and being reported without missing values, the JSD and Chi-square p-values did not show any divergence across each applied imputation technique. However, for the variables where the data had been missing and therefore being imputed through different imputation methods, the JSD and Chi-square p-values for each variable differ across imputation techniques. In such a case, a lower JSD value would be considered as adequate similarity and negligible distributional distortion, whereas a Chi-square p-value (>0.05) recommends no significant statistical distortion for the data being imputed. Overall, it can be observed in Table 3 that Iterative imputation (MICE) indicates minimal distributional distortion for most variables, as evident by low JSD values (<0.05) and non-significant Chi-square p-values (>0.05). KNN imputation demonstrated slightly higher

distributional divergence for certain features as compared to MICE. In such a case, the local averaging strategy of KNN might have induced biases, particularly for features with sparse or uneven categorical distributions. The Simple imputation, on the other hand, showed the highest divergence across multiple variables as compared to MICE and KNN, with significant alterations in categorical distributions ($JSD > 0.20$) and highly significant Chi-square results (p-values near zero). The frequent-category filling strategy caused severe inflation in dominant categories, fundamentally altering the original distributional structures.

However, features such as “NatureofIncident, AccidentDynamics, and CrossWalk” exhibited statistical deviation (Chi-square p-values < 0.05) across each applied imputation technique, as shown in Table 3. The JSD values of these variables for the MICE imputation are slightly higher and close to (< 0.05) in the case of variable “NatureofIncident”; however, overall lower than 0.05 as shown in Table 3 and Figure 3. Similarly, the JSD values of these variables for KNN and simple imputation are higher than MICE and overall greater than 0.05. Even though these variables show statistical divergence across each applied imputation technique, nevertheless, based upon JSD values comparisons, MICE outperformed KNN and Simple imputation with the lowest reported JSD values as shown in Table 3 and Figure 3. Cautiously, in such a situation, data imputation with KNN and Simple imputation would have integrated more domain shifts and data bias in the pedestrian crash dataset for these variables, and therefore, MICE was selected for data imputation due to overall superior data imputation performance.

Moreover, the JSD heatmap matrix (Figure 3) further effectively visualizes the JSD values comparison across each variable for different imputation techniques. The heatmap illustrates the distributional divergences, with darker cells highlighting greater distortion as compared to lighter cells. Overall, it can be observed that MICE imputation shows a lighter divergence with lower JSD values and lighter colour cells together for the variables with statistical deviation, as compared to KNN and Simple imputation. Simple imputation depicts greater distortion for the imputed variables as compared to KNN and MICE. The rigorous validation using JSD, Chi-square tests, and heat map visualization robustly supports adopting MICE imputation for traffic crash datasets, ensuring model reliability and enhancing the validity of traffic safety analyses, which is supported by (L. Li et al. 2017; Li et al. 2020).

Table 4–3. Jensen-Shannon D istance (JSD) and Chi-square p-values for validation of imputation methods

Features	Iterative (MICE)		KNN		Simple	
	JSD	ChiSquare_p	JSD	ChiSquare_p	JSD	ChiSquare_p
Day/Night Time	0.0000	1.0000	0.0000	1.0000	0.0000	1.0
Season	0.0000	1.0000	0.0000	1.0000	0.0000	1.0
Ped_Involved	0.0170	0.2327	0.0143	0.3840	0.2384	0.0
Ped_Age	0.0143	0.0839	0.0134	0.1045	0.2528	0.0
Ped_Gender	0.0127	0.2993	0.0137	0.2472	0.2528	0.0
VehicleInvolved	0.0165	0.4028	0.0174	0.3137	0.2416	0.0
DriverAge	0.0066	0.4326	0.0066	0.4326	0.2807	0.0
DriverGender	0.0427	0.0000	0.0251	0.0019	0.2832	0.0
Ped_Behv	0.0239	0.0511	0.0240	0.0465	0.2484	0.0
NatureofIncident	0.0481	0.0000	0.0642	0.0000	0.2420	0.0
AccidentDynamics	0.0167	0.0000	0.1137	0.0000	0.4194	0.0
CrossWalk	0.0140	0.0000	0.1096	0.0000	0.3668	0.0
RoadFeature	0.0000	1.0000	0.0000	1.0000	0.0000	1.0
RoadSurface	0.0004	0.9984	0.0039	0.8832	0.0605	0.0
RoadType	0.0084	0.7713	0.0032	0.9834	0.0867	0.0
RoadSurf	0.0043	0.5887	0.0043	0.5887	0.1068	0.0
Weather	0.0014	0.9853	0.0022	0.9631	0.0781	0.0
Lighting	0.0000	1.0000	0.0000	1.0000	0.0000	1.0
TrafficLights	0.0000	1.0000	0.0000	1.0000	0.0000	1.0
Visibility	0.0012	0.8739	0.0016	0.8416	0.0897	0.0
TrafficCondition	0.0088	0.2778	0.0074	0.3588	0.1733	0.0
DayofWeek	0.0000	1.0000	0.0000	1.0000	0.0000	1.0

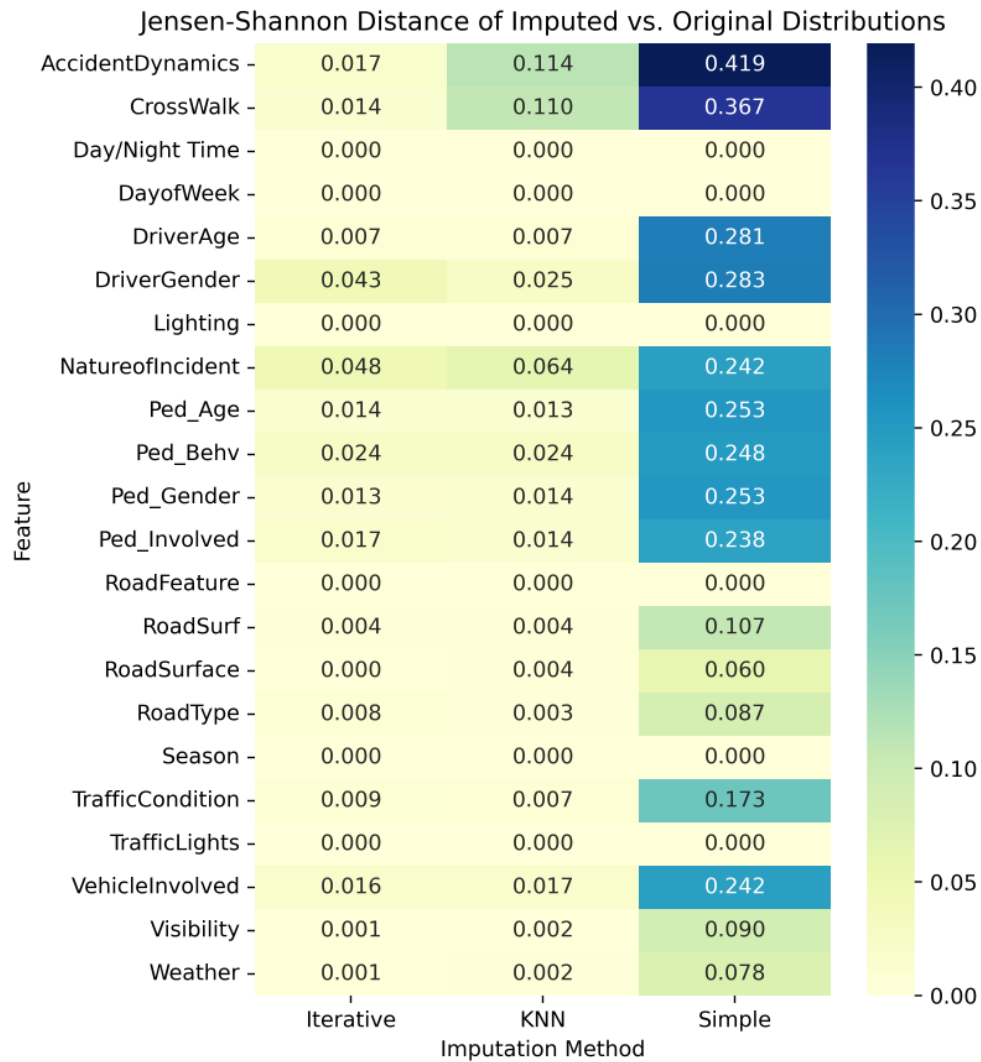


Figure 4–3. Jensen-Shannon Distance of imputed versus original distributions for imputation methods

4.3.3 Models' performance

In this study, each machine learning model was trained on 70% of the data and tested on the remaining 30%, using their optimal hyperparameter settings. Their performance was evaluated using metrics such as Accuracy, F1-Score (micro and macro), and Area Under the Curve (AUC). Among the models tested, the CatBoost model achieved the highest scores across all evaluation metrics, outperforming Random Forest, XGBoost, and Gradient Boosting as shown in Table 4-4. Furthermore, the Precision-Recall and AUC-ROC plot also outperformed Catboost model by demonstrating their superior performance with high Precision-Recall and AUC values as compared to other models, as shown in Figure 4-4.

Table 4–4. Machine Learning Models' Accuracy and Evaluation Metrics score

Model	Accuracy ($\pm$ std)	F1 Score (Micro $\pm$ std)	F1 Score (Macro $\pm$ std)	AUC ($\pm$ std)
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Random Forest	94.2 ± 0.45	93.6 ± 0.63	77.1 ± 0.75	73.2 ± 0.86
XGBoost	92.5 ± 0.40	92.5 ± 0.35	72.9 ± 0.65	75.1 ± 0.50
Gradient Boosting	91.8 ± 0.35	91.8 ± 0.30	72.4 ± 0.60	76.3 ± 0.45
CatBoost	94.8 ± 0.30	94.8 ± 0.28	78.2 ± 0.45	78.5 ± 0.40

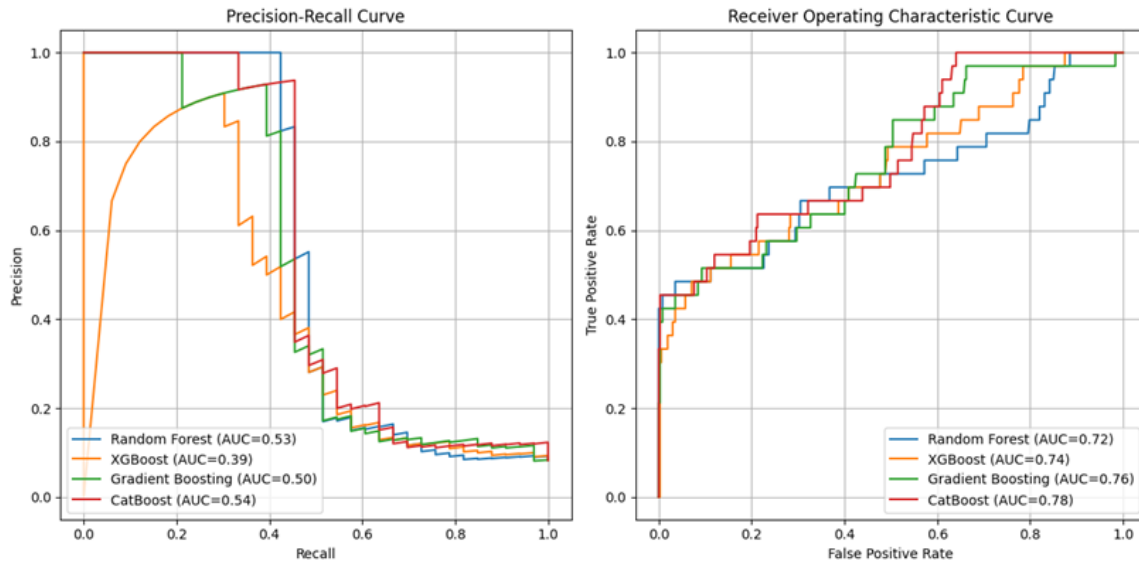


Figure 4-4. Precision-Recall and AUC-ROC plot of Machine Learning models

4.3.4 SHAP analysis

4.3.4.1 Global analysis

The output of the CatBoost model was evaluated using SHAP values to identify the most important features contributing to the prediction of pedestrian crash severity in Palermo, Italy. Figure 4-5 represents the global SHAP analysis, demonstrating how individual features impact the model's predictions. In the figure, the x-axis represents the SHAP values, which measure the impact of each feature on model predictions, while the y-axis ranks the features by their relative importance.

Among the variables, pedestrian gender (e.g., male and female) emerges as the most significant factor influencing whether a crash is predicted to result in severe or non-severe injuries. The second most influential factor is accident dynamics, which describes the nature of the crash, including whether the pedestrian or driver was at fault. Similarly, the nature of incident, a variable capturing the characteristics of both driver and pedestrian behaviour during the crash, is ranked as the third most important feature in predicting the severity of crashes. In addition, day of weeks, which differentiates between crashes occurring on weekdays versus weekends,

is another most important feature. Roadway characteristics such as road type (e.g., one-way roadway, two-way roadway) and road features (e.g., straight section of road, roundabout, intersections) have also shown a significant impact on the model output for predicting crash severity. Driver gender has also been found out as a key variable, potentially reflecting behavioral patterns or risk profiles that influence crash outcomes. In addition to these top features, time of day (e.g., daytime or nighttime), crosswalk presence (e.g., crash occurred or not at a designated pedestrian crossing) and pedestrian behavior (e.g., actions like crossing the street, walking along the road, or standing on sidewalks) at the time of the crash showed a meaningful impact on the model's predictions. While all the above features have shown a significant impact on whether the crash was predicted to be severe or non-severe, nevertheless, features such as road surface, traffic condition, lighting, and pedestrian age had a lower impact on model prediction for crash severity, as illustrated in Figure 4-5.

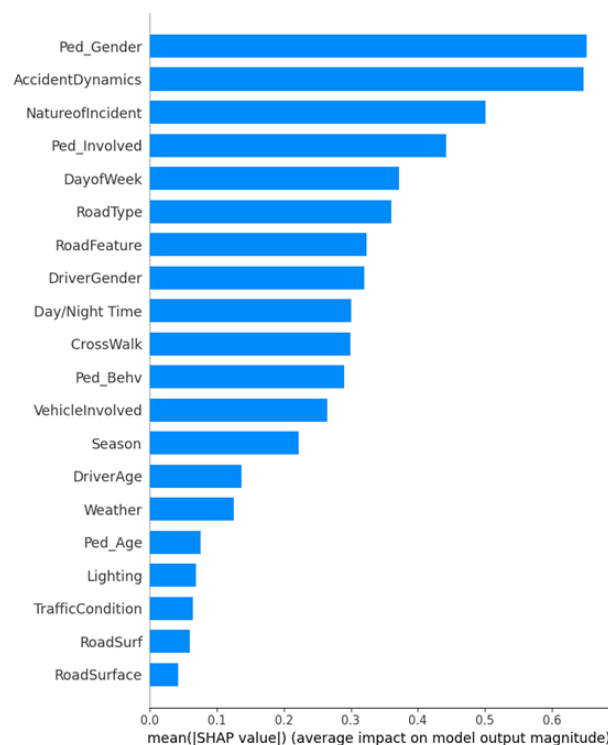


Figure 4–5. Features average impact on model output

4.3.4.2 Local analysis

Figure 4-6 presents a local SHAP analysis, illustrating the contribution of each feature to the CatBoost model's predictions of pedestrian crash severity (severe vs. non-severe injuries). The x-axis represents the SHAP value, where positive values (right) increase the likelihood of severe injury, and negative values (left) decrease it. The y-axis lists the features, and the color

gradient (blue to red) reflects feature values from low to high, indicating their relative impact on predictions.

As shown in Figure 4-6, among the most significant features, pedestrian gender significantly increases the severe outcome of the crashes. Similarly, accident dynamics and nature of incidents (at-fault reasons) show variability in their impact, which means that their influence on the crash severity changes from case to case with involving different at-fault bodies in crashes. Moreover, the feature day of the week also exhibits a significant impact due to the highest positive SHAP values, showing that crashes occurring on weekdays or weekends increase the severity of crashes. In addition, road type and road features have also been identified as the main determinants of crash severity. The local SHAP analysis further highlighted the importance of driver gender, suggesting that driver gender increases the outcome of crashes to be severe. Besides all these features, day/nighttime also shows a prominent impact with positive SHAP values indicating that crashes that occur either in the daytime or nighttime enhance the severity of pedestrian crashes. The crosswalk in the local SHAP analysis also shows a positive impact on the severity of crashes, suggesting that the crashes that occurred at or not at crosswalks increase the severity of pedestrian crashes. Lastly, pedestrian behaviour exhibits variability in its impact, showing that pedestrian behaviour mostly enhances the outcomes of crashes to be severe.

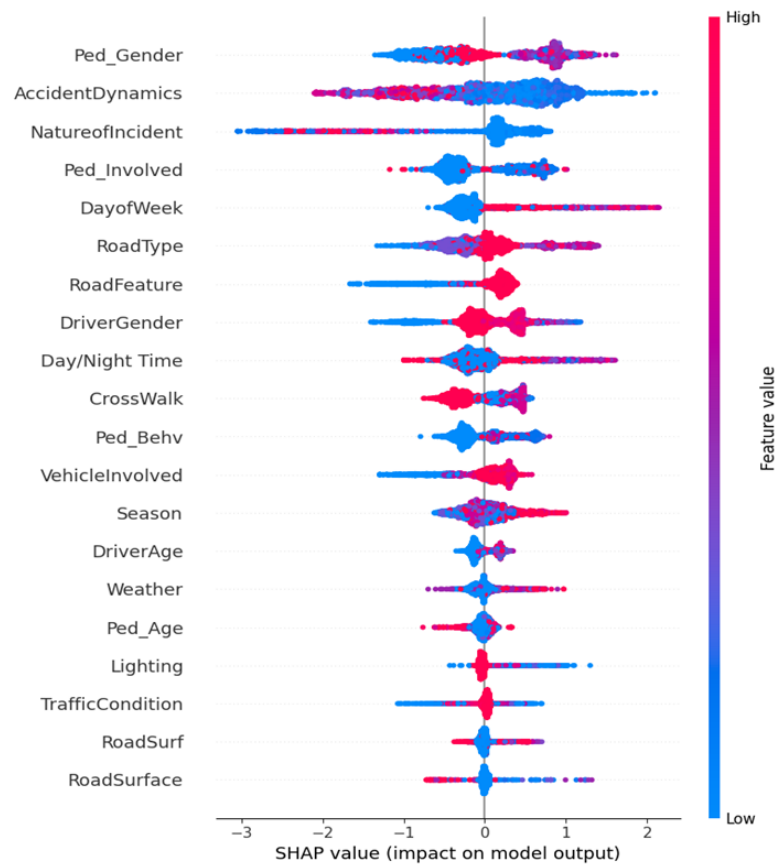


Figure 4–6. Features impact on the severity of pedestrian crashes

4.3.5 Interaction effects

As previously stated, the global and local SHAP analyses presented in Figures 4-5 and 4-6 offer valuable insights by identifying key factors that positively influence the severity outcomes of pedestrian crashes. However, these analyses may not fully capture the complex interactions among multiple influential variables. To address this limitation, the present study further explores these interactions using SHAP interaction dependency plots, which provide a comprehensive understanding of the factors for their influence on the pedestrian crash severity. It is important to mention that for the interaction effects analysis, only those variables that were identified as significant and important in both global and local SHAP analyses, and which demonstrated substantial impact in the SHAP interaction plots, were selected.

For example, the interaction between pedestrian gender and other features reveals that male pedestrians are prone to severe crashes as compared to female pedestrians. As shown in Figures 4-7 and 4-8, male pedestrians on two-way roadways and straight road segments are more likely to experience severe crash outcomes. Similarly, the interaction between pedestrian gender and

time of day (Figure 4-9) indicates that male pedestrians involved in crashes during nighttime hours are at a significantly higher risk of severe injury or fatality. As discussed previously, driver gender plays a pivotal role in crash severity. The interactions between male drivers and environmental factors such as weather and lighting conditions (Figures 4-10 and 4-11) demonstrate that male drivers in rainy weather and under low lighting conditions substantially increase the likelihood of severe pedestrian crashes. In addition, pedestrian behaviour also emerged as a critical determinant. Specifically, pedestrians crossing the street showed a higher probability of being involved in severe crashes. Their interaction with other contextual factors, road features, weather conditions, and lighting (Figures 4-12 – 4-14), reveals that crossing straight road segments during rainy weather and low lighting significantly increases pedestrian crash severity.

Moreover, the temporal features add further depth to the interaction analysis. The interaction between day of the week, crosswalk presence, and day/night timing (Figures 4-15 and 4-16) indicates that pedestrian crash severity is increased during weekdays at crosswalks and during weekends at night. The combination of roadway characteristics and crosswalks also yields significant patterns. As depicted in (Figures 4-17 and 4-18), crashes occurring on two-way roads, particularly at straight sections with crosswalks, are associated with higher severity levels. In this regard, the roadway features in (Figure 4-19) further indicate supporting impact patterns, revealing that pedestrian crossings on straight sections of the road contribute to increased severity in pedestrian crashes. Finally, features related to crash fault dynamics, such as accident type and nature of the incident, also interact meaningfully with other variables. The interactions involving accident dynamics, day of the week, and crosswalks (Figures 4-20 and 4-21) reveal that when drivers are at fault during weekends and crashes occur at crosswalks, the severity of pedestrian crashes significantly increases. This pattern is shown in (Figures 4-22 and 4-23), where driver-pedestrian collisions on weekends at crosswalks result in the most severe outcomes.

