A COMPREHENSIVE ANALYSIS OF WALKING BEHAVIOUR AND SAFETY OF PEDESTRIANS IN URBAN ENVIRONMENT

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A comprehensive analysis of walking behaviour and safety of pedestrians in urban environment

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CERTIFICATE OF ORIGINALITY

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Abstract

Walking is the primary mean of access to essential urban goods and services. Like many metropolitan cities around the world, Hong Kong has been promoting walkability in its urban design and planning policy. Quality of urban walking environment is one of the crucial factors that affect the viability of a city. It can reshape the activity and mobility pattern of the citizens. However, pedestrians are also vulnerable to fatal and severe road injuries. Hence, it is necessary to identify the factors that affect walking behaviour and safety of pedestrians. Then, effective remedial measures can be developed to improve the walking environment and mitigate pedestrian injury risk. In this study, pedestrian walking behaviour and safety in urban environment will be evaluated at different levels. First, relationship between environment, traffic, safety perception and walking behaviour of individual pedestrian is investigated. Second, effects of street design, urban street tree, and traffic characteristics on pedestrian crash risk at the microscopic level are evaluated. Third, association between built environment, road network configuration, transport facilities, population socio-demographics and pedestrian crash risk at the macroscopic level is measured.

At the individual level, effects of walking environment, transport facilities, and personal characteristics on the walking path choice are evaluated using an attitudinal survey. In this part, the stated preference method is adopted to predict the preferred walking path of pedestrians, accessing to the urban rail transit stations. In particular, factors like mixture of indoor and outdoor environment, accessible design, sky and green view, road geometry, socio-demographics and travel habit are considered. Then, the integrated choice and latent variable model is adopted, accounting for the effect of unobserved heterogeneity. On the other hand, effects of weather and traffic conditions on pedestrian safety perception and crossing behaviour are explored using the immersive Cave Automatic Virtual Environment (CAVE) experiment. For example, relationship between adverse weather conditions like rain and fog, vehicle speed, and

pedestrian safety perception is examined. Furthermore, the casual inference approach, with inverse probability of treatment weight, is adopted to account for the possible confounding factors.

At the microscopic level, effects of road geometric design, transport facilities, and urban street trees on the pedestrian crash risk of individual streets are evaluated. For example, data on tree density and tree canopy cover is used. In addition, comprehensive pedestrian count data is also available for the estimation of pedestrian crash exposure. Furthermore, the multivariate Bayesian spatial approach is applied, accounting for the effects of spatial dependency and multivariate correlation.

At the macroscopic level, the roles of footbridges and underpasses in pedestrian safety at the zonal level are explored. With the three-dimensional digital map of pedestrian network, it is possible to estimate the connectivity of pedestrian network and accessibility of crossing facilities like footbridges and underpasses. Then, the Poisson lognormal approach is adopted, accounting for the effect of overdispersion. Furthermore, data on land use, road network, street environment, traffic characteristics, pedestrian crash, and population socio-demographics are usually aggregated at different spatial scales. To this end, the multiple membership multilevel modeling approach is adopted, accounting for the effects of hierarchical data structure and spatial correlation on the association measure of pedestrian crash risk at both microscopic and macroscopic levels.

To sum up, findings of perceptional survey, immersive CAVE experiment, and micro- and macroscopic level pedestrian crash model should shed light on the effective urban design and planning policy that can improve the walking environment and promote walking as the sustainable transportation mode in Hong Kong. Therefore, overall quality of living can be enhanced.

List of Publications

Publications arising from the thesis

Manman Zhu, N.N. Sze*, Sharon Newnam (2022). Effect of urban street trees on pedestrian safety: A microscopic level pedestrian casualty model using multivariate Bayesian spatial approach. *Accident Analysis and Prevention*, 176, 106818.

Manman Zhu, N.N. Sze*, Sharon Newnam, Dianchen Zhu (2023). Do footbridge and underpass improve pedestrian safety? A Hong Kong case study using three-dimensional digital map of pedestrian network. *Accident Analysis and Prevention*, 186, 107064.

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Manman Zhu, Daniel J. Graham, Nan Zhang, Zijin Wang, N.N. Sze* (2025). Influences of weather on pedestrian safety perception at mid-block crossing: A CAVE-based study. *Accident Analysis and Prevention*, 215, 107988.