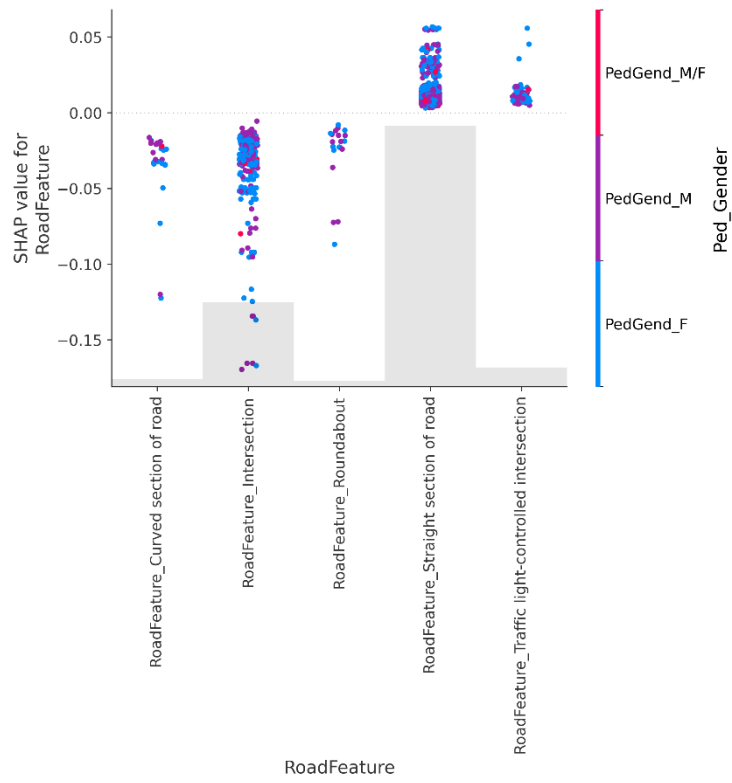


Figure 4–7. Interaction effects between pedestrian gender and road features

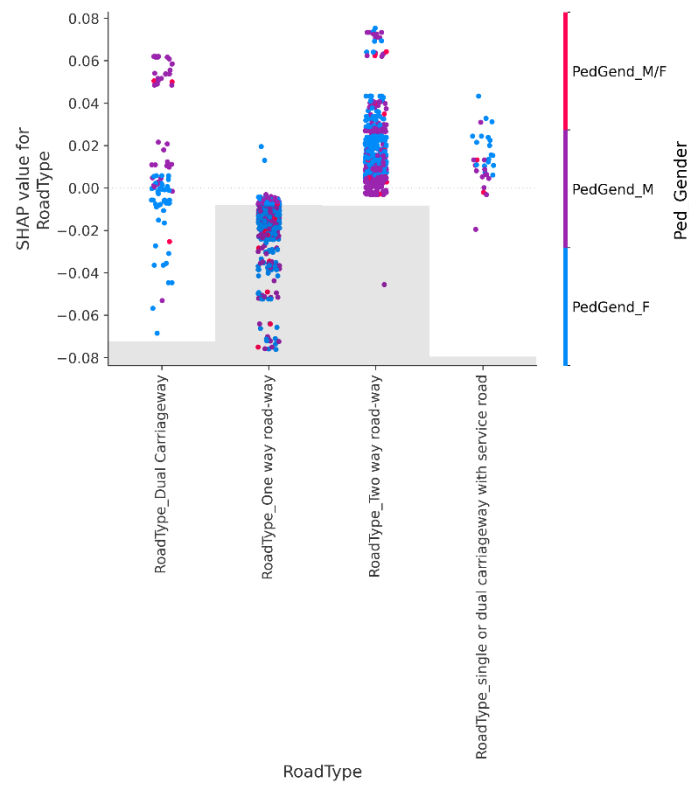


Figure 4–8. Interaction effects between pedestrian gender and road types

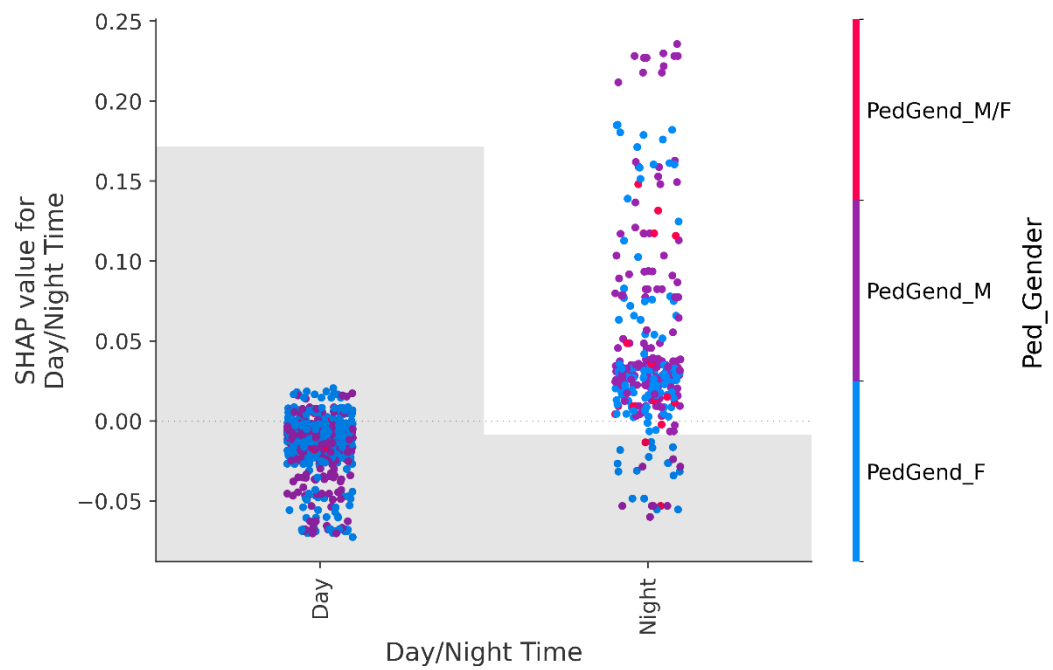


Figure 4–9. Interaction effects between pedestrian gender and day/nighttime

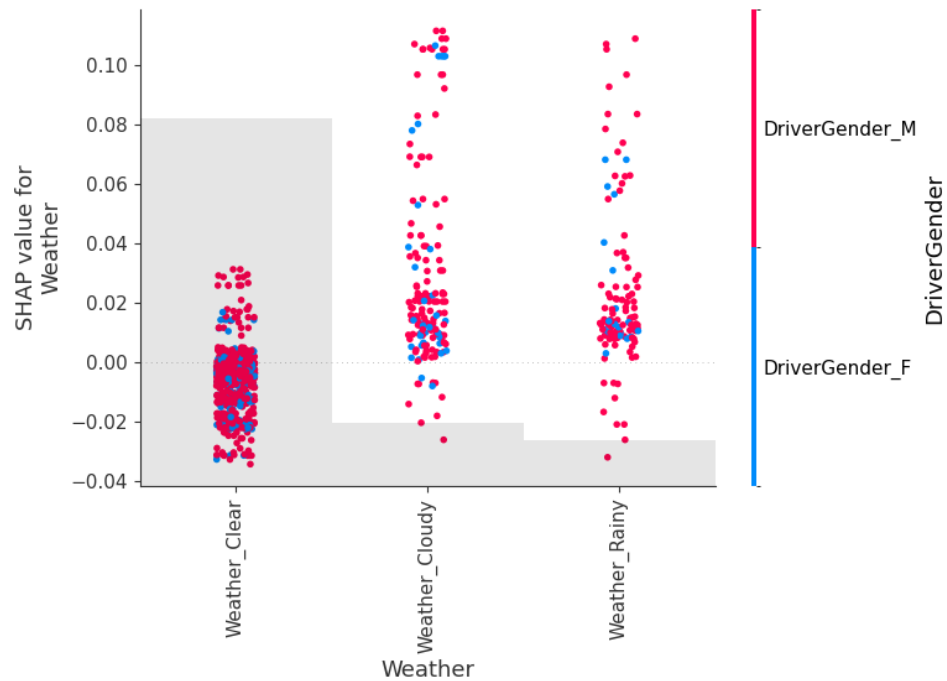


Figure 4–10. Interaction effects between driver gender and weather

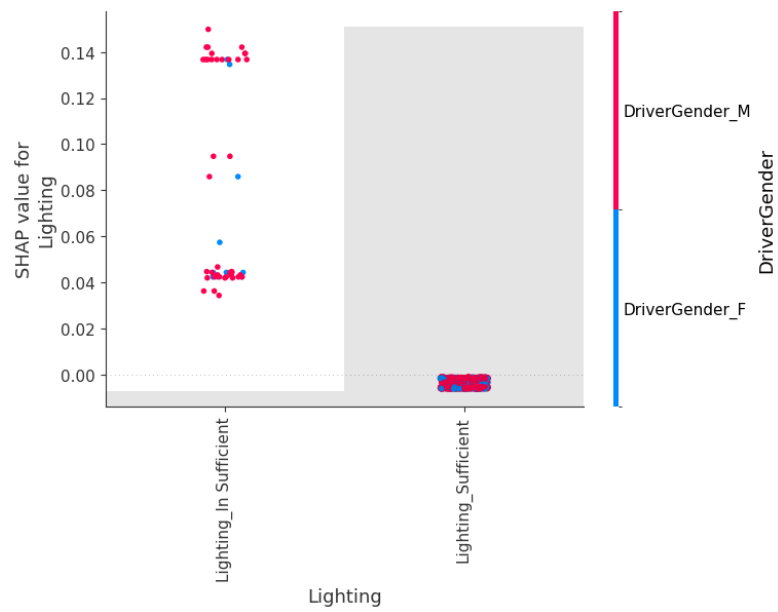


Figure 4–11. Interaction effects between driver gender and lighting

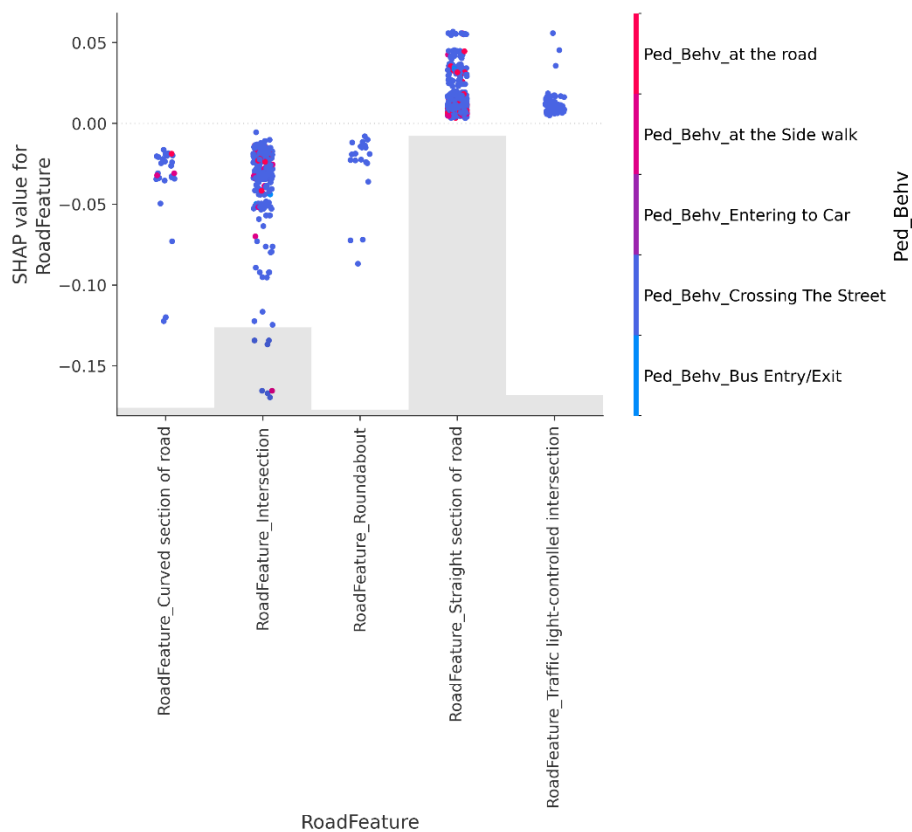


Figure 4–12. Interaction effects between pedestrian behaviour and road features

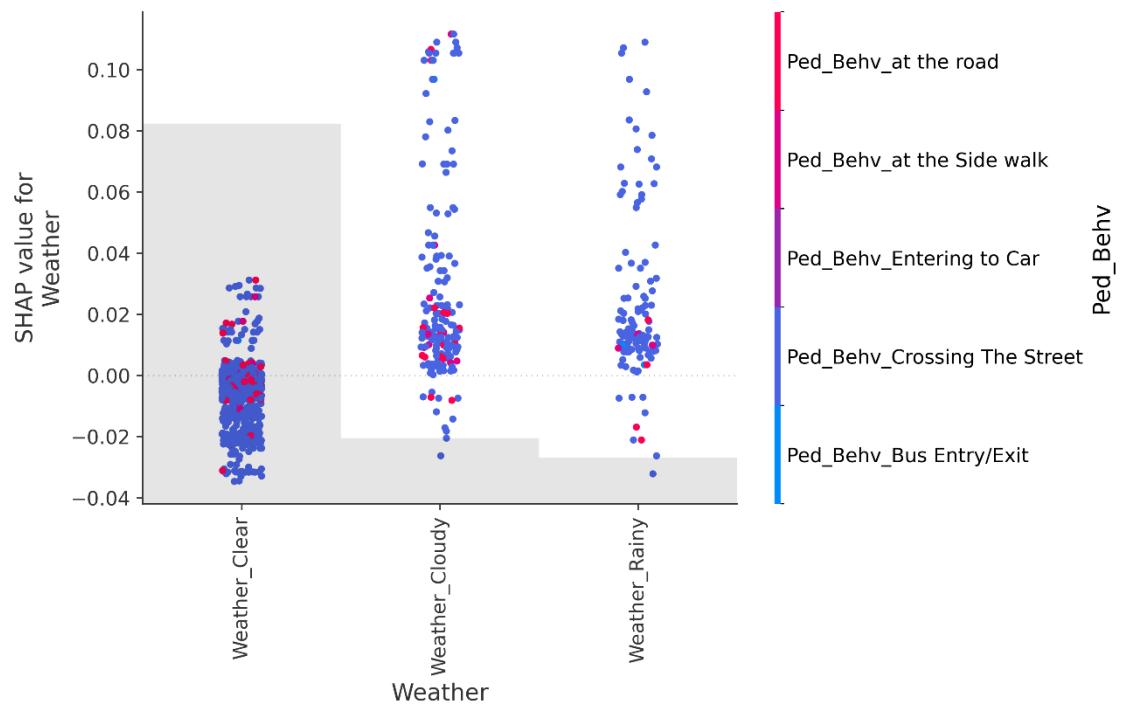


Figure 4–13. Interaction effects between pedestrian behaviour and weather

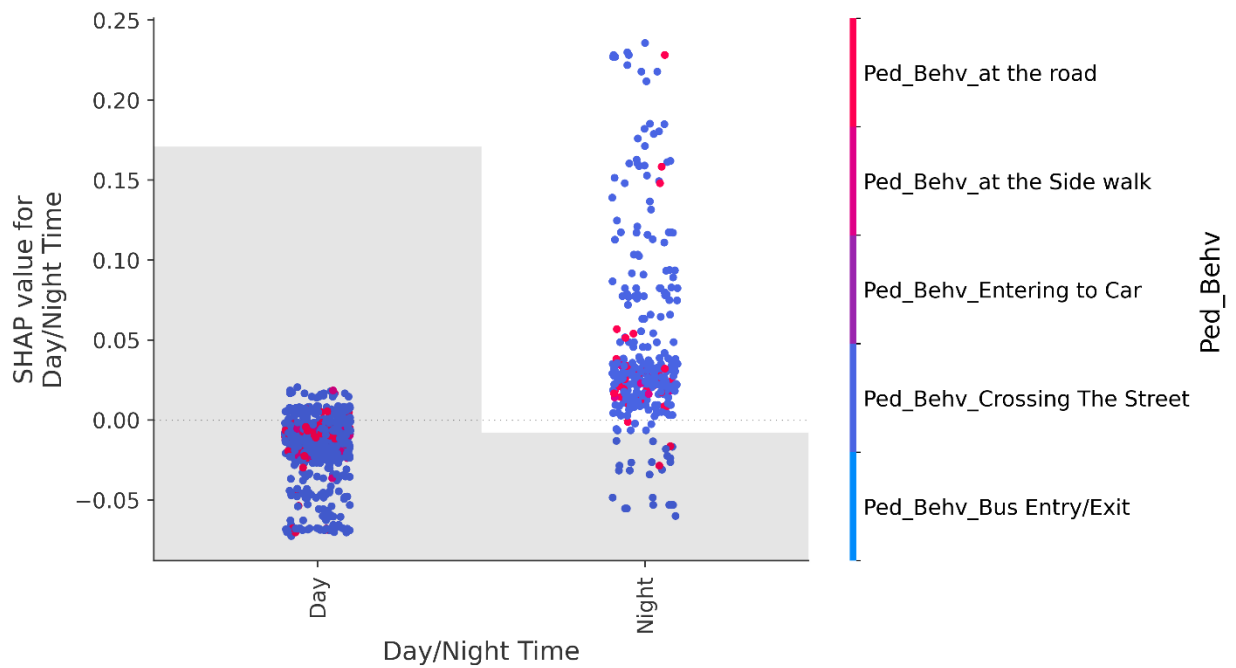


Figure 4–14. Interaction effects between pedestrian behaviour and day/nighttime

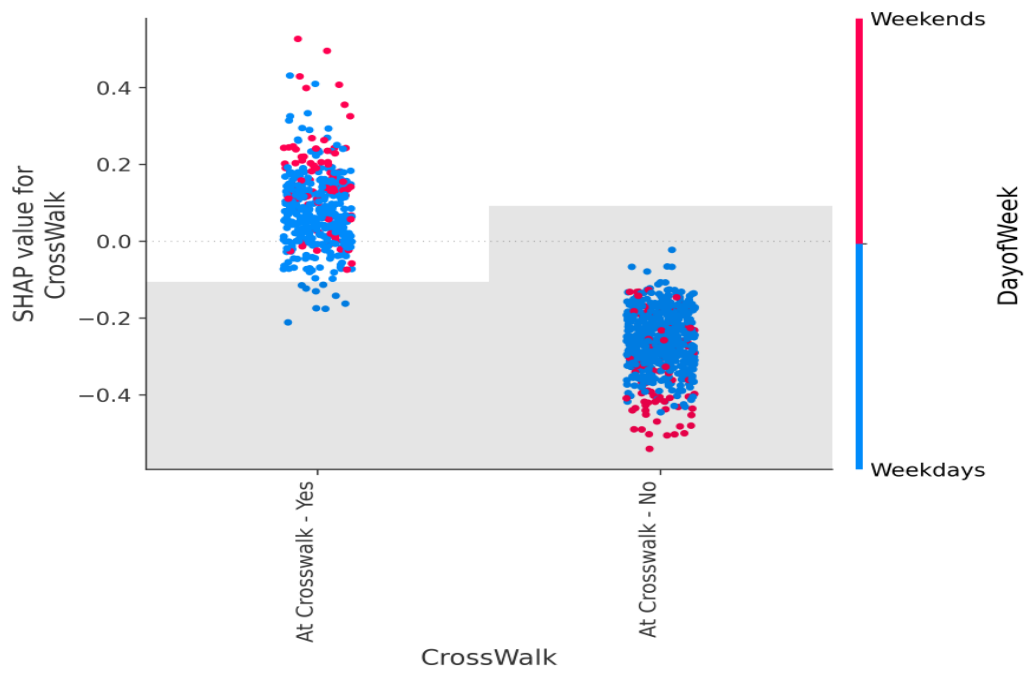


Figure 4–15. Interaction effects between day of week and crosswalk

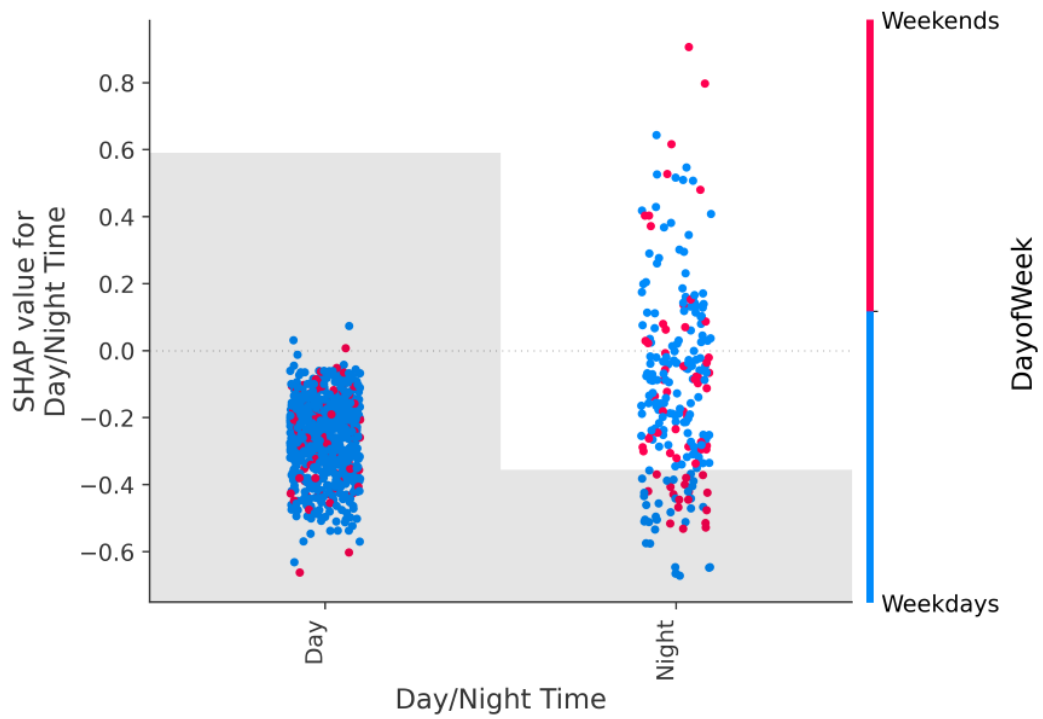


Figure 4–16. Interaction effects between day of week and day/nighttime

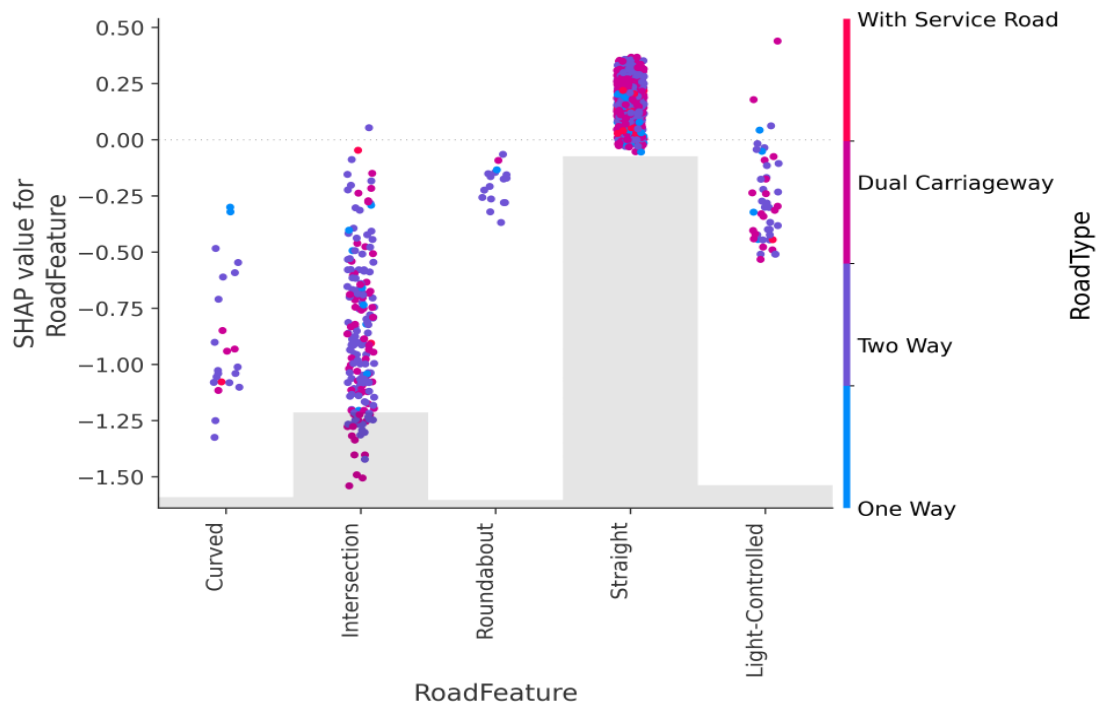


Figure 4–17. Interaction effects between road type and road features

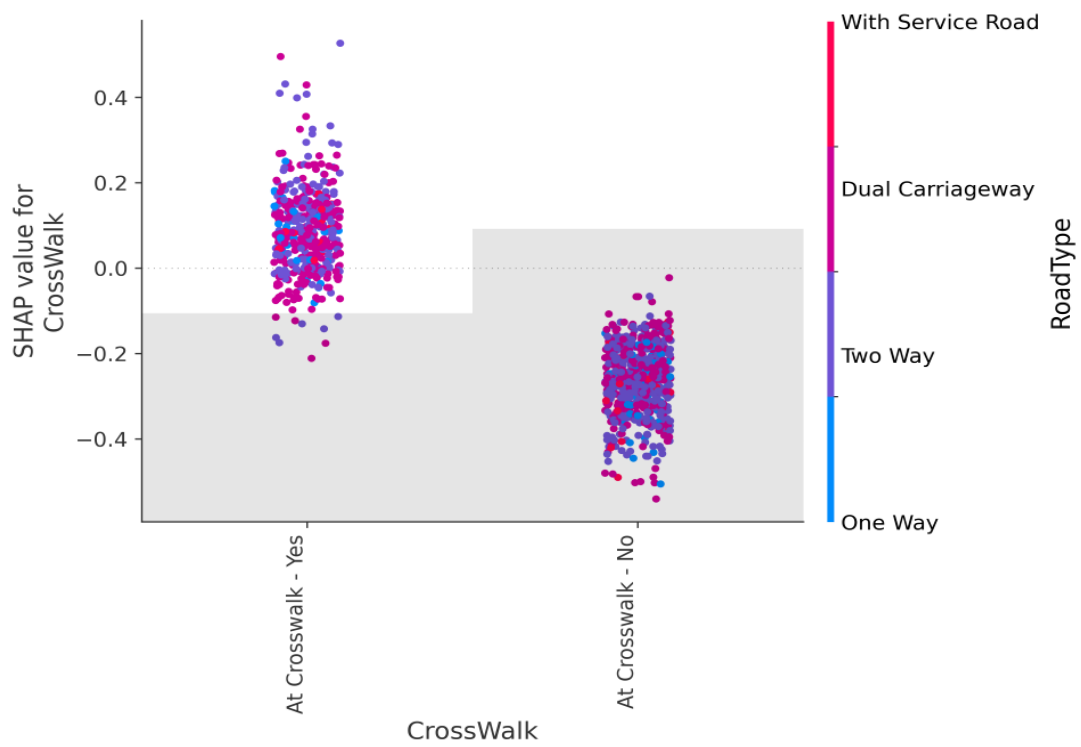


Figure 4–18. Interaction effects between road type and crosswalk

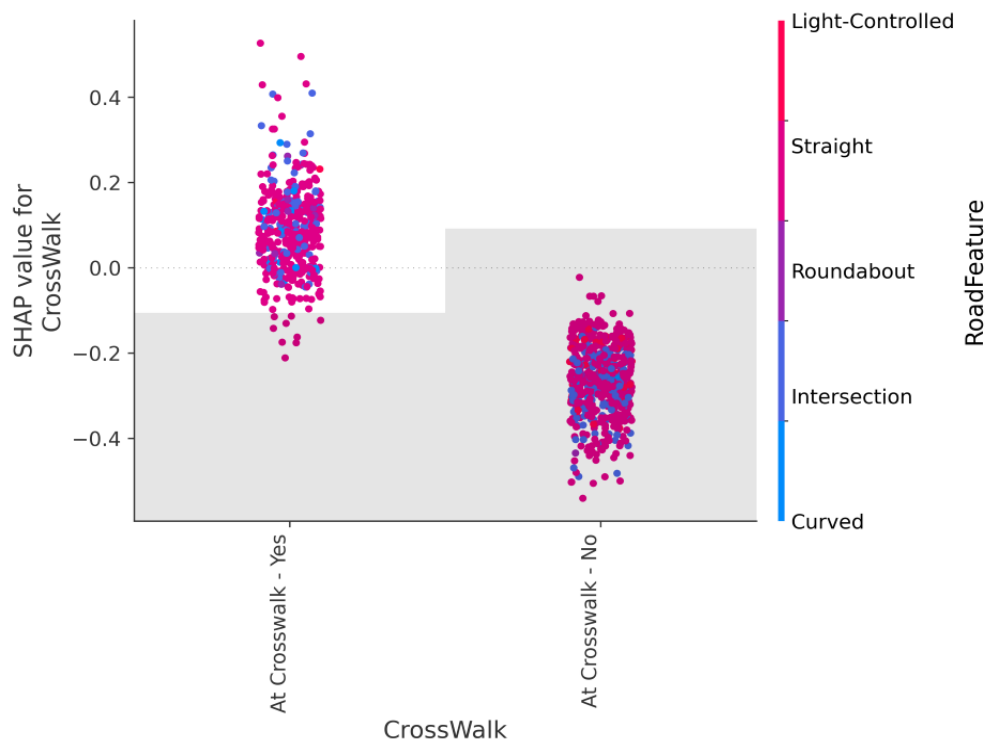


Figure 4–19. Interaction effects between road features and crosswalk

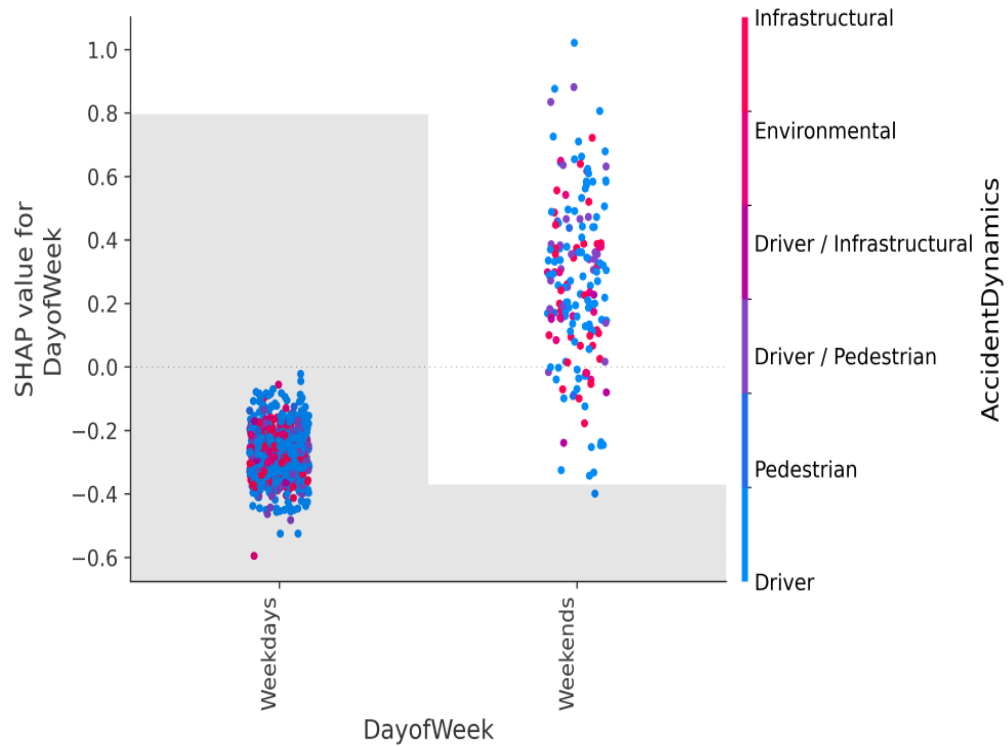


Figure 4–20. Interaction effects between accident dynamics and day of week

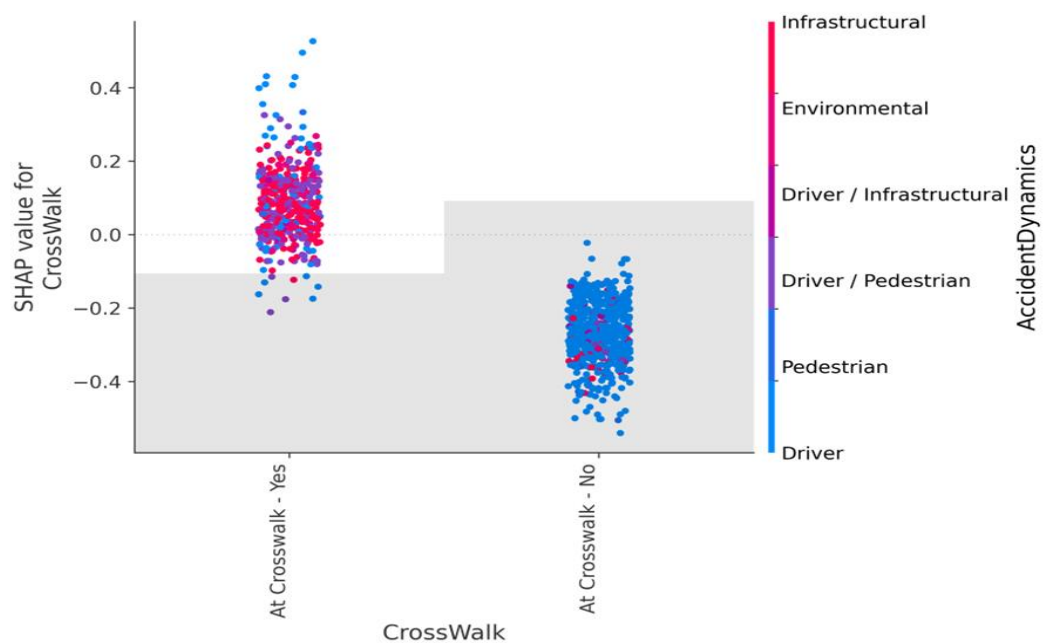


Figure 4–21. Interaction effects between accident dynamics and crosswalk

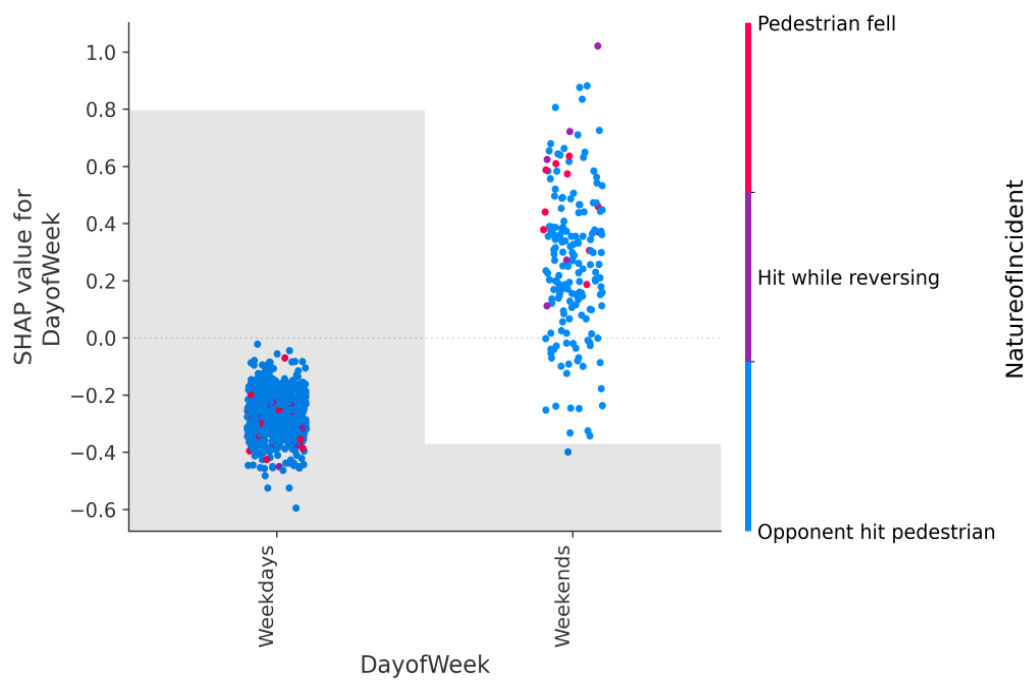


Figure 4–22. Interaction effects between nature of incidents and day of week

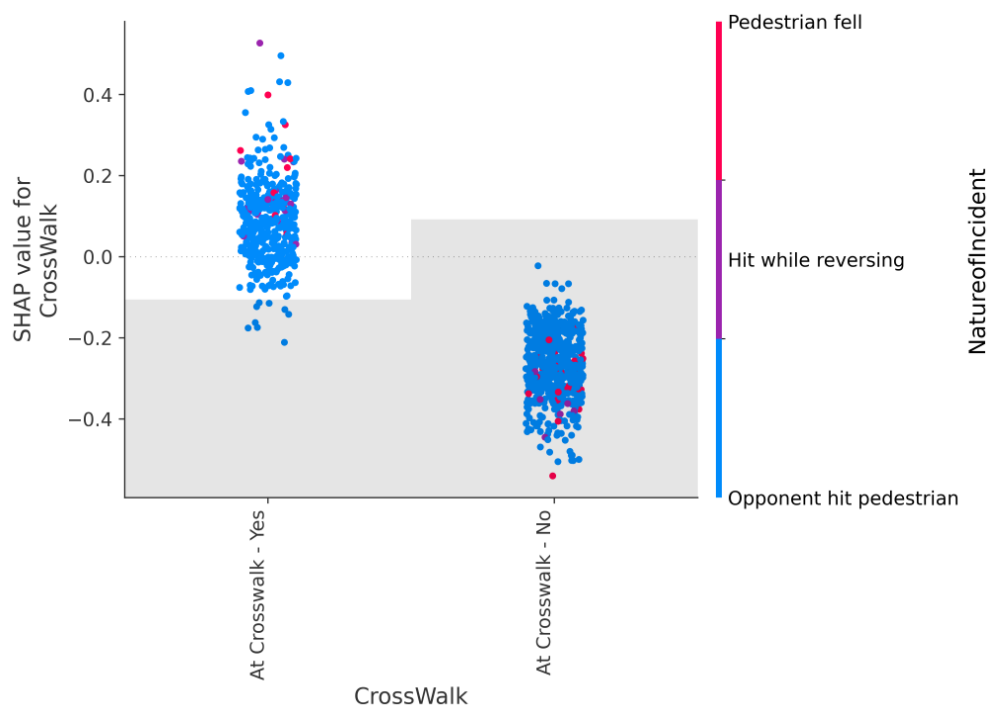


Figure 4–23. Interaction effects between nature of incidents and crosswalk

4.4 Discussion

4.4.1 Demographic characteristics

The study findings from local SHAP analyses indicate that pedestrian gender is one of the most significant factors influencing the severity of pedestrian crashes. This result is consistent with previous studies (Clifton et al. 2009; Tay et al. 2011; Onieva-García et al. 2016; Toran Pour et al. 2018; Jaber and Al-Sahili 2022). The increased vulnerability of pedestrians in crashes may stem from risky behaviors while walking or crossing streets, along with the physiological sensitivity of their bodies (Moyano Díaz 2002; Harris and Jenkins 2006; Granié 2009; Rosenbloom et al. 2011; Dunbar 2012; Prato et al. 2012; Brosseau et al. 2013; Islam and Jones 2014), which can further increase the severity of crash outcomes. Further analysis of interaction effects (Figures 4-7, 4-8, 4-9) highlights that male pedestrians are prone to severe crashes. Male pedestrians on two-way roads and straight sections of road face increased risk due to longer crossing times, complex traffic patterns, and their risk-taking behaviour (Tarko and Azam 2011; Abay 2013; Chen et al. 2019; Useche et al. 2021). Similarly, male pedestrians are more likely to experience severe crashes at nighttime due to reduced visibility and their tendency for bold and risky behaviour while crossing streets (Prato et al. 2012; Hossain et al. 2023).

Demographic factors, such as driver gender, have been identified as key variables in local SHAP analyses of pedestrian crash severity outcomes, which is in line with studies (Mohamed et al. 2013; Forbes and Habib 2015; Pour-Rouholamin and Zhou 2016; Prato et al. 2018; Song et al. 2020; Alogaili and Mannering 2022; C. Wang et al. 2022). This is primarily because drivers are more likely to engage in risky behaviours such as speeding, sudden lane changes, overtaking, which can increase the risk of pedestrian crashes (Gray et al. 2008; Paleti et al. 2010; Razi-Ardakani et al. 2018). The analysis of interaction effects shown in Figures 4-10 and 4-11 suggests that male drivers are particularly prone to severe pedestrian crashes under certain conditions, such as inadequate weather conditions and low lighting situations. For instance, the interaction effects showed that rainy weather combined with risky driving behaviours increases the likelihood of severe pedestrian crashes due to wet road surfaces and reduced skid resistance (Zhai et al. 2019). Similarly, low lighting conditions, which reduce visibility, increase the severity of pedestrian crashes when combined with intoxicated behaviour by male drivers (Sanders et al. 2022; Hossain et al. 2023).

4.4.2 Pedestrian behaviour

Pedestrian behaviour at the time of a crash has been shown to significantly affect the severity of pedestrian crashes in local SHAP analyses. This is primarily because of various abnormal pedestrian behaviours—such as crossing the street, walking on the footpath, standing on the street or at a public transit station, dashing or darting out, and entering or exiting a vehicle, which have been consistently associated with an increased risk of severe pedestrian crashes (Mitman et al. 2008; Tarko and Azam 2011; Abay 2013; Xu et al. 2013; Haleem et al. 2015; Li et al. 2021). In addition to these, distractions while walking or crossing the street, such as using electronic devices, engaging with pets or people, or being distracted by objects, which hinder pedestrians' awareness of their surroundings, reducing their ability to react to oncoming traffic, increases the likelihood of a crash (Nasar and Troyer 2013; Thompson et al. 2013; Mwakalonge et al. 2015; M.M. Hossain et al. 2024). Further analysis of pedestrian behaviour in combination with other variables, as seen in the interaction effects from Figures 4-12, 4-13, and 4-14, reveals that pedestrian street crossing is significantly associated with increased crash severity. For instance, on straight road sections where vehicle speeds are high, jaywalking, particularly at midblock locations, can substantially heighten the severity of crashes (Dong et al. 2018; Kwayu et al. 2022). Similarly, pedestrian street crossings during adverse weather conditions, such as rain, also contribute to more severe pedestrian crashes. Rainy weather can

cause pedestrians to misjudge the approaching speed of vehicles, which encourages them to be more aggressive and take more risks while crossing the street (Sun et al. 2015; Zafri et al. 2020; Ansariyar and Jeihani 2023). In addition, pedestrian crossings at night are associated with increased crash severity. More specifically, crossing the roads at night during the low visibility due to darkness and absence of streetlights significantly raise the risk of severe pedestrian crashes (Haleem et al. 2015; Hossain et al. 2023).

4.4.3 Temporal factors

Temporal features, such as the day of the week and time of day, have been found to significantly influence the severity of pedestrian crashes. The research of temporal features significantly evolves around investigating the stability of the impact of different characteristics on the severity of pedestrian crashes over each temporal feature effect, such as day of week, years, and time of day (Behnood and Mannering 2016; Li et al. 2021; Alogaili and Mannering 2022; Natalia Barbour 2024). For instance, day of week affects the severity of pedestrian crashes, through a variance in the effect of different factors such as demographic, crash, time and environmental, roadway characteristics across weekdays and weekends (Li et al. 2021). Similarly, time of day, such as daytime and nighttime, impacts the severity of pedestrian crashes, due to differences in the influence of factors such as vehicle, roadway, crash, and driver, related characteristics between daytime and nighttime, with severe crashes happening in the nighttime over time (Alogaili and Mannering 2022). The interaction between day of week with crosswalks in Figure 4-15 revealed that pedestrian crash severity increases on weekdays. This is because on weekdays, particularly during daytime hours, pedestrian activity and road traffic volume are higher, driven by daily commuting and work routines. This increased interaction between pedestrians and vehicles, particularly on crosswalks, elevates the likelihood of crashes, especially during peak hours like early mornings. During these hours, when traffic is heavy, pedestrian crashes are more likely to result in severe or fatal outcomes (Bo Du 2024). In addition, the conjunction between day of the week and time of day in Figure 4-16 shows that on weekends, crash severity increases at nighttime. On weekends, late hours, often associated with social and nightlife activities, lead to an uptick in pedestrian traffic, particularly in urban areas. Moreover, nighttime and late hours also present challenges, such as low visibility, increased vehicle speeds (due to reduced traffic), driver fatigue, and impaired walking or driving due to alcohol consumption. These factors can significantly increase the severity of pedestrian crashes (Kim et al. 2010; Abay 2013; Aziz et al. 2013; Mohamed et al. 2013; Mokhtarimousavi et al. 2020; Li et al. 2021).