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Chapter 1 Introduction

1.1 Research background

In the context of transit-oriented development, walking or cycling often constitutes a significant portion of travel time, which is crucial for enhancing urban mobility (Su et al., 2021a). Walkability is considered a key determinant of urban vitality, especially in densely populated and highly active cities. Many metropolises worldwide, including Hong Kong, Melbourne, London, Nanjing, and Tokyo, are actively promoting walking through urban design and planning policies. These cities have implemented innovative urban and transportation planning frameworks to enhance walkability, thereby improving the built environment, accessibility, and pedestrian safety. For instance, in Hong Kong, nearly 90% of daily trips rely on public transportation, with walking being the primary means of accessing these services and other essential urban amenities (Sze and Christensen, 2017). As walking becomes the main mode of accessing various urban facilities from transit stations, understanding how urban environment design elements influence pedestrian walking behaviour is crucial. In 2021, Hong Kong developed a comprehensive walking strategy to improve the pedestrian environment (Transport Department, 2021). The characteristics of pedestrian facilities, such as sidewalks, footpaths, crosswalks, footbridges, underpasses, landscaping, street trees, and public spaces, significantly impact pedestrian walking behaviour. The quality of the urban walking environment is vital for the city's sustainability, as it can reshape citizens' activity and mobility patterns.

Pedestrian activities are prevalent in urban areas, particularly within transit-oriented developments, yet pedestrian safety remains a significant concern due to their vulnerability to severe injuries in road crashes. Globally, pedestrians account for approximately 25% of all road fatalities, while in the Asia-Pacific area, pedestrians represent 14-22% of road deaths (World Health Organization, 2023). For instance, as illustrated in Figure 1.1, the total number of traffic accidents in Hong Kong experienced fluctuations over the seven years from 2017 to 2023. During the years 2017 to 2020, the proportion of pedestrian-related traffic accidents relative to the total number of traffic accidents showed an overall declining trend. However, from 2021 to 2023, this proportion exhibited an upward trend. Additionally, Hong Kong, characterized by its dense population and reliance on walking as the primary means of accessing public transportation, still reports an alarmingly high proportion of pedestrian fatalities, accounting for 56% of the total road deaths (Transport Department, 2022). Studies have shown that pedestrian crash frequencies are notably higher in areas surrounding metro stations and streets with numerous public transit stops, potentially due to unsafe crossing behaviours (Osama and Sayed, 2017; Raveesh et al., 2020; Sung et al., 2022). In Hong Kong, inattentiveness and reckless crossing are significant contributory factors to pedestrian-related road crashes, with a substantial proportion occurring at intersections without signal control and on footpaths or verges (Hong Kong Police Force, 2023; Transport Department, 2022; Zhu et al., 2024). Identifying factors that influence perceived safety risks and the likelihood of reckless crossing behaviour, especially at crash-prone locations like mid-block crossings, is essential for enhancing pedestrian safety (Hou et al., 2022; Rupp et al., 2016; Zhu et al., 2021). Hence, it is necessary to identify the factors that affect walking behaviour and safety of pedestrians. Then, effective remedial measures can be developed to improve the walking environment and mitigate pedestrian injury risk.

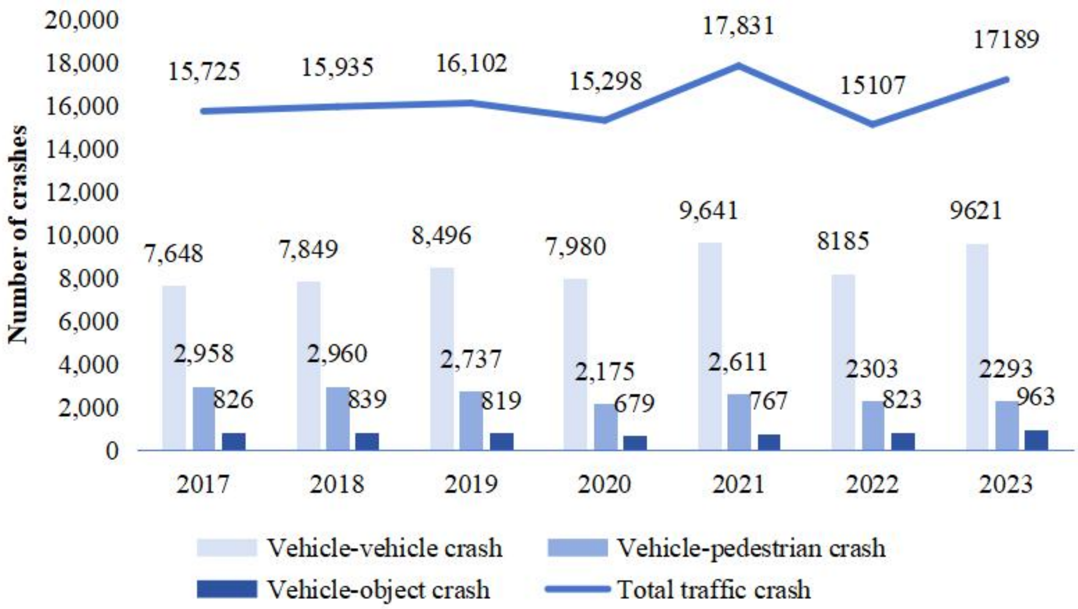


Figure 1.1 Road traffic crashes in Hong Kong from 2017 to 2023

1.2 Motivation and problem statement

This research aims to comprehensively explore pedestrian walking behaviour and safety in urban environment through interrelated aspects that analyze the impact of metro system accessibility, pedestrian network infrastructure, and street greening on pedestrian safety and walking behaviour at individual, microscopic, and macroscopic levels. The motivation and problem statement of the thesis is dedicated to the following aspects.