4.4.4 Roadway characteristics

local SHAP analyses in Figure 5 have revealed that road type and features as prone to impacting the severe outcome of pedestrian crashes. The roadway type impacts the severity of pedestrian crashes due to the number of lanes and the designated speed limits on a roadway (Aziz et al. 2013; Sasidharan et al. 2015; Pour-Rouholamin and Zhou 2016). Whereas roadway features such as intersections, roundabouts, and straight sections increase the severity of pedestrian crashes due to existing as conflict points between pedestrians and traffic. Among these, the straight section and the intersection are prone to pedestrian crashes due to the high probability of conflict between pedestrians and vehicles (Peng et al. 2020; Das et al. 2021). The interactions of road characteristics—such as road type and geometric features—with pedestrian crosswalks, as illustrated in Figures 4-17, 4-18, and 4-19, reveal a notable increase in crash severity involving pedestrians when incidents occur on two-way roadways, straight road segments, and at crosswalks. Specifically, two-way roads, especially those with multiple lanes and opposing traffic, tend to reduce drivers' and pedestrians' visibility, increase the complexity of traffic interactions, and often necessitate longer crosswalks. These factors collectively increase the pedestrian exposure time and the likelihood of severe injuries during collisions (Dommes et al. 2014). Moreover, such roads are commonly designed to accommodate higher traffic volume and speed limits, which further increase the severity of crash outcomes involving vulnerable road users (Pour-Rouholamin and Zhou 2016). Previous research consistently supports these findings (Aziz et al. 2013; Haleem et al. 2015; Song et al. 2020; Alogaili and Mannering 2022).

4.4.5 Accident dynamics and nature of incidents

In this study, the accident dynamics and nature of incident variables have been recognised as the accident at-fault reasons. The SHAP values in the local analyses indicate that the at-fault reason plays a critical role in determining crash severity. However, interestingly, their local SHAP analyses show a distinct distribution of SHAP values. This means that their effect on the severity of crashes varies from case to case while involving different at-fault bodies. The fault in such crashes is associated with observed factors that are in conjunction with pedestrian at-fault, driver at-fault or both (Ulfarsson et al. 2010). In most cases, these at-fault reasons for pedestrians and drivers in pedestrian-vehicle crashes are associated with their abnormal behaviours (Zhang et al. 2014). The interactions of accident dynamics and nature of incidents in Figures 4-20, 4-21, 4-22 and 4-23 with day of week and crosswalks revealed supporting crash severity impact patterns with identifying drivers at-fault in common. These figures show that drivers when reported at fault while hitting pedestrians on weekends and on crosswalks

increase the severity of pedestrian crashes. This is supported by involving drivers at fault due to their age, intoxication, and reckless behaviour (Ulfarsson et al. 2010).

Combining walkability assessments at different scales in measuring spatial inequalities in access to railway stations

Promoting inclusive, safe, and sustainable cities is one of the key objectives of the United Nations Agenda 2030. To this end, ensuring equitable access to efficient and affordable mass rapid transit systems can foster greater social inclusion and reduce transport inequalities. In this regard, ensuring good pedestrian accessibility to railway stations, which connect individuals to urban and peripheral zones and transport networks, serves as a priority for policymakers. In this perspective, it is not surprising that 15-minute cities and transit-oriented development are widely debated concepts and applied with policies encouraging sustainable transportation modes and building inclusive communities. However, disparities in policy practice seem to exist between urban and suburban areas in many European cities. The quality of pedestrian infrastructure is not at the same level in different areas, which can create social and transport equity challenges with lower access to public transport services. This situation led to less usage of public transport and eventually led to dependence on private vehicles, which can create congestion, pollution challenges.

Taking into account these considerations, this chapter presents the study referred to as RA3, which aims to investigate the impacts of road connectivity and pedestrian network quality on spatial and social equity in access to railway stations in the case study (Palermo, Italy). In this regard, fourteen railway stations located in Palermo (Italy) were considered for analysis. The study proposes a GIS-based approach combining walkability assessments at different scales. Firstly, walkability around railway stations was analyzed considering meso-scale indicators related to road connectivity (road density, intersection density, Ped-shed ratio). After that, to assess the quality of pedestrian infrastructure, micro-scale walkability indicators related to (practicability, safety, and pleasantness) were considered to evaluate street-level walkability around railway stations. While combining both the assessments, big disparities in accessibility between railway stations located in suburban areas and city centre were found. The limited accessibility for the railway stations located in peripheral cores represents a social equity

challenge, undermining the effectiveness of rail services as equitable modes of transportation. The findings of the study can be a decision-support tool, identifying what priority measures are needed and where to improve the quality of the pedestrian network to improve accessibility to the railway stations, to overcome the social and transport equity challenges.

5.1 Methodology

Spatial inequalities in access to the railway service were assessed by combining two different approaches based on Geographic Information Systems (GIS). Firstly, a meso-scale walkability assessment was used, evaluating three indicators related to network connectivity: road density, intersection density, and Pedestrian Catchment Area Ratio (also known as Ped-shed ratio) as estimated by (Schlossberg 2006). The description of these indicators and their impacts on the walkability of railway station areas is reported in Table 5-1. These indicators are well-known in literature, can be easily calculated using GIS software, and represent different aspects of network connectivity. Although they may seem to be correlated, each of these different measures of connectivity may reflect subtle differences in the way in which the built environment influences pedestrian access to railway stations. In order to clarify this statement, Figure 5-1 represents three different cases. Although usually high road and intersection density can lead to a better accessibility (Figure 5-1a), high value of road density does not preclude that there may be few intersections and many roads with cul-de-sacs, not leading to a walkable area and forcing pedestrians to lengthen their routes (Figure 5-1b). Moreover, although one would expect that areas with more roads would have more intersections, this cannot be true, as shown in Figure 5-1b. Thus, on the one hand, analyzing road density is important to understand how much the road network is extensive and if there are alternative routes between origin and destination; on the other hand, analyzing intersection density is important because it gives insight into the connectivity of the road network that might not be evident from simply looking at the length of the network. Pedestrian Catchment Area ratio was chosen to evaluate how much the road network covers the 500m-buffer area around the railway station. This cannot be correlated to the road density and the intersection density as shown in Figure 5-1c. The figure shows that having higher values of road density and intersection density doesn't mean that also the PCA ratio is higher. Moreover, Pedestrian Catchment Area ratio measures how much the urban fabric and land use can hinder accessibility.

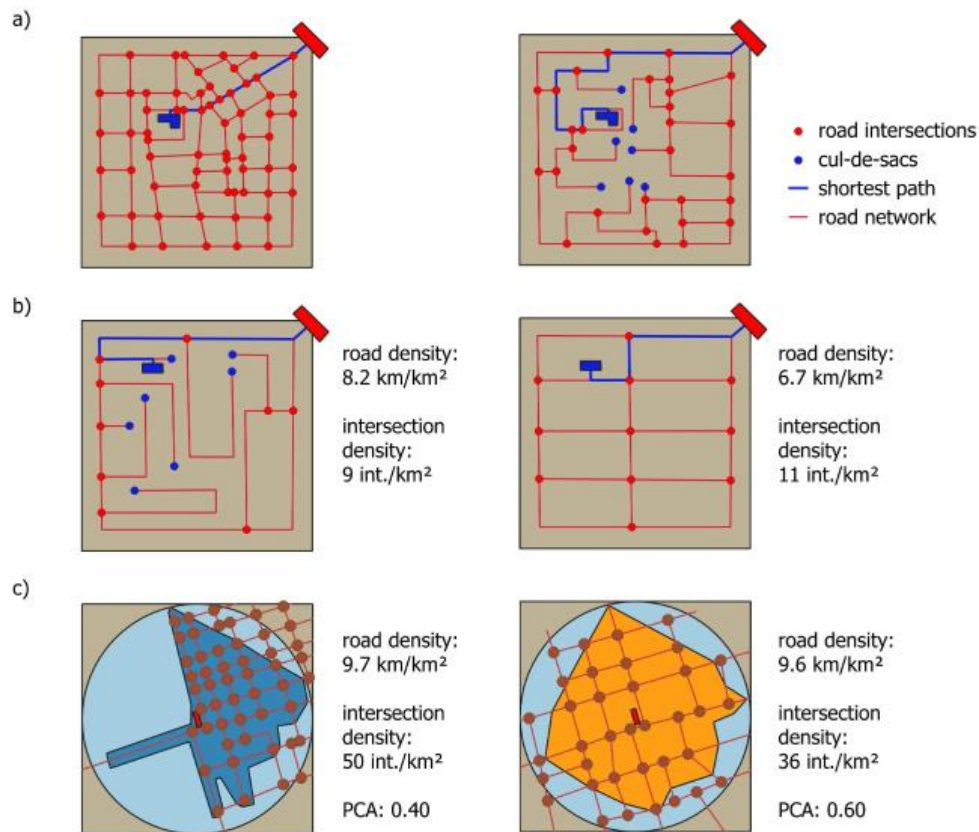


Figure 5–1. The impacts of road density and intersection density on walkability

Therefore, a well-connected network has many short links, numerous intersections, and minimal dead ends, providing continuous, direct routes to destinations and covering the theoretical service area (buffer area) to the greatest extent possible.

Table 5–1. Network connectivity indicators

Indicator	Definition	Impact
Road density	Total street length per 1 km ² area.	Higher road density means more roads are present in a given area, which can lead to better accessibility.
Intersection density	Number of road intersections per 1 km ² area, where intersections are the junctions at which three or more road segments intersect.	A high intersection density indicates a walking-friendly environment, allowing pedestrian to change direction frequently and reach destinations following a more direct route.
Pedestrian Catchment Area ratio (PCA)	The ratio between the network-defined service area, considering a walkable network distance (for example, 500 m) from a fixed point, and the theoretical service area considering Euclidean distances (buffer with a radius of 500 m).	PCA ratio measures how well the road network covers the area around a specific key destination. Values of the ratio close to 1 indicate extremely walkable areas, while a score less than 0.30 would reflect an inaccessible walking environment. Although there has not been enough research to determine an optimal PCA score, it is suggested that a minimum score of 0.5-0.6 is a useful threshold (Schlossberg, 2006).

We compared the values that these indicators assume across railway station areas to assess whether spatial inequalities in access to railway stations related to road connectivity exist. A network connectivity index for each station (CI_s) was calculated according to the following equation:

$$CI_s = \frac{1}{3} \left[\frac{RD_s}{\max(RD_k)} + \frac{ID_s}{\max(ID_k)} + \frac{PCA_s}{\max(PCA_k)} \right] \quad (5.1)$$

where RD_s , ID_s , and PCA_s are the values that road density, intersection density, and PCA ratio assume for the stations, while $\max(RD_k)$, $\max(ID_k)$, and $\max(PCA_k)$ are the maximum values reached by these indicators for the station k , considering all the railway station areas chosen as study areas.

Moreover, we evaluated how the road network connectivity affects social equity, considering that the impacts on access of residents and employees to railway stations depend also on the distribution of residential buildings and activities in the railway station areas. Indeed, as Figure 5-2 shows, the impacts of road connectivity on the access to two railway stations having the same network-defined service area are not equal: a great number of people living and working in the buffer area of the railway station A (in the left) are excluded by the network-defined service area while the same road network connectivity has less impacts on exclusion of people living in the buffer area of the railway station B (in the right). For this reason, we calculated the percentage of people living and working in the buffer area that lives and work within and outside the network-defined service area. Living and working outside the network-defined service area means being excluded from access to the nearest station, being more than 500 m from it.

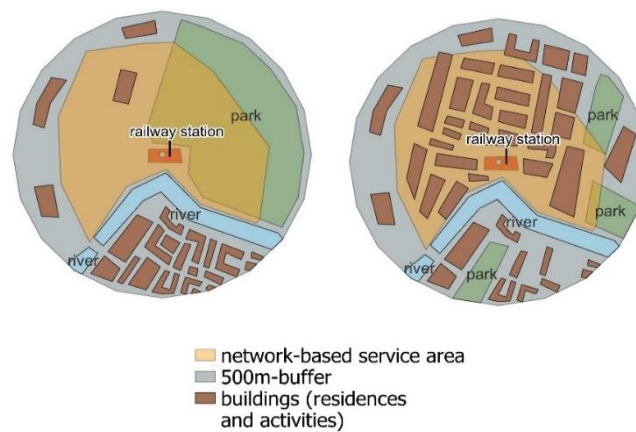


Figure 5–2. Two railway stations having the same network-defined service area with different impacts on access.

Finally, a second approach was adopted to investigate disparities in access to railway stations. Since pedestrians' walking experience is also influenced by several factors related to the quality of the pedestrian environment, a micro-scale walkability assessment was implemented to investigate how the quality of the pedestrian network at street level affects access to railway stations. Indeed, the people who live and work within the network-defined service area may experience a perception of unsafety and difficulties in accessing railway stations, and give up on using the train service as the main mode of transport for their daily commute. For street-level walkability assessment, the pedestrian network can be built in GIS software as a layer, considering sidewalks and crosswalks (Figure 5-3). This pedestrian network was built in the network-defined service area of each railway station.

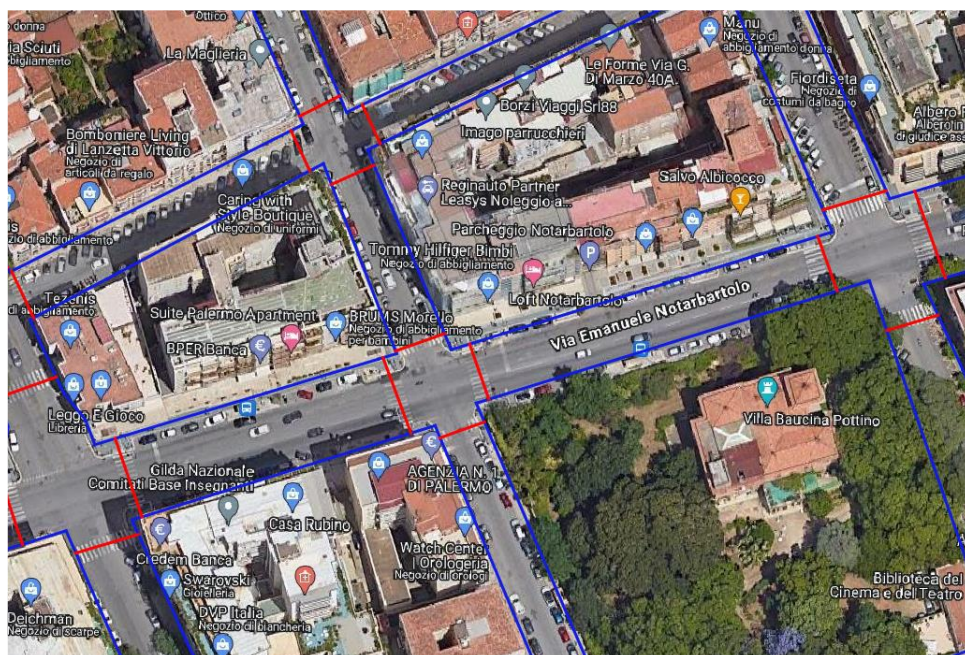


Figure 5–3. The pedestrian network: sidewalks (blue) and crosswalks (red)

Once the pedestrian network was built, the micro-scale walkability assessment tool developed by (D'Orso and Migliore 2020a) was adopted to assess the quality of pedestrian infrastructure. Indicators related to practicability, safety, and pleasantness of the pedestrian environment were considered, and a score was assigned to them for each sidewalk, according to the rules listed in Table 5-3. Since the evaluation of microscale walkability indicators was based on both objective and subjective aspects of the quality assessment and therefore score was assigned to each indicators through Google Street View and site inspection.

Among these categories, practicability focused on the practical aspect of walking, considering pedestrian comfort and ease (Appolloni et al. 2019). This evaluation category, intended to

evaluate how the existing sidewalk quality might influence the practical usability of pedestrian infrastructure, which is based on the following three indicators: pavement slope, pedestrian level of service, and obstacles/decay (Appolloni et al. 2019). In this regard, the pavement slope is necessary to evaluate as an inclined slope could be difficult for older pedestrians and people with disabilities, such as wheelchair users, to walk on. An optimal pavement slope will be the one with less than 5% longitudinal slope (Italian Ministry of Public Works Decree, 14 June 1989, No. 236). Similarly, pedestrian level of service (LoS) is considered to assess the temporary obstacles such as street parking, presence of stalls, and non-permanent obstacles on sidewalks, such as insufficient width of sidewalk, discontinued sidewalks, and the presence of poles, trees, which could result in a low walkability environment. In this regard, sidewalks with a good level of service will be the ones with fewer obstacles, considering the pedestrian flow.

In addition, obstacles or decay are referred to as the surface quality assessment of the pavement of sidewalks. The sidewalk with degraded pavement, such as the presence of potholes, cracks, and other depressions due to adverse weather conditions, inadequate maintenance, shocks, poor cleaning, fixation of unnecessary urban furniture or equipment, low quality materials, etc., results in sidewalks being unsafe, uncomfortable, and less attractive (Corazza et al. 2016). These distresses on the sidewalks might encourage pedestrians to do jaywalking or walk directly on the streets, which could lead to unsafe behavior while putting pedestrians in risky situations (Corazza et al. 2016). Therefore, the purpose of this indicator is to assess and identify different kinds of distress to evaluate the surface quality of sidewalks for the pedestrian network in the catchment area of each railway station.

In this regard, thanks to GeoLab, different distresses on the sidewalks were identified and a score was assigned based on the surface quality assessment of the sidewalks. Since Geolab has expertise in assessing road pavement quality, these distresses were classified based on the classification provided by the methodology of the Pavement Condition Index (PCI) designed by the American Society for Testing and Materials (ASTM) for asphalt pavement, following the approach already adopted in (Corazza et al. 2016) with the development of the sidewalks condition index (SCI). Among these distresses are potholes, block cracks, patching, corrugation, bleeding, raveling, etc. However, in our case, other distresses were added to the classification in order to include the types of distresses suffered by pavements made using jointed concrete blocks or pavers. According to this framework, the following sidewalk distresses were classified as shown in Table 5-2.

Table 5–2. Sidewalk distress types of classification

Distress type	Surface material type	Description	Typical causes
Potholes	Asphalt, concrete blocks, pavers	Bowl-shaped holes with rough edges and missing material	Water infiltration, neglected cracking
Block Cracking	Asphalt, concrete blocks	Interconnected cracks forming large rectangular blocks	Surface materials shrinkage due to aging, temperature cycling, and binder hardening
Linear Cracking	Asphalt, concrete blocks	Long straight crack (longitudinal or transverse) to the path	Pavement shrinkage, temperature fluctuations, and construction joints
Patching / Utility Cut Patching	Asphalt, concrete blocks, pavers	A replaced or repaired pavement section with visible boundaries	Previous excavation (e.g., for utilities), or removal of damaged sections
Corrugation	Asphalt	Rippled or wavy surface perpendicular to pedestrian flow	Instability in asphalt mix under repeated loading, braking
Ravelling	Asphalt	Surface disintegration starting with the loss of fines, then aggregate	Binder hardening, poor compaction
Deformation due to Roots	Asphalt, concrete blocks, pavers	Pavement bulging or cracking due to tree root intrusion	Root growth under the pavement slab lifting surface
Deformation due to Run-off Water	Asphalt, concrete blocks, pavers	Surface rutting, erosion, or displacement due to water flow	Poor drainage design, surface water scouring
Depressions	Asphalt, concrete blocks, pavers	Localized dips in pavement that often collect water	Subgrade settlement, poor compaction
Edge Disruption (Edge Cracking)	Asphalt, concrete blocks, pavers	Cracks or damage along pavement edges	Lack of lateral support, erosion, vegetation intrusion
Pop out	Concrete block, pavers	Detachment of the sidewalk block	Reactive aggregates, moisture, poor surface preparations
Surface abrasion	Concrete blocks, pavers	Abrasion of the block surface	Foot traffic, deicing salts, weak surface finish, lack of sealing
D cracking	Concrete blocks, pavers	Closely spaced crescent-shaped hairline cracking pattern. Occurs adjacent to joints, cracks or free edges, and initiates in slab corners.	Inadequate compaction of the underlying subgrade at the time of construction



Figure 5–4. Potholes (left) and depressions (right) in sidewalks.



Figure 5–5. D cracking (left) and linear cracking (right) in sidewalks.



Figure 5–6. Utility Cut Patching (left) and edge cracking (right)

Similarly, pleasantness or attractiveness has been taken into consideration to assess visual aesthetic qualities, aesthetic appeal, interest, and comfort of the pedestrian environment (Basu et al. 2022). This includes the indicators such as availability of street furniture, benches, sun/rain protection, availability of shops and green areas, and a nice architectural context in the surroundings, all of which depict a comfortable, pleasant, and attractive walkable environment. These indicators assess the quality of pedestrian infrastructure in terms of the availability of facilities, ease, and friendliness in the pedestrian network, which eventually affects the mode and route choice of pedestrians to walk or not to walk. The purpose of this indicator in the study is to evaluate the pleasantness and attractiveness of the pedestrian network in the catchment area of the railway station, which can affect the pedestrian perception of taking the railway as their means of mobility.

In addition, safety indicators are critical to assess, as pedestrians are vulnerable to traffic crashes (Kim et al. 2023). Pedestrians' sense of safety is essential for promoting walking, as they are unlikely to walk for enjoyment unless they feel secure (Alfonzo 2005). The safety assessment of the pedestrian network is based on the concept of the level of avoidance of danger from motorized traffic (Appolloni et al. 2019). Therefore, all of the indicators reported in Table 5-3 related to safety are considered to assess the quality of existing infrastructure in terms of

their perceived and physical impact on the safety of pedestrians, considering the pedestrian network in the catchment area of the railway station. For instance, lighting assessment is important as the absence of lighting poles and low lighting at night leads to reduced visibility, which can create a hazardous environment for pedestrians (perceived risk of crime) while walking on the sidewalks. In this regard, (Ariffin and Zahari 2013) stated that the perception of security is connected to street lighting and social factors, such as being familiar with the neighborhood, beliefs, and gender (Battista and Manaugh 2018).

Similarly, higher traffic flow on the roadway near to sidewalk can increase the noise, pollution, and perceived sense of interaction of pedestrians with vehicles, particularly at crosswalks, and therefore could impact the safety of pedestrians in their unprecedented interactions with vehicles (D'Orso and Migliore 2020a). In this perspective, the higher speed on the roadway next to the sidewalk also affects the safety perception of pedestrians: the roadway with 30 km/h speed limit is considered safe, whereas the ones with 50 km/h are considered risky for pedestrians (D'Orso and Migliore 2020a).

In addition, the protection of vehicles is based on the concept of assessing pedestrians walking freely from risks originating from vehicles (Appolloni et al. 2019). In this regard, the absence of barriers on sidewalks protecting pedestrians from vehicles will be considered unsafe, whereas their presence will be considered as the sidewalk existing being safe to walk on (Landis et al. 2001). The driveways' presence on the sidewalks disrupts the pedestrian infrastructure and also impacts the perceived safety of pedestrians due to their interaction with vehicles while walking on the sidewalks. The assessment of driveways is important as a high number of driveways present on the sidewalks could create a risky environment for pedestrians.

In this study, weights were attributed to practicability, safety, and pleasantness based on their importance in the context of perceived pedestrians' perception of the quality of the pedestrian realm, as shown in Table 5-3. The weights are the same used by (D'Orso and Migliore 2020b), derived from a literature review of walkability assessments performed in similar contexts. Among these categories, higher weights were considered for safety due to its most significant influence on the pedestrian perception of route choice decision, and due to which it also significantly impacts walkability (Castelluccio et al. 2015; Ruiz-Padillo et al. 2018).

As already modified in (D'Orso et al. 2023), some changes to the indicator scores and some crosswalk-specific safety indicators were considered, as shown in Table 5-4. For the crosswalk assessment, only safety-related indicators were considered in the study, as crosswalks are

usually considered hotspots for pedestrian-vehicle conflicts (Sheykhfard et al. 2021). Therefore, indicators such as lighting, traffic flow, traffic speed, presence of pedestrian-specific signals, and visibility were considered, all of which are important to assess the safety of crosswalks.

Table 5–3. Micro-scale walkability indicators for sidewalks, as reported in (D’Orso et al. 2023)

Category	Weight	Indicator	Value	Description
Practicability	0.3	Pavement slope	0	Steep slope for older people and wheelchair users (>5%)
			1	Non-perceptible slope (<5%)
		Pedestrian LOS	0	High pedestrian flows, insufficient sidewalk width or presence of obstacles (LOS = E, F)
			1	LOS = C, D
			2	Low pedestrian flows, adequate pavement width or absence of obstacles (LOS = A, B)
		Decay	0	Very degraded pavement
			1	Presence of some potholes or depressions
			2	No potholes or depressions, pavement in good condition
Pleasantness	0.3	Street furniture	0	Absence of litter bins, benches, and other elements of street furniture
			1	Presence of litter bins, benches, and other elements of street furniture
		Sun/Rain protection	0	Lack of shelter from the sun or rain
			1	Presence of shelters from sun or rain
		Green areas	0	Absence of flowerbeds or green areas
			1	Presence of flowerbeds or green areas
		Shops	0	Absence of shops
			1	Presence of shop windows and shops
		Architectural context	0	Degraded architectural context (presence of graffiti, degraded facades, industrial buildings or abandoned buildings)
			1	Pleasant architectural context (absence of graffiti, degraded facades, industrial buildings or abandoned buildings)
Safety	0.4	Lighting	0	Poor or no lighting
			1	Adequate and efficient street lighting according to UNI standard (UNI 11248)
		Traffic flow and speed	0	High traffic volumes (>1000 vph) or high speeds (>50 km/h)
			1	In other cases
			2	Free flow (<300 vph) and low speeds (<30 km/h)
			0	Absence of barriers to protect pedestrians from vehicles

Protection from vehicles	1	Presence of protection elements
Driveways	0	Presence of driveways along the route
	1	Absence of one or more driveways

Using GIS software, a database of the pedestrian network quality was created. Indeed, we included indicators as new fields in the attribute table of the layer representing the pedestrian links; in this way, each row of the attribute table refers to each arc of the network, whereas each column corresponds to each indicator and its respective assigned score. A quality index was assessed for each crosswalk and each sidewalk, using the following formulas:

$$QI_{sw} = Praticability \times 0.3 + Pleasantness \times 0.3 + Safety \times 0.4 \quad (5.2)$$

$$QI_{cw} = Safety \times \frac{5}{7} \quad (5.3)$$

Each sidewalk and crosswalk can obtain a quality index ranging from 0 to 5. For each railway station area, the percentage of km of pedestrian network having a quality index under a threshold was evaluated to identify the areas with low walkability in terms of the quality of the pedestrian network.

Table 5–4. Micro-walkability indicators for crosswalks, as reported in (D’Orso et al. 2023)

Category	Indicator	Value	Description
Safety	Lighting	0	Poor or no lighting
		1	Pedestrian-oriented lighting
	Traffic flow and speed	0	High traffic volumes (>1000 vph) or high speeds (>50 km/h)
		1	In other cases
		2	Free flow (<300 vph) and low speeds (<30 km/h)
	Traffic lights	0	Absence of traffic lights at the crosswalk
		1	Traffic lights at the crosswalk but presence of conflicts between vehicles and pedestrians
		2	Traffic lights that eliminate conflict points between vehicles and pedestrians
	Visibility	0	No crosswalks or very poor crosswalk visibility

1	Good crosswalk visibility
2	Excellent crosswalk visibility

Combining different walkability approaches, we identified the railway station areas having the lowest accessibility and creating the most disadvantaged communities.

5.2 Study area

Fourteen railway stations distributed throughout the city area were considered as a case study (Figure 5-7). These stations are along the railway line connecting the nearest airport (Punta Raisi), located outside the city, to the city main station and from this to the Palermo Roccella station, in the south-eastern suburb of the city. This railway line extends for approximately 37 km, of which 20 are within the municipality boundaries. This railway line connects several neighborhoods, business hubs, commercial areas, and cultural attractions, including many tourist spots, and therefore plays a pivotal role in uplifting the city's economy. Therefore, the railway service has great potential as a mode of transport for the city inhabitants and tourists visiting the city, representing a connection with the city center, especially for people living in suburban areas.

However, a recent study conducted by (D'Orso and Migliore 2020a) highlighted that the pedestrian environment around the catchment areas of some railway stations in Palermo is not satisfactory. Poor walkability affects pedestrian accessibility to the railway stations, also influencing the mode choice of residents for the first- and last-mile journey. Eventually, in some cases, this led to less usage of public transport and encourage people to use private vehicles, generating more traffic congestion and pollutant emissions.

It is therefore not surprising that the motorization rate of Palermo is 62.4 passenger cars per 100 inhabitants, showing that several neighborhoods are very car-dependent. Also, according to the Sustainable Urban Mobility Plan of Palermo (Comune di Palermo, 2019), the modal share for private vehicles is 78%. On the other hand, the modal share for public transport is 9%, whereas for walking it is 12%, manifesting much less usage of public transport by residents than private cars. Therefore, based on the high motorization rate and consequent modal share, we chose the historical city of Palermo as a case study to measure the spatial inequalities in accessing the railway stations across the city and identify the disadvantaged communities.

For each railway station, a walkable catchment area considering a 500 m straight line distance from the railway station was assessed. Indeed, catchment areas are generally defined as buffers

with a radius that is usually calculated as the distance that the residents are willing to walk to the railway stations, assuming they are all able to walk. Therefore, we created a buffer having a radius of 500 m around each railway station using QGIS, an open-source GIS software. The characteristics of the railway stations in terms of population within the walkable catchment area, number of job opportunities (employees), number and type of points of interest (POIs), and land use are reported in Table 5-5.

The census data were derived from the 15th Italian General Census of Population and Housing (ISTAT 2011). The employee data were derived from the 9th Italian General Census of Industry and Services (ISTAT 2015). These data, although not up-to-date, represent the most complete available to the public. ISTAT also provided the shapefiles of the census zones in which the city is divided. We used the Intersection tool in QGIS to find the census zones falling within the walkable catchment areas.

Starting from the shapefile data representing buildings provided by the Municipality of Palermo, (<https://opendata.comune.palermo.it>) we created a layer including all the buildings within the walkable catchment areas and then classified them into residential and non-residential. We calculated how many people live in the railway station areas, using the following GIS apportioning method. First, we apportioned the population data of the census zones into the buildings falling within them in proportion to the volume of the buildings; then, we considered only the buildings falling within the walkable catchment areas and calculated the population living in each railway station area.

For the employee data, a different GIS apportioning method was followed; we gathered and apportioned data from the census zones based on the proportion of the census zones falling within the catchment area. For example, considering a census zone having 100 employees, if 50 % of this census zone falls within the railway catchment area, we considered 50 employees ($50 \% * 100$) in the calculation of the number of total employees working within the catchment area.

The POIs for pedestrians within the catchment areas were imported and counted using the QuickOSM plugin, selecting “amenity” as key. We considered as POIs several types of amenities: schools, universities, hospitals, banks, postal offices, public buildings, theatres, cinemas, groceries, and tourist spots. To understand the main land use in each walkable catchment area we considered the percentage of residential buildings in relation to the total number of buildings, the number of employees and POIs.

As it can be noted, 7 railway stations are located in suburban areas and 7 in the urban core. The railway station areas located in the northern suburbs are predominantly residential. La Malfa and Roccella areas are predominantly commercial since shopping malls are located in these areas. Except for the Guadagna area, the railway station areas in the urban core are mixed-use with high population and activity densities. Considering the data reported in Table 5-5, we can see that the overall accessibility of the railway service in Palermo is not very good: only 15% (93,806) of the people living in Palermo and 27% (51,190) of the employees which live and work, respectively within the 500m-buffers around the stations.

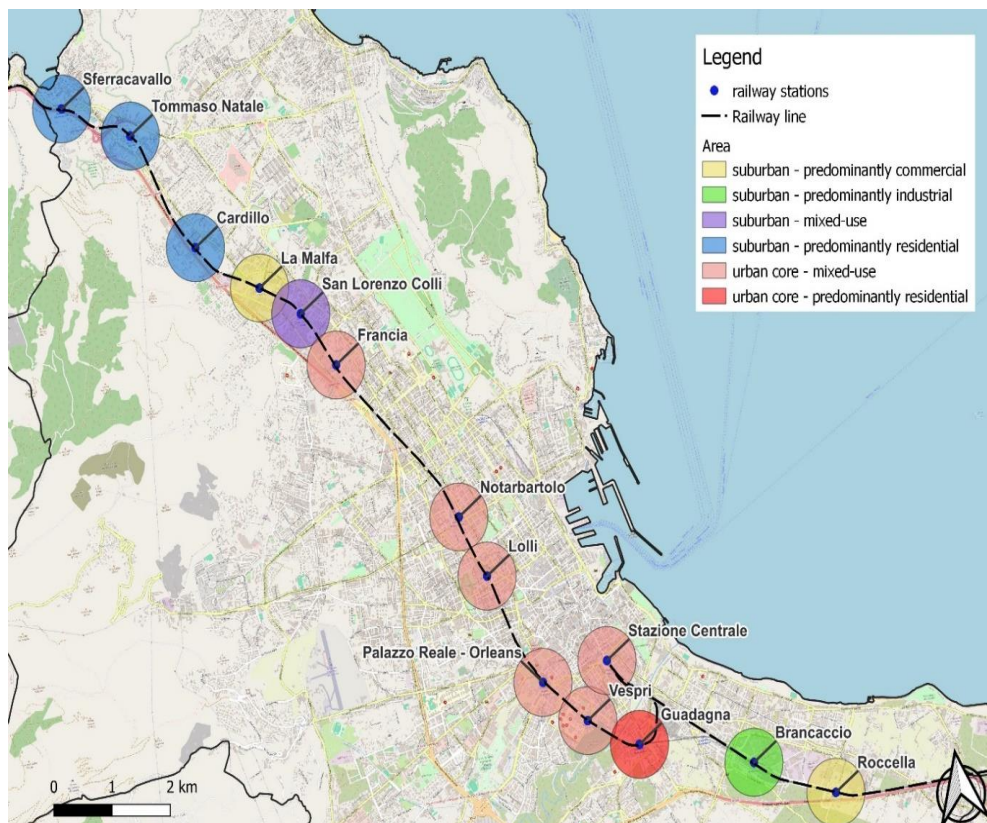


Figure 5–7. Railway stations

Table 5–5. Railway stations metrics

Railway station	Population	Employees	Number of POIs	Main POIs	Land use
Brancaccio	2508	3545	4	Industrial area, supermarket	Suburban – predominantly industrial
Cardillo	2414	417	1	Supermarket	Suburban – predominantly residential
Francia	5086	3265	36	Supermarket, cinema, school, pharmacy, local shops	Urban core – mixed use
Guadagna	9780	1579	11	Groceries, school, post office	Urban core – predominantly residential
La Malfa	2347	3207	12	Shopping malls, supermarkets	Suburban – predominantly commercial
Lolli	15648	6429	198	Cinema, theater, school, restaurants, local shops	Urban core – mixed use
Notarbartolo	13184	6207	78	Cinema, theatre, school, local shops	Urban core – mixed use
Palazzo Reale - Orleans	9503	7285	84	University, groceries, small shops, tourist spot	Urban core – mixed use
Roccella	78	138	23	Shopping mall	Suburban – predominantly commercial
San Lorenzo Colli	1995	5293	51	Supermarkets, restaurants	Suburban – mixed use
Sferracavallo	2871	451	13	Restaurants, post office	Suburban – predominantly residential
Stazione Centrale	13543	6343	169	Restaurants, small shops, churches, government agencies	Urban core – mixed use
Tommaso Natale	6089	977	9	Groceries, small shops, cinema, post office	Suburban – predominantly residential
Vespri	8762	6056	34	Hospital, local shops	Urban core – mixed use

5.3 Results

In this section, we reported the results of the application of our methodology to the case study.

5.3.1 Road density

In order to assess the road density and the intersection density for each railway station area, a square area of 1 km² around each railway station and centered on it was evaluated using QGIS. The 1 km² square area around railway stations is representative enough of the pedestrian environment that transit users can experience. Different studies in literature recommend 500 m meters as optimum to define the railway station catchment area, and no more than 1 km kilometer of actual walking distance, including all detours (ITDP, 2017). A distance of 500 m meters represents about a 10-minute walk, and a distance of 1000 m represents about a 20-minute walk at an average urban speed of approximately 3 km kilometers per hour, including wait time at intersections.

Then, we uploaded the road network of Palermo derived from OpenStreetMap (www.openstreetmap.org) using the QuickOSM plugin, and we clipped it considering the square areas as an overlay layer, as it can be seen in Figure 5-8. Finally, we calculated the length of all the road segments falling within the square area of 1 km² around each railway station. Table 5-6 shows the road density for each railway station area. It can be noted that Stazione Centrale, Palazzo Reale – Orleans, Lolli and Notarbartolo areas – all located in the urban core – have the highest values of road density. In contrast, the suburban railway station areas of Brancaccio, San Lorenzo Colli and Cardillo have the lowest ones.

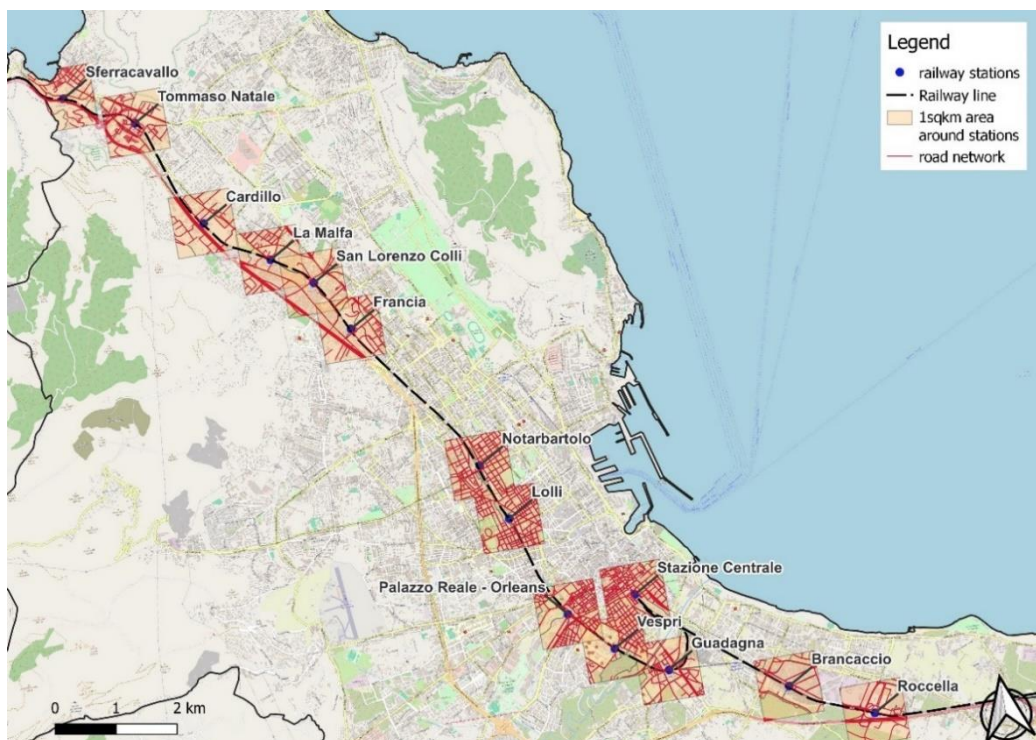


Figure 5–8. Road density calculation

Table 5–6. Road density

Railway stations	Road density [km/km ²]
Brancaccio	9.104
Cardillo	11.998
Francia	14.692
Guadagna	14.586
La Malfa	13.179
Lolli	22.437
Notarbartolo	20.647
Palazzo Reale - Orleans	22.796
Roccella	14.653
San Lorenzo Colli	9.836
Sferracavallo	13.345
Stazione Centrale	25.9
Tommaso Natale	17.981
Vespri	13.142

5.3.2 Intersection density

Using the “Build Graph” tool of the Networks plugin in QGIS, we created a new layer representing all the nodes (road intersections and cul-de-sacs) considering the road network as input. The layer has two attributes: an id number and the number of road segment converging in the node (nb). We used this last attribute to simply distinguish road intersections and cul-de-sacs in the map (Figure 5-9). Road intersections are the junctions at which three or more road segments intersect ($nb > 3$), while cul-de-sacs were identified as nodes where only a road segment converges ($nb = 1$). The value of intersection density for each railway station area is reported in Table 5-7. As it can be noted, Stazione Centrale, Palazzo Reale – Orleans, and Lolli areas in the urban core have the highest values while Roccella, Cardillo, Brancaccio, and San Lorenzo Colli – all located in suburban areas – have the lowest ones.

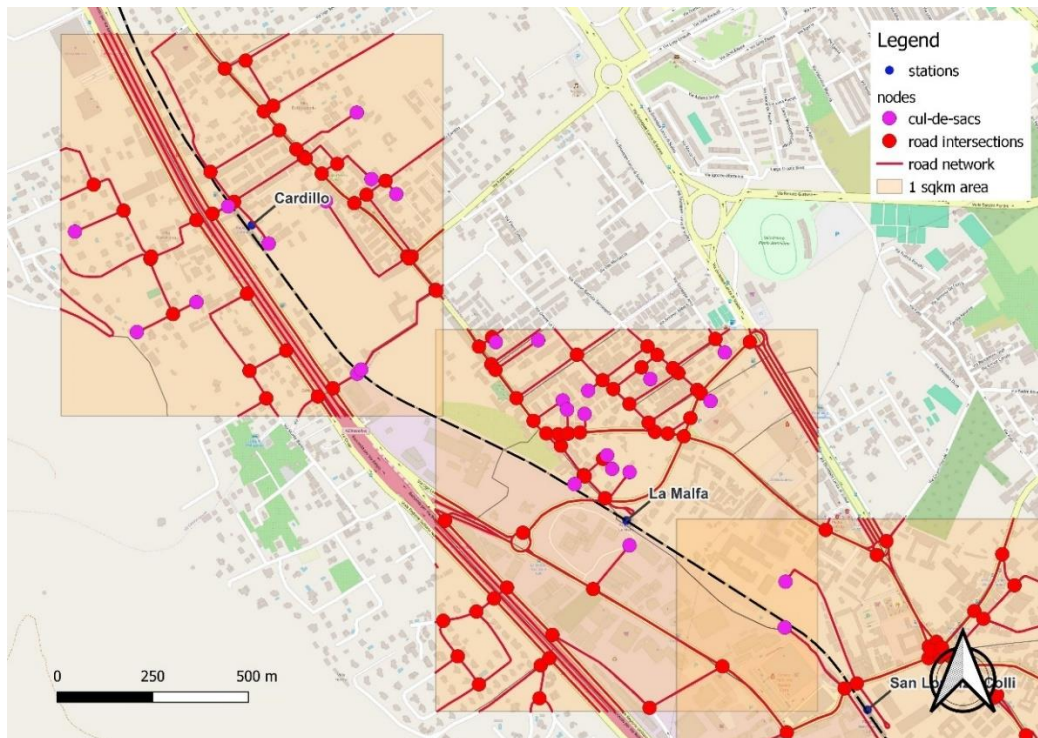


Figure 5–9. Intersection density calculation

Table 5–7. Intersection density

Railway stations	Intersection density [int/km ²]
Brancaccio	34
Cardillo	33
Francia	65
Guadagna	92
La Malfa	48
Lolli	209
Notarbartolo	171
Palazzo Reale - Orleans	247
Rocella	33
San Lorenzo Colli	39
Sferracavallo	55
Stazione Centrale	286
Tommaso Natale	96
Vespri	90

5.3.3 Pedestrian catchment area ratio

Using Buffer and Service Area tools in QGIS, we estimated the theoretical service area and the network-defined service area of the railway stations, respectively (Figure 5-10). Indeed, we identified the portion of the road network within 500 m meters from the station, using the Service Area tool. Then, we built the network-defined service areas as polygons, considering the parcels and the building that can be accessed from the portion of the road network within 500 m meters from the railway stations. The PCA ratios for each railway station area are reported in Table 5-8.



Figure 5–10. Pedestrian Catchment Area ratio

All stations have poor pedestrian accessibility, reaching a PCA ratio below 0.5. This finding is related to the presence of some context-specific conditions. For example, many railway stations (like Sferracavallo, Tommaso Natale, Cardillo or Francia) are near Viale Regione Siciliana, a primary road with two separate carriageways having a speed limit of 70 km/h and few pedestrian underpasses or overpasses located only in specific points; this road can be considered as a pedestrian hostile road, limiting the pedestrian accessibility of these railway stations. Another element limiting access is the presence of the railway tracks, and occupy a large area that is unpassable for pedestrians. This is valid not only for suburban railway stations (like Brancaccio) but also for Stazione Centrale which is the main railway station in the urban core. Possibly, an infrastructure improvement (such as the construction of overpasses or underpasses) can help in mitigating these limitations to pedestrian accessibility and can enhance the PCA ratios reaching the optimal threshold. The railway station areas of Cardillo

and Sferracavallo are the most inaccessible, as the network-defined service area is reduced right by the presence of Viale Regione Siciliana. Once again, the railway station areas in the city centre (Stazione Centrale, Guadagna, Notarbartolo, Palazzo Reale – Orleans) appear to have the highest values.

Table 5–8. Pedestrian Catchment Area ratio

Railway stations	PCA ratio
Brancaccio	0.28
Cardillo	0.08
Francia	0.21
Guadagna	0.44
La Malfa	0.18
Lolli	0.33
Notarbartolo	0.44
Palazzo Reale - Orleans	0.42
Roccella	0.27
San Lorenzo Colli	0.27
Sferracavallo	0.09
Stazione Centrale	0.49
Tommaso Natale	0.26
Vespri	0.22

5.3.4 Impacts of network connectivity on social equity

To assess the level of network connectivity for each railway station area, we calculated the network connectivity index using Equation 5.1. The network connectivity index for each station is reported in Table 5-9. As can be noted, Cardillo, Sferracavallo, Brancaccio, La Malfa, and San Lorenzo Colli areas – all located in suburban areas – have the lowest values of network connectivity index. In contrast, Lolli, Notarbartolo, Palazzo Reale – Orleans, and Stazione Centrale, located in the urban core, have the highest values of network connectivity index.

Table 5–9. Network Connectivity Index

Railway stations	Network Connectivity
	Index
Brancaccio	0.347
Cardillo	0.247
Francia	0.408
Guadagna	0.594
La Malfa	0.348
Lolli	0.757
Notarbartolo	0.764
Palazzo Reale - Orleans	0.867
Roccella	0.411
San Lorenzo Colli	0.356
Sferracavallo	0.297
Stazione Centrale	1
Tommaso Natale	0.520
Vespri	0.424

However, network connectivity affects spatial access to the railway stations in a way that depends on the distribution of residential buildings and activities in the service area. Thus, we evaluated the impacts of network connectivity on social equity. First, the population residing in residential units within a 500m buffer zone was determined. Subsequently, the number of residents within the network-defined service area, delineated by a 500m network distance from each railway station, was assessed (Table 5-10). The difference between the population living within the 500m buffer and the network-defined service area represents the excluded population, i.e. the number of people living outside 500 meters from the railway station and at risk of social exclusion. We considered some demographic characteristics identifying vulnerable social groups, such as older people, the unemployed, and foreigners, to understand the impacts of network connectivity on social exclusion. As can be noted in Figure 5-11 (top), the railway stations located in peripheral zones such as Brancaccio, Sferracavallo, and La Malfa areas have the highest percentage of excluded population. For instance, the Brancaccio railway station is inaccessible to all foreigners, to all the unemployed, and 95% of people aged over 65 living within the 500 m buffer, and this means that the use of the train service is precluded or made difficult for groups already at risk of social exclusion. However, if the absolute numbers

are considered, Lolli, Notarbartolo, Stazione Centrale, and Vespri railway stations have the highest numbers of excluded population. This is reasonable because core areas have higher population density than suburban ones.

Table 5–10. Population within the 500m buffers and the network-defined areas

	Population	Female	People over 65	Unemployed	Foreigners
Within the 500-m buffers					
Brancaccio	2508	1290	367	131	13
Cardillo	2414	1239	328	117	34
Francia	5086	2762	1451	150	44
Guadagna	9780	5102	1710	470	93
La Malfa	2347	1231	264	135	19
Lolli	15648	8430	3011	601	1408
Notarbartolo	13184	7363	3311	390	280
Palazzo Reale - Orleans	9503	4870	1658	451	469
Roccella	78	37	9	2	2
San Lorenzo Colli	1995	1069	403	87	59
Sferracavallo	2871	1463	512	157	51
Stazione Centrale	13543	6825	2200	621	2802
Tommaso Natale	6089	3107	775	371	49
Vespri	8762	4610	1696	405	390

	Population	Female	People over 65	Unemployed	Foreigners
Within the network-defined service area					
Brancaccio	31	16	7	0	0
Cardillo	943	482	129	45	12
Francia	1750	957	553	48	17
Guadagna	7172	3722	1193	369	82
La Malfa	469	247	50	26	5
Lolli	6092	3243	1139	236	646
Notarbartolo	6041	3406	1470	181	152
Palazzo Reale-Orleans	3399	1746	612	162	158
Roccella	33	17	4	1	2
San Lorenzo	735	392	135	32	19
Sferracavallo	374	189	58	18	8
Stazione Centrale	6459	3237	1034	286	1581
Tommaso Natale	3346	1720	436	205	32
Vespri	1977	1051	416	71	38

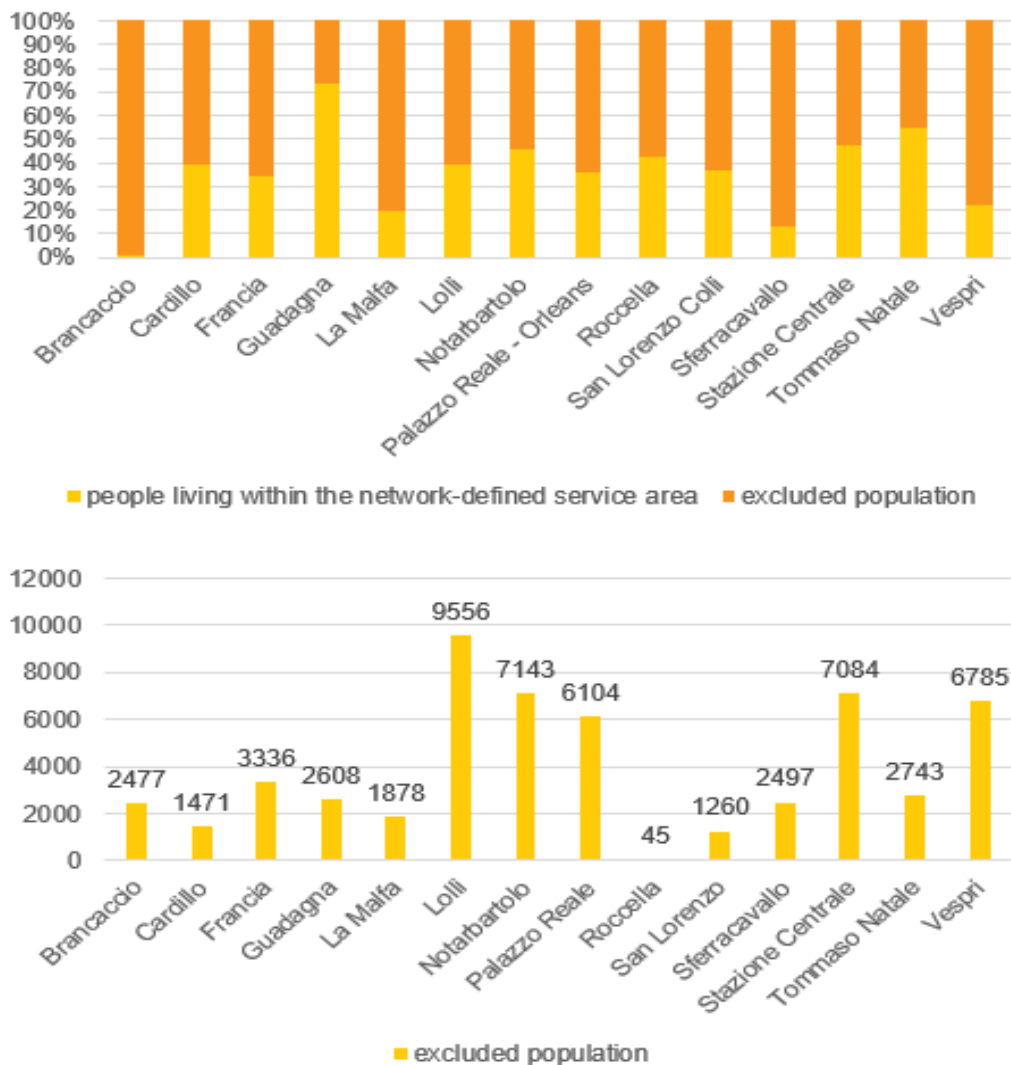


Figure 5–11. Top: Percentage of people living in the buffer that live within the network-defined service area and outside it (excluded population). Bottom: excluded population

Given the railway service's potential as a mode of transportation for reaching job opportunities and POIs, the next step involved estimating the number of employees within both the 500m buffer area and network-defined service area (Table 5-11). As Figure 5-12 (top) shows, we found that Sferracavallo, Francia, and Cardillo have the highest percentage of excluded employees. However, Palazzo Reale, Lolli, and Vespri have the highest number of excluded employees (Figure 5-9, bottom). This is reasonable because urban core areas have higher activity density than suburban ones.

Table 5–11. Employees within the 500-m buffers and the network-defined areas

Within the 500-m buffers	enterprises	employee (ENT)	No Profit Organizations	employee (NPO)	public institutions	employee (PI)	total employees
Brancaccio	190	3265	9	20	3	260	3545
Cardillo	116	415	5	1	0	0	417
Francia	384	1459	33	27	10	1779	3265
Guadagna	267	1039	13	16	9	523	1579
La Malfa	169	1791	9	156	6	1259	3207
Lolli	1769	4502	116	260	17	1667	6429
Notarbartolo	1697	3940	98	126	23	2141	6207
Palazzo Reale - Orleans	430	1252	53	104	25	5929	7285
Roccella	12	49	0	0	1	89	138
San Lorenzo Colli	211	2835	11	122	9	2336	5293
Sferracavallo	120	286	5	3	3	162	451
Stazione Centrale	1237	3670	60	76	26	2596	6343
Tommaso Natale	150	788	15	2	3	188	977
Vespri	339	874	20	72	7	5109	6056

Within the network-defined service area	enterprises	employee (ENT)	No Profit Organizations	employee (NPO)	public institutions	employee (PI)	total employees
Brancaccio	79	1814	1	3	0	3	1820
Cardillo	24	75	1	0	0	0	75
Francia	107	229	13	1	4	73	303
Guadagna	180	759	8	1	6	114	874
La Malfa	54	847	2	66	2	295	1208
Lolli	704	1615	44	122	6	214	1952
Notarbartolo	878	1924	41	42	7	472	2438
Palazzo Reale-Orleans	209	716	22	51	9	594	1360
Roccella	4	16	0	0	0	10	26
San Lorenzo	80	1168	3	56	4	457	1682
Sferracavallo	10	37	1	1	1	6	44
Stazione Centrale	764	2554	41	43	17	1264	3861
Tommaso Natale	77	331	7	0	1	8	339
Vespri	118	338	6	20	2	1365	1724

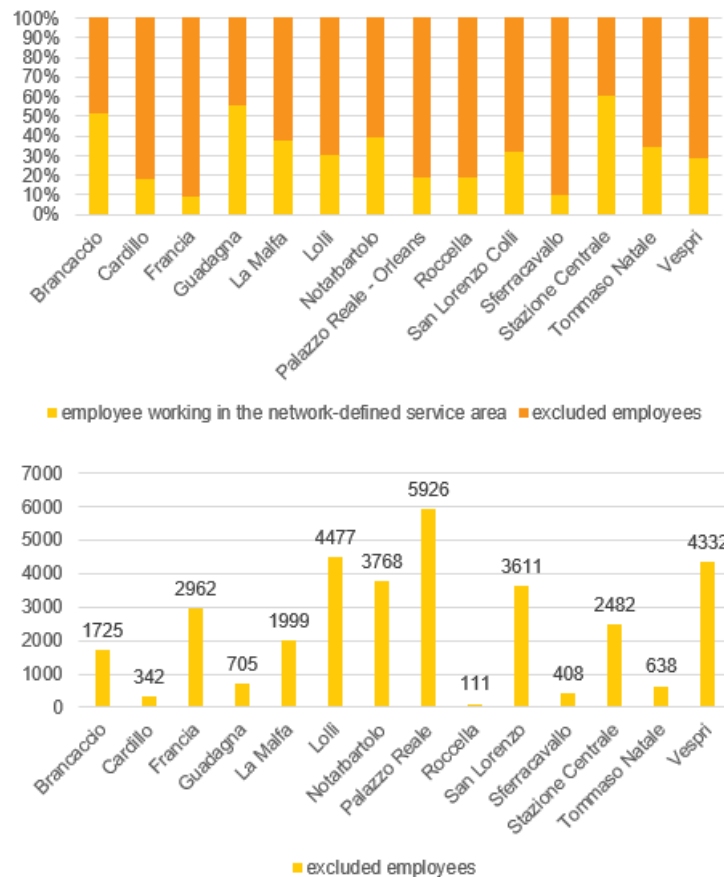


Figure 5–12. Top: Percentage of employees working in the buffer that work within the network-defined service area and outside it (excluded employees). Bottom: excluded employees

5.3.5 Quality of the pedestrian network

Considering the network-defined service areas around the railway stations, the micro-scale approach was followed. First, the pedestrian network was developed using QGIS, identifying all the sidewalks and crosswalks. Using the QuickMapServices plugin, we imported the Google Satellite map as a base map into QGIS to identify the location of sidewalks and crosswalks and build the network as a new linear layer. The layer attribute table contains as many records as the number of sidewalks and crosswalks within the railway network-defined service areas and as many columns as the number of indicators to be evaluated. The level of practicability, safety, and pleasantness of each pedestrian link (sidewalk or crosswalk) was assessed, assigning a score to each indicator based on objective assessments and quantitative measures of the existing conditions conducted through site inspections or using Google Street View where the site inspection was not possible, without considering perceptions or opinions. The weights for practicability, pleasantness, and safety were considered equal to 0.3, 0.3, and 0.4, respectively, since safety has a bigger impact on walkability for users. Finally, a Quality Index was

calculated for each pedestrian link as shown in Table 5-12. The assessment of the quality of pedestrian infrastructure within the network-defined service areas of the railway stations was a time-consuming process, as the pedestrian network was composed of 4299 pedestrian links. At the end of the process, the quality map was built based on the estimated quality index for each station (Figure 5-13).

As it can be seen in Table 5-12, the railway stations located in the suburban core such as Brancaccio, Cardillo, and Sferracavallo have more than 70% of kilometers of pedestrian network having a quality index below 2. Similarly, La Malfa and San Lorenzo have more than 50% of their kilometres of pedestrian network below this threshold, also showing low walkability environments. On the other side, railway stations located in the urban core, such as Lolli and Notarbartolo, have a good-quality pedestrian network (more than 50% and 30% of the pedestrian network has a quality index over 3). In addition, the station Palazzo-Reale-Orleans has the highest range of pedestrian network existing in the high quality index (4-5) as compared to all the other stations located in the urban and suburban core of the case study.

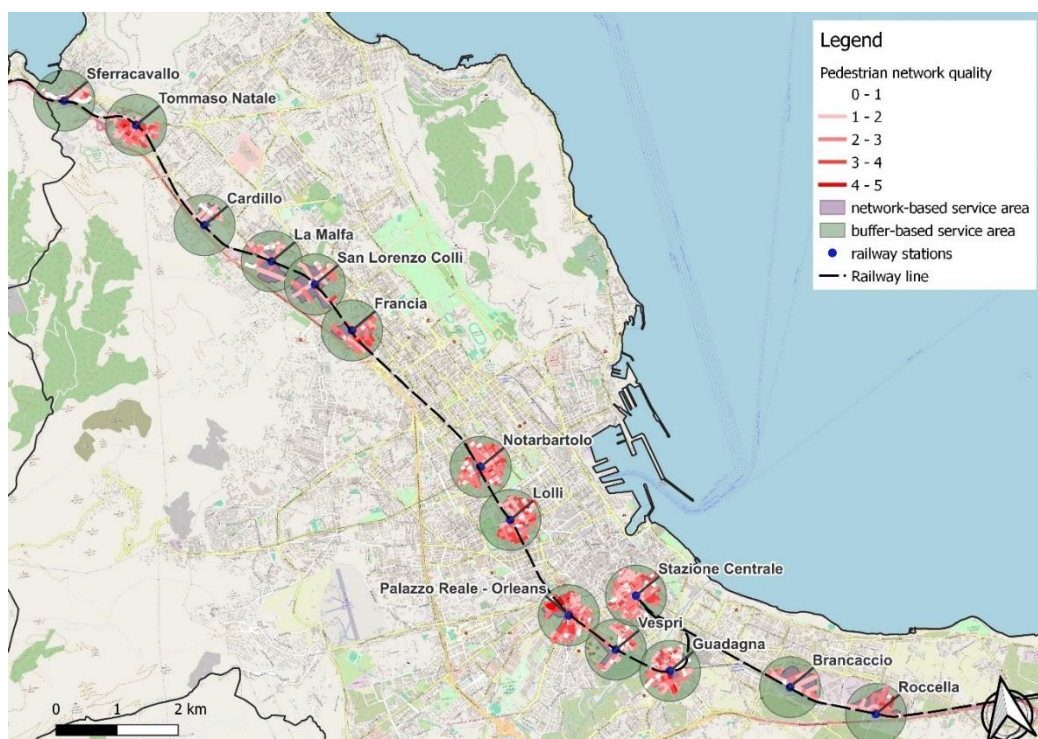


Figure 5–13. Quality of the pedestrian network

Table 5–12. Percentage of km of pedestrian network within the network-defined service area having a quality index falling within a given range

Railway stations	0-1	1-2	2-3	3-4	4-5
Brancaccio	7.3	61.8	30.3	0.5	0.0
Cardillo	10.4	73.2	16.3	0.1	0.0
Francia	1.9	13.1	65.3	19.5	0.3
Guadagna	18.0	18.8	45.0	14.4	3.7
La Malfa	4.6	50.1	38.0	7.3	0.0
Lolli	1.6	6.8	32.1	58.0	1.5
Notarbartolo	1.8	8.9	47.2	35.7	6.3
Palazzo Reale - Orleans	7.3	18.2	42.0	22.7	9.9
Roccella	5.1	19.0	60.7	11.8	3.5
San Lorenzo Colli	6.9	49.6	37.5	5.9	0.1
Sferracavallo	21.0	57.8	17.2	4.0	0.0
Stazione Centrale	9.1	22.9	42.0	24.4	1.7
Tommaso Natale	1.2	38.1	33.3	19.9	7.5
Vespri	12.2	31.5	45.6	10.6	0.0

5.4 Discussion

Combining the two walkability assessment approaches, we found that the railway stations located in the urban core have shown overall adequate network connectivity and quality of pedestrian infrastructure as compared to peripheral core stations. For instance, urban core railway stations such as Lolli have a good level of network connectivity and the highest level of quality of the pedestrian infrastructure. Similarly, Stazione Centrale station has the highest level of network connectivity but a quality with middle values: only 26% of the pedestrian network has a quality index over 3, while more than 40% has a quality index ranging from 2 to 3. In addition, Palazzo-reale-orleans station has the second-highest network connectivity index with also covering a maximum range of the pedestrian network existing in the high-quality index of (4-5). The station Notarbartolo has the third highest network connectivity index among other railway stations and has the second highest percentage (35.7) of km of pedestrian network existing in the good quality index range of (3-4). On the other side, the railway stations located in the suburbs, such as Brancaccio, Cardillo, La Malfa, San Lorenzo Colli, and Sferracavallo have been reported with poor road network connectivity and quality of pedestrian

infrastructure. These stations are the most inaccessible and disadvantaged areas, having both poor network connectivity and pedestrian network quality. Therefore, we focused on these stations to underline the issues and propose solutions, identifying the priority actions to be implemented.

5.4.1 Brancaccio Station

Brancaccio station (Figure 5-14) is characterized by a limited network-defined service area due to the absence of roads that go beyond the railway tracks and connect the densely populated southern part with the station. This is reported in Tables 5-6, 5-7, and 5-9 with a poor road density, intersection density, and network connectivity index estimated in the catchment area of the Brancaccio station. This eventually limits the accessibility to the station for the population living in the southern part of the railway station. Therefore, Brancaccio Station also faces significant challenges with social equity. As we can see from Figure 5-11 and Table 5-10, this station in the network-defined service area is only accessible to 1.2% of the total population reported in the 500m buffer area of the station. This shows a huge number of the excluded population, with zero accessibility to the expats and unemployed living in the network-defined service area of the station. In addition, the station accessibility to the most vulnerable population groups aged over 65 years is also quite low, with only 7 aged people capable of accessing the station in the network-defined service area out of a total of 367 living in the buffer area of the station. Most people in their older age are most probably dependent on public transport and particularly on the railway for their mobility solutions, due to being unfit for driving their private vehicles due to health issues. Therefore, the station's inaccessibility to these social groups poses significant social and transport equity challenges. In this situation, a pedestrian overpass over the rail tracks could be constructed to provide safe and direct access to the station for maximizing the railway station accessibility, especially for the people living in the southern part of the railway station, to maximize the inclusion of excluded social groups.

Moreover, the quality of pedestrian infrastructure in the catchment area of railway station is also not satisfactory, which eventually affects pedestrian accessibility to the railway station. This has also been shown in Table 5-12 and Figure 5-14 where the quality of pedestrian infrastructure for Brancaccio station for 70% of the pedestrian network kilometers exists in the low-quality index range of below 2. As shown exemplary in Figures 5-15, 5-16, and 5-17, sidewalks of the pedestrian network leading to the railway station have numerous constraints, such as insufficient width, degraded pavement, discontinuity, and are frequently obstructed by garbage and tree roots. Also, the pedestrian crossings shown in Figures 5-15, 5-16, and 5-17

are not well maintained. The crosswalk has poor visibility of the zebra cross marking and is unequipped with pedestrian-specific signals, being present on a high-speed limit (50 km) roadway named “Via Salvatore Corleone”. Such unsafe crosswalks existing on the high point of conflict (midblock) can lead to severe crash outcomes due to high speed on the straight section of road in an unprecedented interaction between vehicles and pedestrians. Therefore, to improve the pedestrian accessibility to the railway station, it is crucial to enhance the quality of pedestrian infrastructure with having less constraints on the sidewalks and crosswalks.

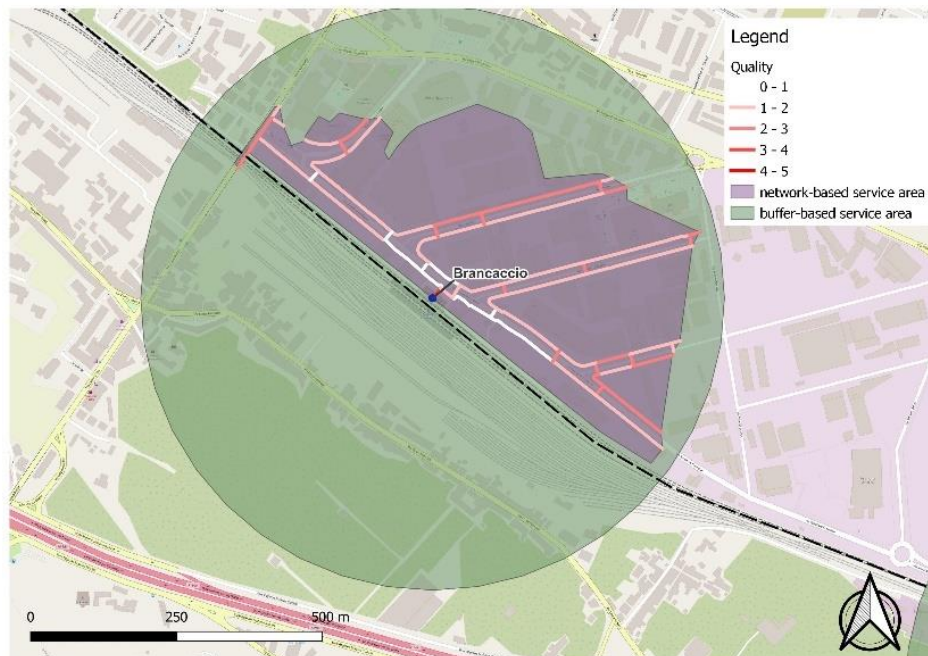


Figure 5–14. Quality index of pedestrian infrastructure around Brancaccio station



Figure 5–15. Quality of pedestrian infrastructure in the station area; degraded pavement, presence of trees, unsafe crosswalk



Figure 5–16. Quality of pedestrian infrastructure in the station area; degraded pavement, presence of trees, unsafe crosswalk



Figure 5–17. Quality of pedestrian infrastructure in the station area; degraded and discontinued pavement, presence of trees, unsafe crosswalk

5.4.2 Cardillo Station

Cardillo Station (Figure 5-18), located in the peripheral core, is characterized by a reduced network-defined service. The road density, intersection density, and network connectivity index estimated for Cardillo station in Tables 5-5, 5-6, and 5-8 are also low, showing complexities with network connectivity within the catchment area of Cardillo station. This has also been reported in Table 5-8, where the pedestrian catchment area of the Cardillo station is the lowest compared to all the other railway stations located in urban and suburban cores. The poor quality

of the pedestrian network based on meso-scale walkability indicators shows that the Cardillo station is one of the most inaccessible stations for pedestrians.

In this regard, one of the key factors that limits Cardillo Station accessibility is the presence of a high-speed limit (70km/h) roadway named “Viale Regione Siciliana” next to the station. This high-speed roadway affects pedestrian accessibility to the station due to the absence of frequent safe pedestrian crossings, with only the availability of few pedestrian underpasses. This situation significantly affects the mode choice of pedestrians for choosing the railway as their means of mobility. Moreover, limited network connectivity also highly affects the accessibility of social groups. For this reason, as reported in Table 5-10 and Figure 5-11, the accessibility of the Cardillo station for different social groups, in the network-defined service area, is low compared to the population living in the 500m buffer area of the station. Particularly considering the numbers of females and people aged over 65 between the network-defined service area and the 500m buffer area of the station in Table 5-10, the station is accessible to 482 females out of 1239 and 120 people aged over 65 out of 328. Moreover, Cardillo station have also high number of excluded employees, showing poor reachability to job opportunities and POIs as reported in Table 5-11 and Figure 5-12. These numbers identify disparities in terms of accessibility for social groups, highlighting social and transport equity challenges.

In addition, the Cardillo station also poses constraints with the quality of pedestrian infrastructure due to the majority of road network (70% of kilometres) existing with low quality index (below 2), as shown in Table 5-12, and Figure 5-18. As we can see in exemplary Figure 5-19, in front of the railway station, there is the absence of sidewalks and crosswalks, with only the presence of a pedestrian line with insufficient width. This shows significant infrastructural and safety constraints, which can put pedestrians at high risk while walking to the station and then crossing the roadway to reach the station area. Similarly, in another exemplary Figure 5-20, we can see that the sidewalks on the street in the station area are equipped with insufficient width. The crosswalks shown in Figure 5-20 also exist with poor zebra cross markings and the absence of a pedestrian-specific crosswalk signal. In addition, street parking shown in Figure 5-20 is another prominent factor that affects walkability due to occupying pedestrian walking space. The street parking can also limit the visibility for pedestrians and drivers while putting pedestrians at high risk while crossing the street. This shows the low quality of pedestrian infrastructure in the catchment area of Cardillo station, which significantly affects pedestrian accessibility to the railway station for using the railway as their means of mobility. Therefore, to improve pedestrian accessibility, it is crucial to upgrade existing pedestrian infrastructure,

which can significantly help in enhancing walkability and encourage railway use among diverse social groups.



Figure 5–18. Quality index of pedestrian infrastructure around Cardillo station



Figure 5–19. Quality of pedestrian infrastructure in front of the station; no sidewalk and crosswalk present



Figure 5–20. Quality of pedestrian infrastructure in the station area; insufficient width of sidewalks, unsafe crosswalk, street parking

5.4.3 Sferracavallo Station

Among other suburban core railway stations, Sferracavallo is also reported to have the lowest pedestrian catchment area ratio and network connectivity index, as shown in Tables 5-7, 5-8. The defined service area of Sferracavallo station is also affected by the presence of high-speed limits (70km/h) roadway “Viale Regione Siciliana”. This shows that the walking environment around Sferracavallo station also poses challenges to pedestrians. Moreover, this situation also impacts the accessibility of different social groups to the train station. Among the 2871 population living in a 500m buffer area of the station, the station is only accessible to 374 people in the network-defined service area, showing significant constraints in terms of accessibility for different social and vulnerable groups, as reported in Table 5-10 and Figure 5-11, highlighting the social and transport equity challenges. In addition, Sferracavallo station is also among the train stations with the highest number of excluded employees in terms of reaching job opportunities and POIs, as reported in Table 5-11 and Figure 5-12.

The quality index of pedestrian infrastructure for Sferracavallo station also exists in the range below 2, as shown in Table 5-12 and Figures 5-21. This indicates that nearly 70% of the road network lacks adequate pedestrian infrastructure, posing significant constraints for pedestrians. This is evident in Figures 5-22 and 5-23, which highlight micro-scale (practicability, pleasantness, safety) issues near the station area. In Figure 5-22, we observe a high-speed roadway adjacent to the station, with no sidewalks and crosswalks. This situation greatly endangers pedestrians while walking or crossing in shared conditions with motorized traffic.

Similarly, Figure 5-23 depicts the main road in the railway station area, “Via Sferracavallo,” which features degraded sidewalk surfaces and municipal trash cans, creating a hazardous and unpleasant walking environment. Furthermore, Figure 5-23 shows that the crosswalks on “Via Sferracavallo” have poorly visible zebra cross markings and lack pedestrian crossing signage and traffic signals. This scenario presents safety challenges, putting pedestrians at risk when crossing the roadway and during unpredictable interactions with vehicles, potentially leading to serious pedestrian accidents. These challenges in pedestrian infrastructure severely affect walkability and accessibility to the railway stations, suggesting the need for prioritized interventions to enhance the quality of pedestrian infrastructure.

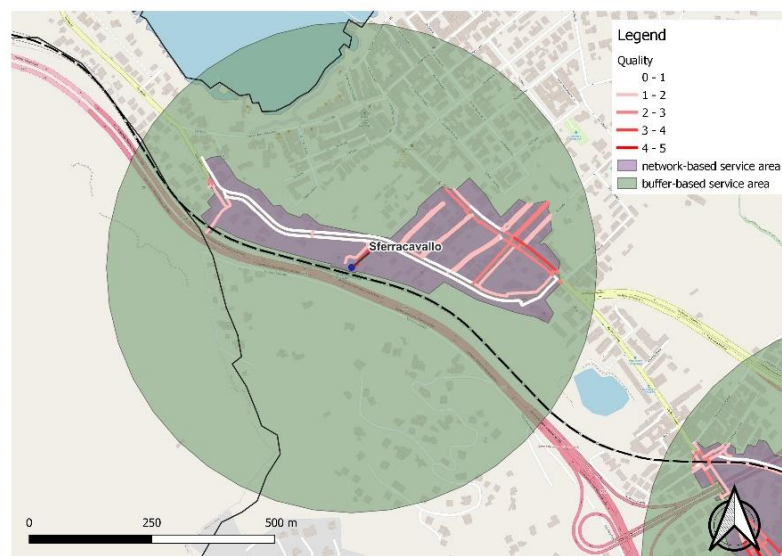


Figure 5–21. Quality index of pedestrian infrastructure around Sferracavallo station



Figure 5–22. Quality of pedestrian infrastructure in front of the station; high-speed roadway, no sidewalk, and crosswalk



Figure 5–23. Quality of pedestrian infrastructure in the station area; degraded pavement, presence of trash cans, unsafe crosswalk

5.4.4 La Malfa Station

La Malfa railway station also depicts environments with low walkability in the study area. This station has the third-lowest pedestrian catchment area ratio (0.18) after Cardillo and Safarracavallo stations, as reported in Table 5-8. It shows that station accessibility is quite low as the network-defined service area is quite small. Moreover, the station is also reported for the third inadequate network connectivity index values, as shown in Table 5-9, showing overall poor road density, intersection density. The low network connectivity index around the station also significantly affects social groups. Therefore, the station has also been reported for the high percentage of excluded population in Table 5-10 and Figure 5-11. Considering the total population of 2347 living in the 500m buffer area of the station, only 469 people have access to the station in the network-defined service area. These numbers show significant social equity challenges in the catchment area of the La Malfa station.

In addition, the quality of pedestrian infrastructure around the station is unsatisfactory. Fifty percent of the kilometers of pedestrian network exist in the quality index range of below 2, as shown in Table 5-12 and Figures 5-24. As depicted in Figures 5-25, 5-26, and 5-27 considering the indicators of practicability and safety, the station has inadequate pedestrian infrastructure due to degraded pavements, insufficient sidewalk width, the presence of obstacles such as light poles and trees, the absence of barriers, and unsafe crosswalks, all of which highlight significant safety and infrastructural issues. For example, in Figure 5-25, on the right side, the

sidewalks for pedestrians in the network-defined service area of the station are missing, forcing pedestrians to share a roadway with vehicular traffic while walking to the station. This represents an infrastructural issue impacting the pedestrian level of service and safety, as pedestrians may feel insecure while walking to the train during any trip generation case. Similarly, Figure 5-26 presents infrastructure and safety challenges due to narrow width, degraded pavements, and faded crosswalks at the intersection. Intersections are often considered critical conflict points for pedestrians, whereby poor infrastructure quality can create risky situations. Furthermore, in Figure 5-27 the midblock crosswalk is faded and lacks a pedestrian-specific traffic signal. Midblock areas are recognized as hotspots for severe pedestrian crashes due to being a primary conflict point and the high speed of traffic. In these circumstances, a pedestrian crossing the roadway, especially at night due to low visibility, could face hazardous conditions that greatly compromise their safety. The absence of sidewalks, as illustrated on the left side of Figure 5-27, further emphasizes a significant infrastructure issue for pedestrians. Collectively, all these factors critically affect pedestrian accessibility to the railway station, underscoring the necessity for constructing new infrastructure alongside upgrading the existing facilities.

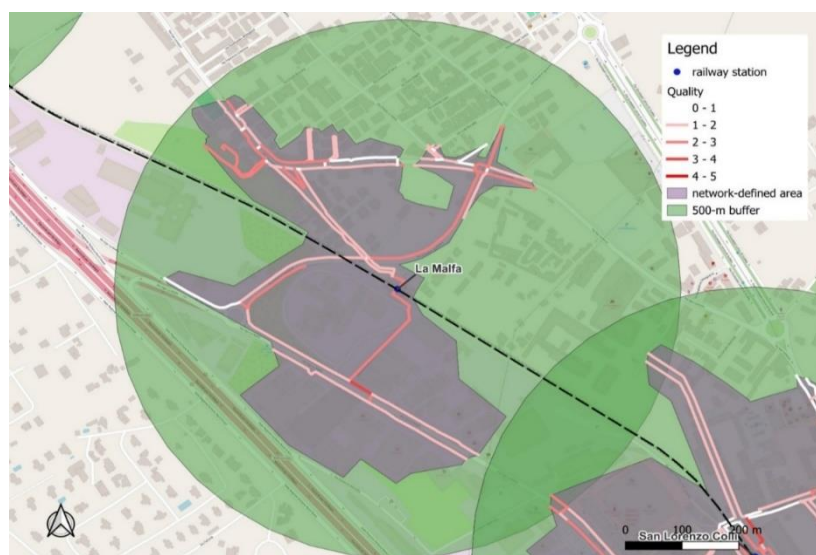


Figure 5–24. Quality index of pedestrian infrastructure around la Malfa station



Figure 5–25. Quality of pedestrian infrastructure in the catchment area of the station; no sidewalk present

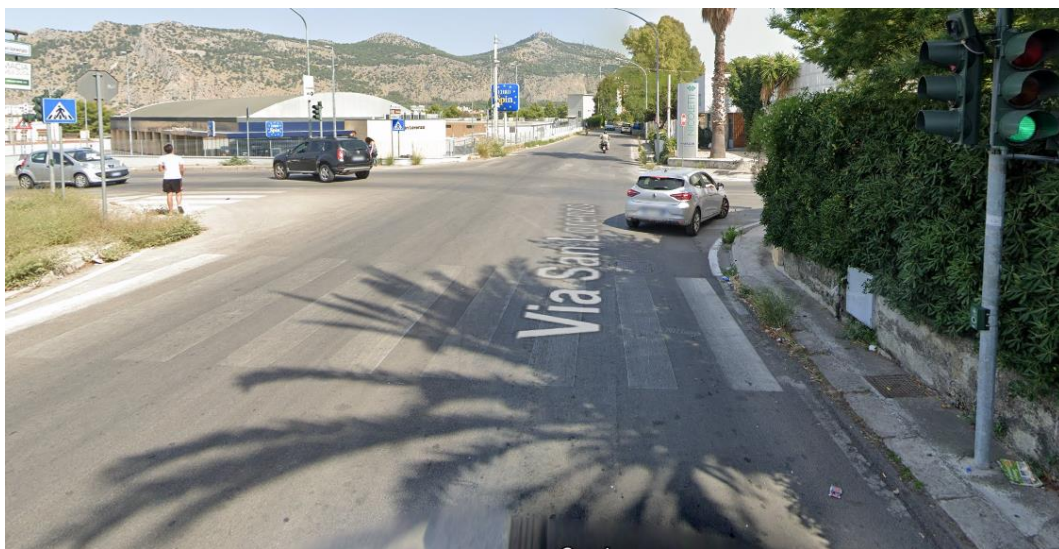


Figure 5–26. Quality of pedestrian infrastructure in the catchment area of the station; sidewalk with insufficient width, unsafe crosswalk at intersection



Figure 5–27. Quality of pedestrian infrastructure in the catchment area of the station; no sidewalk present on the left side, presence of trees, and unsafe crosswalk at midblock

5.4.5 San Lorenzo Colli station

The station San Lorenzo Colli also faces challenges with network connectivity and the quality of pedestrian infrastructure. For instance, assessing the quality of accessibility of the station based on meso-scale indicators such as road density and intersection density, the station has been reported with a low network connectivity index, as shown in Table 5-9. This factor hugely impacts the accessibility of different social and vulnerable groups in the network-defined service area of the station. For these purposes no wonder that the station has also been reported with the highest percentage of excluded population. In this regard, the station is only accessible to 36 % of the total population living in the 500m buffer area of the station, as shown in Table 5-10 and Figure 5-11. These numbers depict significant social and transport equity constraints.

In addition, the San Lorenzo Colli station also displays poor walkability environments when assessed on the basis of microscale walkability indicators such as practicability, safety, and pleasantness, as reported in Table 5-12 and Figure 5-28 below. For instance, in Figures 5-29 and 5-30, as can be seen that on the street named as “Via Stazione S. Lorenzo” and “Via Giuseppe Tranchina”, very next to the station, there are no sidewalks for pedestrians to walk on and pedestrians have to share the roadway with vehicular traffic while walking to the train station. The absence of basic infrastructure for pedestrians in the nearby area of the station depicts a low pedestrian level of service and significant safety issues. Similarly, Figure 5-31 displays a crosswalk present at the intersection being faded and without a pedestrian-specific signage board or traffic signals. The crosswalks on multilane roadways are usually built longer due to wider road width and due to which pedestrian exposure time increases during crossing

the roadway. Therefore, crosswalks at high-conflict points (intersection) without basic pedestrian crossing facilities poses significant safety challenges for pedestrians. In addition, the intersection shown in Figure 5-32, located very next to the train station on “Via Stazione S. Lorenzo” is present without a crosswalk and footpath. This poses significant safety constraints for pedestrians during their unprecedented interaction with vehicular traffic while walking or crossing in the vicinity of a train station area. Collectively, all these factors affect the mode choice of pedestrians and their accessibility in terms of choosing railways as their means of mobility. Therefore, it is recommended to develop new infrastructure as well as upgrade existing ones, to improve accessibility, which will eventually assist in the inclusion of social groups, reducing social and transport equity challenges.

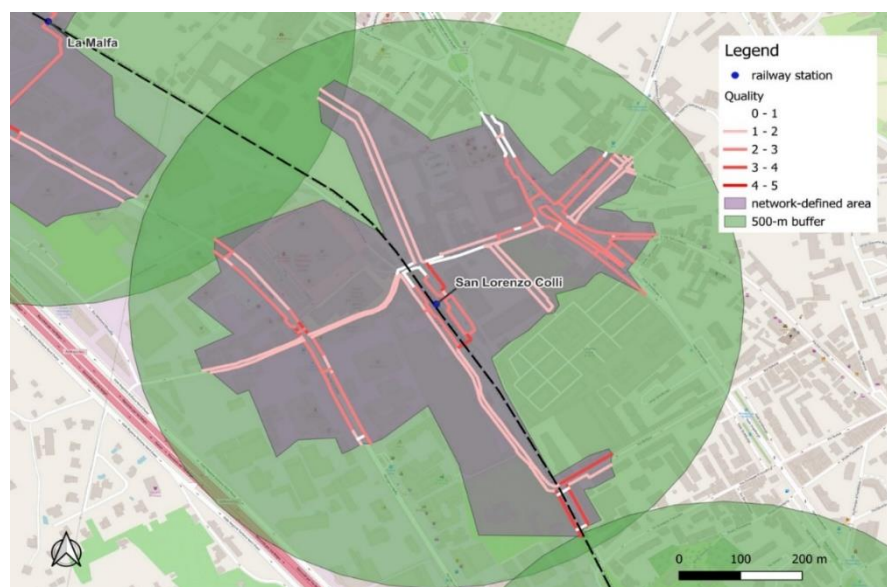


Figure 5–28. Quality index of pedestrian infrastructure around San Lorenzo Colli station



Figure 5–29. Quality of pedestrian infrastructure in the catchment area of the station; no sidewalk present



Figure 5–30. Quality of pedestrian infrastructure in the catchment area of the station; no sidewalk present



Figure 5–31. Quality of pedestrian infrastructure in the catchment area of the station; unsafe crosswalk at intersection



Figure 5–32. Quality of pedestrian infrastructure in the catchment area of the station; no sidewalk and crosswalk present at intersection

Conclusions and Policy Recommendations

With the growing urban transport challenges, promoting active transport as a sustainable means of transport is becoming popular and necessary. Active transport, such as walking, is vitally recognized as a key element in creating sustainable and inclusive urban environments. Among other active transport modes, walking holds a substantive position due to its accessibility, affordability, low environmental impact, and numerous health benefits. Consequently, the concept of walkability, which can be defined as how conducive the built environment is to walking, has become the cornerstone in urban planning and transport policies. This brings the attention of scholars and policymakers to the needs of pedestrians. Thus, the concept of vulnerability becomes essential. Pedestrians are known as vulnerable road users due to being physically exposed and prone to severe injuries in traffic collisions due to their unprotected state compared to other road users. In this regard, enough of the existing literature and policies emphasize pedestrian vulnerability in terms of safety. While pedestrian vulnerability in terms of safety is undoubtedly important, this thesis highlighted how a comprehensive understanding of vulnerability should also include the risk of social exclusion due to poor accessibility. From this perspective, the definition of vulnerability was expanded to encompass the extent to which individuals or social groups are susceptible not only to being victims of road traffic accidents but also to the social exclusion resulting from car-oriented planning and inadequate pedestrian infrastructure. For instance, a pedestrian network may be safe in terms of road design; however, if its quality makes it inaccessible to some social groups, particularly to the most vulnerable, such as elderly people and people with disabilities, then it is equally affecting pedestrians' vulnerability compared to safety issues.

In addition, the thesis showed that limited network connectivity equally affects pedestrian vulnerability, impacting social inclusion. Indeed, it is evident that limited pedestrian accessibility directly affects individuals' access to essential services and public transit facilities and therefore leads to social and transport equity challenges. Therefore, it is important to recognize that accessibility itself may constitute a form of vulnerability. In this realm,

expanding the concept of vulnerability to accessibility allows for a more inclusive approach to urban planning and transport policy. Moreover, in this broader view, walkability is not limited to creating safer streets, but also equally emphasizes designing public spaces that maximize access to essential services by vulnerable social groups.

Taking into account these considerations, the research objectives were achieved, and the research questions have been answered by the research articles (RA). The contribution of each RA in responding the research questions is shown in the following table and described more extensively in the upcoming part of this conclusion chapter.

Table 6–1. Addressing the specific objectives of the thesis

Research objectives	Research questions	Research articles
O1 (Exploring the concept of vulnerability of pedestrians as vulnerable road users)	RQ1	RA1
	RQ2	RA2
	RQ3	
O2 (Expanding the concept of vulnerability)	RQ4	RA3
O3 (Investigating the link between road safety and walkability)	RQ5	

This thesis has explicitly evaluated pedestrian vulnerability in terms of safety and accessibility while exclusively expanding the concept of vulnerability to the risk of social exclusion. In terms of pedestrian safety assessment, the research has chosen two main aspects that significantly affect pedestrian vulnerability. The first one is evaluating the role of travel speed on pedestrian vulnerability in terms of vehicle-to-pedestrian interactions. In this background, the research started from a literature review as stated in Chapter 2 and explored the impact of different kinds of speed on the consequences of vehicle-to-pedestrian interactions and related crashes. From the literature review, this research observed that undoubtedly single-dimensional speed indicators, such as impact speed, mean travel speed, and speed limits, have been found to have a significant impact on the severity of vehicle-to-pedestrian crashes; however, they might not be able to capture the speed fluctuations across different speed ranges. To cover this gap, this research has exclusively examined the impact of the range of percentile speed on the severity of vehicle-to-pedestrian crashes by taking Palermo as a case study. As stated in Chapter 3, the crash data from Police departments may not be useful to understand the aspect of speed in terms of its influence on the severity of such crashes due to absence of impact speed data in

the acquired crash dataset; however, it could be useful in acquiring speed information and understanding the related dynamics due to availability of other variables that are adjoint with consequences of such crashes. Therefore, to better understand the percentiles' speed impact on the severity of such crashes, this research has acquired percentile speed data from TomTom speed database for the crash locations that resulted in vehicle-to-pedestrian crashes. The research applied a discrete outcome model aimed at forecasting the fatal and severe injury risk (FSI) and found a significant relationship between percentile speed and FSI risk. The study further evaluated the model's efficiency in a trial-and-error speed reduction scenario. RA1 provides critical insights into the potential of speed management policies with the following key findings:

- The results from this study showed that fatal and severe injury risk (FSI) increases as speed percentiles increase, with high risk in the upper percentile speed (50th-85th) as compared to lower percentile speeds (15th-50th).
- The study evaluated the discrete model performance in a counterfactual analysis and found that speed reductions of 3 km/h and 5 km/h have significant effects on the FSI risk reduction in crashes involving pedestrians and vehicles.
- The study also identified several fatal and severe injury locations on the roadways in the case study realm where vehicular traffic exceeds the speed limits, posing a risk for pedestrians due to higher speeds and emphasizing the need for targeted interventions to enforce compliance with the speed limits.

Based on the above findings, the study suggests the following policy recommendation:

- The study results emphasize the installation of speed cameras and intelligent speed assistance systems (ISA) on roadways with frequent speed limit violations. These smart tools can significantly help with speed control in the realm of speed limits without constant police enforcement.
- The outcome of the study also supports the installation of traffic calming measures. Traffic calming measures such as speed bumps, raised crosswalks, and narrowed lanes can significantly help in reducing vehicle speed. These measures can be installed and adopted in the realm of existing infrastructure on the streets in the historic city centre or other high pedestrian activity zones, which can significantly help in reducing the severity of pedestrian crashes.
- The study's outcome suggests targeted speed-limit reduction in high-risk areas. For instance, in the streets that are networked in the historic city centre and other high

pedestrian areas such as tourist attractions, school zones, and residential areas, the speed limits could be adjusted and reduced from 50km/h to 40 km/h or 30 km/h, considering the vehicular traffic volumes and their exposure to pedestrians throughout time of day. In this regard, the research has shown that adjusting even modest speed limit reductions can significantly help in reducing the risk and frequency of severe pedestrian crashes (Hu and Cicchino 2024).

- In recent years, many cities are experimenting with a reduction of speed limits involving most of the road network of the entire urban area. A case is Bologna in Italy, which has become a “City 30” by extending the 30 km/h limit to about 70% of the roads in the urban area, with results on accident rates that seem promising and in line with other European cities that have already experimented this model such as Madrid, London and Brussels. However, there has been much debate, especially among the public and politicians, on the implementation of such a policy. Even some scholars argue that since the 30 km/h speed limit is generally part of a wider plan to promote sustainable mobility, which can involve other measures such as public transport improvements, bike-sharing programs, or structural changes, it’s hard to understand how each of them contributes to the overall results. The study reported in RA1 highlighted how a reduction in speed limit is essential to reduce the severity of road crashes. However, the real data that were examined suggested that in many roads in where road accidents occurred, speed limits are not respected by most of the road users. Thus, extensions in the reduction of the speed limits must be accompanied by traffic calming actions and other actions to increase pedestrian safety. The role of these actions is highlighted by the comparison of two collector roads with great pedestrian activity in Palermo (via Roma and via Notarbartolo) based on the accident data. Via Notarbartolo, having traffic-lighted pedestrian crossings, barriers to avoid jaywalking, and sidewalk extensions, provides a quite safe environment for pedestrians. On the other hand, via Roma, not having traffic-lighted pedestrian crossings and even marked pedestrian crossings in several intersections, and creating opportunities for people to jaywalk, represents a hotspot for road accidents involving pedestrians. Moreover, the study showed that, from the perspective of an extension of the 30 km/h speed limit, it is also important to take into account the role that the roads play. Extending the speed limit reduction in local roads is quite easy, but it is more complicated to do so on wide roads that connect neighbourhoods and different parts of the city and that serve as public transportation corridors, also because traffic calming actions cannot always be

implemented. For example, Via Roma and Viale Strasburgo are both wide two-way collector roads having the role to connect different parts of the city and having high pedestrian activity due to the presence of commercial activities. The possibility of having alternative corridors represents an opportunity for Via Roma to be a 30 km/h road. After all, Via Roma is located in a restricted traffic area, and its role as a fast connection between neighbourhoods is actually a distorted role. On the other hand, Viale Strasburgo represents the sole road connecting the suburban areas located in the northern part of the city to the city center. In this case, reducing the speed limit may represent an action in conflict with the role this road plays. The findings of the study suggested that a solution for increasing pedestrian safety may be the reduction of the conflicts through the installation of new traffic-lighted pedestrian crossings.

- The study outcomes also support the “Movement & Place” transport planning framework. According to this smart concept, the urban zones can be classified and prioritized based on the concept of “Place” and “Movement”. For instance, the streets can be classified based on function: lower speeds in "Place" areas (e.g., markets, squares) while maintaining efficient traffic flow on "Movement" corridors. Consequently, according to this concept, the streets can be redesigned to the “Place” concept and the pedestrian infrastructure can be improved in the “Place” zones, which should prioritise pedestrian safety.

The second main aspect that is crucial to consider in order to assess pedestrian vulnerability in terms of safety is analysing factors influencing pedestrian injury severity. The main purposes of doing such analyses are to identify key factors, understand their impact on the severity of pedestrian crashes, and propose policies to mitigate their effects in the future. In this regard, the current research started from a literature review as stated in Chapter 2 and observed several factors that have been reported for their impact on the injury severity of pedestrian crashes. In addition, the RA2 also explored several statistical and machine learning methods to understand their efficiency in predicting the pedestrian injury crash severity while modelling the complex nature of crash datasets. From the literature review, the current study observed that extensive research has been conducted in analysing the pedestrian crash severity; however, gaps remain in evaluating those factors in the realm of densely built and historically constrained city centers. It was also found from the literature that some studies have evaluated the pedestrian injury severity in the ancient Italian context; however, gaps remain in evaluating such factors in the case study context (Palermo, Italy). Therefore, to bridge the gap, this study analyses the severity of pedestrian crashes through a comprehensive machine learning-based framework from the

pedestrian crash dataset acquired from the Palermo municipal police. The study utilized different machine learning tools to handle missing values, injury severity class imbalances, and interpretable machine learning tools such as SHAP analysis to predict injury severity of pedestrian crashes with the following key findings:

- The study results showed that, among different applied machine learning data imputation methods, the multivariate imputation by chained equations (MICE) got a high accuracy score. This finding supports the superior performance of the MICE technique for handling missing data for different variables in crash datasets.
- The outcome of the study also showed that machine learning models are prominent in identifying the severity of pedestrian crashes while capturing the complex and non-linear relationships among variables, and are also capable of simultaneously handling missing data and injury severity class imbalance challenges. Among applied machine learning models, the Catboost achieved the highest accuracy.
- The study results also emphasize the SHAP technique's proficiency in identifying the underlying relationships between dependent and independent variables while covering the drawbacks of machine learning models, usually called “Black Boxes”.
- The Global and Local Analyses by SHAP revealed that the independent variables, such as pedestrian gender, accident dynamics, nature of incidents, day of week, road type, road features, driver gender, day/night time, crosswalks, pedestrian behavior have a significant impact on Catboost model outcome in identifying the severity of pedestrian crashes.
- The interaction effects further revealed the complex interrelationship among these variables on the pedestrian crash severity. For instance, considering the pedestrian gender, the results showed that male pedestrians are prone to severe crashes on two-way roadways, along the straight segments of roads, and when the crash occurred during nighttime.
- The dependence plots by interaction effects further found that among driver gender, male drivers are involved in severe crashes during rainy weather and under low lighting conditions.
- The interaction effects analysis also identified the pedestrian behaviour in the realm of severity of crashes and found that pedestrians, when crossing the street, significantly increase the severity of pedestrian crashes. The pedestrian behaviour comparison with other variables showed that pedestrians when crossing the street at the straight segments

and in rainy weather, and under low lighting significantly increase the severity of pedestrian-involved crashes.

- The dependence plots also identified the temporal features' impact on the severity of pedestrian crashes and found that crash severity increases on the crosswalks during weekdays and weekends at night.
- The interaction effects also revealed the intricate and supporting pattern of road type and features' impact on the pedestrian crash severity. It found that the pedestrian crashes that occurred at the two-way road's straight section and on the crosswalks increased the severity of pedestrian crashes. In this regard, looking into road features, it showed that pedestrian crossings on straight sections of the road contribute to increased severity in pedestrian crashes.
- The interaction effects analysis through dependence plots further depicts the crash-at-fault mechanism on the pedestrian crash severity and found that the driver at fault during weekends and when the crash occurs at crosswalks, highly increases the severity of pedestrian crashes.

Based on the key findings outlined above, the study has the following policy recommendations.

- Considering the male pedestrian involvement in severe pedestrian crashes, it highlights the need for pedestrians' gender-based targeted safety interventions awareness campaigns through culturally relevant platforms like sports, education, and community events that prioritise addressing the behaviour-focused risk factors associated with male pedestrians in the historical urban structure to potentially minimise the crash severity and exclusively promote safe walking motives. Moreover, safety upgrades to the existing pedestrian infrastructure, with improved lighting on the streets and crosswalks, particularly in the pedestrian activity-dense historic city centre, together with speed control interventions, can also help in improving the safety of male pedestrians.
- The male drivers role in severe pedestrian crashes underscores the risky driving behaviours of male drivers and suggests observing and monitoring the risky behaviours with the installation of enforcement surveillance devices, particularly in the narrow streets of high pedestrian historic city centre zones, to potentially reduce the severity of pedestrian crashes due to drivers' behaviours. Moreover, considering Palermo's traffic-congested environment, it is also recommended to initialize the driver behaviour monitoring programs and integrate them into the traffic enforcement initiatives while promoting responsible driving habits among male drivers. The same policies could be

adopted to tackle the driver's involvement in crashes due to their faults, mostly due to reckless driving behaviours.

- In order to counter the effect of temporal features on pedestrian crash severity, it is crucial to consider a historical and touristic compact urban layout of the city and observe pedestrian activities and traffic dynamics on weekdays through times of day. In peak hours, when there is a high chance of vehicle-to-pedestrian interaction, the traffic and pedestrian-specific signal timings could be adjusted considering the vehicle and pedestrian movements at the high-conflict points to minimize the potential risk of a crash. Furthermore, to reduce the severity of pedestrian crashes at crosswalks on weekdays, their safety can be enhanced at intersections and mid-block locations through the installation of pedestrian-activated signals, high-visibility markings, rectangular rapid-flashing beacons, refuge islands, speed tables, and more. This will help in calming the traffic and the safe crossing of pedestrians at the crosswalks usually considered high-conflict points during high commuting hours throughout weekdays. Similarly, to minimize the severity of crashes during late-night hours on weekends, it is important to monitor high speed - especially on the narrow streets mostly located in the historic city centre - intoxicated driving, while improving lighting to reduce the risk of unexpected conflicts between pedestrians and vehicles, which could result in severe pedestrian crashes.
- The study outcome regarding pedestrian behaviour involvement in severe pedestrian crashes emphasises the targeted need for intervention to educate pedestrians about the safe crossing of streets and to opt for utmost care while walking on the sidewalks or entering or exiting from public transit/cars, together with jaywalking enforcement. In this situation, the prevalence of on-street parking in the city also significantly affects pedestrian crossing due to limiting pedestrians' and drivers' visibility and forcing pedestrians to cross unpredictably between parked vehicles. This increases the risk of unsafe crossings, and therefore, targeted safety intervention needs to be adopted to limit the on-street parking in the vicinity of pedestrian crossings. Also, providing sidewalk extensions could be an effective action to reduce pedestrian crossing distances, increase the visibility of pedestrians who want to cross, and limit the vehicle speed, thanks to the narrowness of the roadways.
- The study findings with regard to roadway characteristics for increased severity of pedestrian crashes highlight the need for adjustments to speed limits and infrastructural

improvements to overcome the severity of crashes. In addition, a variable speed limit policy that is already adopted in other countries could be included in the Italian regulatory framework and suggested for adopting on the two-way roads, considering the dynamics of traffic flow and pedestrian movements in high pedestrian activity zones to minimize the impact and risk of collisions at high-conflict points such as straight sections of roads and crosswalks. Moreover, since two-way roads are usually occupied with multiple lanes, this eventually increases pedestrian exposure time and risk during crossing. Therefore, to specifically improve the safety of crosswalks on such roadways, the same pedestrian safety enhancement policies discussed above for improving the safety of crosswalks could be adopted on the two-way straight sections of roads.

While the studies mentioned above explicitly explore pedestrian vulnerability in terms of safety through a multifaceted analytical framework, with key findings and policies discussed, the RA3 examines pedestrian vulnerability through the lens of accessibility. In this regard, Palermo railway network stations were chosen as a case study. The study analyzes the impacts of road network connectivity and the quality of pedestrian infrastructure on spatial and social equity in accessing these railway stations. It considers different social groups and assesses their accessibility as potential vulnerability by combining both meso-scale and micro-scale walkability assessments. A crucial aspect of this assessment lies in the micro-scale indicators, among which safety is particularly significant, along with practicability and pleasantness. Safety is a core concern in pedestrian planning and also a direct measure of vulnerability; therefore, higher weights were assigned to safety when assessing the quality of pedestrian infrastructure. Unsafe sidewalks with poor lighting, lack of physical barriers, high-speed adjacent traffic, and unsafe crosswalks directly affect vulnerable groups, such as children, the elderly, and people with disabilities. Hence, this study expands the concept of vulnerability to include both the physical and social vulnerability of pedestrians through a meso-scale walkability assessment approach. The study emphasizes that pedestrians are not only vulnerable to crashes or crimes, but also that the physical design and quality of infrastructure significantly impact pedestrian vulnerability when they fail to meet the needs of all users. To that end, a substantial literature review regarding inequalities in accessibility to railway stations was presented in Chapter 2. From the review of past studies, it was noted that a considerable amount of literature has assessed pedestrian accessibility to railway stations through multifaceted walkability assessment frameworks; however, gaps remain in addressing the issues related to the case study (Palermo, Italy). Few studies, such as (D'Orso and Migliore 2020), have assessed the walkability environment around some railway stations and found

disparities in the quality of pedestrian infrastructure; however, no study has explored walkability combining meso- and micro-scale assessments. Therefore, this study attempts to address the gaps in the literature. It identifies significant disparities in pedestrian accessibility to these railway stations located in urban and peripheral areas, with the following key findings:

- The study results showed that considering the meso-scale and micro-scale walkability assessment approaches, the railway stations located in the urban core have better network connectivity and quality of pedestrian infrastructure as compared to the railway stations located in the peripheral core.
- From the network connectivity disparities perspective, the urban railway stations such as Stazione Centrale, Palazzo Reale – Orleans, Notarbartolo, and Lolli have the highest network connectivity index. However, the peripheral area railway stations such as Cardillo, Sferracavallo, Brancaccio, La Malfa, and San Lorenzo Colli have the lowest network connectivity index.
- The study observed that all the railway stations have a pedestrian catchment area ratio below 0.5, which shows overall poor pedestrian accessibility.
- The study also found a significant impact of the network connectivity on social equity. The suburban core railway stations, such as Brancaccio, Sferracavallo, and La Malfa areas, have the highest percentage of the population excluded from the network-defined service areas of stations. Particularly, the Brancaccio railway station is inaccessible to foreigners and the unemployed living in the network-defined service area of the station.
- The study also revealed that suburban core railway stations such as Sferracavallo, Francia, and Cardillo have a high percentage of exclusion of employees, while considering their accessibility to job opportunities and points of interest.
- Considering the quality of pedestrian infrastructure assessment around the railway stations, the studies observed that the urban core railway stations, such as Lolli and Notarbartolo have a satisfactory quality index of pedestrian network, with more than 50% and 30% of the pedestrian networks with a quality index over 3. In addition, the Palazzo-Reale-Orleans station got the highest proportion of pedestrian network with a high-quality index (4-5).
- The study results also showed that suburban core railway stations such as Brancaccio, Cardillo, Sferracavallo, with 70%, and La Malfa, San Lorenzo, with 50% of the pedestrian network existing with a quality index below 2, depict a low walkability environment.

- The study also observed that the roadway named “Viale Regione Siciliana” has a significant impact on pedestrian network connectivity, limiting the pedestrian accessibility in the catchment area of two suburban core railway stations, Cardillo, and Sferracavallo.
- The analysis of the micro-scale walkability assessment indicators in the network-defined service area of each station identified several infrastructural flaws that significantly impact the pedestrian accessibility. Among these are sidewalks with insufficient width, degraded pavement, occupied by trash cans, light poles, and tree roots, etc. Similarly, the crosswalks during quality assessment were found to be existing with poor visibility of zebra cross markings, absence of pedestrian-specific signals, which can significantly increase the risk of severe pedestrian crashes.
- The analysis of the micro-scale walkability assessment indicators also found that some railway station areas, such as San Lorenzo Colli, La Malfa, and Sferracavallo catchment areas, have pedestrian routes with no basic infrastructure, such as sidewalks and crosswalks. This depicts significant infrastructural and safety challenges while putting pedestrians at high risk due to walking to the station while sharing the roadway with vehicular traffic.

Based on the above findings, the study has the following policy recommendations.

- In order to increase the pedestrian network connectivity, new pedestrian links could be constructed to enlarge the road network connectivity. The suburban core railway stations with reported poor walkability environment have the potential for expanding the pedestrian network due to the presence of low-density areas or undeveloped land. Therefore, this expansion could be done in the realm of 15-minute cities and transit-oriented development planning concepts, which prioritize the sustainable mobility motives and can also help to combat the social equity challenges, with eventual expansion of accessibility to already excluded populations and employees.
- The study recommends prioritising suburban core zones equally with urban zones concerning the infrastructural development fund. City centres in medium-sized European cities, predominantly established as historical urban centres, typically feature the conveniently designed structure of a 15-minute city, promoting walking through a grid-like network of narrow streets, high population density, and proximity to services. Thus, in the city centers, fewer efforts are needed to improve pedestrian access to essential services and transit hubs. On the other hand, the complexity of suburban

development led to unbalanced and inequitable situations, resulting in residential neighborhoods that serve few purposes other than housing and require long travel times for residents to satisfy their daily needs. Thus, compared to urban zones, the suburban zones need more attention in terms of infrastructural development funds to enhance the pedestrian access to transit hubs and other routine services.

- The study also recommends that, to maximize the accessibility of sub-urban core railway stations (Cardillo, and Sferracavallo) limited due to the presence of a high-speed roadway named “Viale Regione Siciliana”, new overpasses or underpasses could be constructed to ensure safe crossing of pedestrians on such a high roadway. Moreover, these new overpasses or underpasses must be very well controlled through cameras to be perceived as actually safe.
- The study outcome suggests installing pedestrian priority zones in the vicinity of suburban core railway stations. These pedestrian zones could be installed with narrowed lanes, speed bumps, and curb extensions, which can significantly help in reducing vehicular traffic speed on high-speed limit roadways existing next to railway stations.
- The study results suggest that it is important to build basic infrastructure, such as sidewalks and crosswalks, in the catchment area of railway stations where it is missing. Also, considering the existing low-quality pedestrian infrastructure, it is recommended to do low-cost fixes and permanent installations. For instance, the quality of sidewalks could be increased by repairing the pavement with degradation and removing other permanent and temporary obstacles. In addition, pedestrian safety barriers can be installed on the sidewalks existing on the high-speed road network. Whereas the safety of crosswalks can be enhanced with repainting the zebra crossings and permanent installation of pedestrian traffic signals in the vicinity of railway stations.

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