First, understanding pedestrian safety and walking behaviour at the individual level is crucial for enhancing the overall pedestrian experience in urban environments. Pedestrians often prioritize safety, comfort, and aesthetic appeal over merely choosing the shortest path, indicating that walking behaviour is influenced by a complex interplay of neighborhood-level attributes, street-level characteristics, and uncontrollable factors such as weather (Basu et al., 2023; Sevtsuk et al., 2021; Zhu et al., 2023a). In addition, safety perception, shaped by personal attitudes and social norms, plays a significant role in influencing pedestrian walking behaviour, including path and crossing choices (Lehtonen et al., 2016; Ram and Chand, 2016; Sayed et al., 2022). Thus, identifying factors that affect walking behaviour and pedestrian safety perception is essential for developing effective interventions.

Second, this study is motivated by the need to understand pedestrian safety at a microscopic level, focusing on specific entities such as road segments, intersections, and crosswalks. Previous research indicates that road characteristics, transport facilities, traffic control measures and environmental factors significantly impact pedestrian crash risk at a microscopic level (Kim, 2019; Koh et al., 2014; Zhao et al., 2020). However, in microscopic-level pedestrian safety research, urban greenery is a contentious factor. While increasing the proportion of street tree canopies can enhance the walking environment and encourage walking (Nehme et al., 2016), street trees are also considered roadside hazards due to potential visibility issues (Budzynski et al., 2016). Despite these insights, the specific impact of street tree density and canopy coverage on pedestrian injury risk remains underexplored, particularly when considering spatial dependency and crash exposure.

Last but not the least, the motivation for this study stems from the need to comprehensively understand pedestrian safety at a macroscopic level, particularly in complex urban environments like Hong Kong. Previous research has explored the relationship between various influencing factors and pedestrian crash frequency across different geographical units, considering elements such as population density, demographics, socio-economics, road network characteristics, and the built environment (Hu et al., 2020; Osama and Sayed, 2017; Su et al., 2021b). However, much of this research has focused on cities with limited footbridge or underpass networks, overlooking the unique topographical features of cities like Hong Kong, where extensive networks and hilly terrains significantly influence pedestrian route choices. Moreover, the modifiable areal unit problem and boundary crash problem highlight the complexities of spatial analysis in pedestrian safety, where the configuration and scale of geographical units can affect statistical inferences (Shin et al., 2020; Li et al., 2020a; Zhai et al., 2018; Zhai et al., 2019a). Therefore, at the macroscopic level, the roles of footbridges and underpasses in pedestrian safety at the zonal level are explored by considering the effects of spatial correlation.

1.3 Objectives

This research aims to assess walking behaviour and safety of pedestrians in urban environment at individual, microscopic, and macroscopic levels. The Figure 1.2 illustrates a comprehensive research framework comprising three primary components: individual, microscopic, and macroscopic level analysis. In response to the existing concerns elaborated in Section 1.2, the specific research objectives can be given as follows.

Firstly, the relationship between the environment, traffic, safety perception, and the walking behaviour of individual pedestrians is investigated. On one hand, the effects of weather conditions, walking attributes, environmental factors, available facilities, socioeconomic characteristics, and individual latent attitudes on metro passengers' walking preferences and behaviours are assessed. On the other hand, influences of weather conditions on pedestrian safety perception are examined, whereas confounding factors including traffic and pedestrian characteristics are controlled for.

Secondly, the effects of street design, urban street trees, and traffic characteristics on pedestrian crash risk at a microscopic level are estimated. The roles of road geometry, traffic characteristics, tree density, and tree canopy on pedestrian crash risk at the road segment level are explored.

Thirdly, the effects of the built environment, road network configuration, transport facilities, and population characteristics on pedestrian crash risk at the macroscopic level are explored. On one hand, the connectivity of the pedestrian network and the accessibility of crossing facilities are assessed, and the relationship between pedestrian network characteristics and pedestrian safety is evaluated. On the other hand, the study evaluates the impact of walking accessibility and different spatial scale data, such as land use, socio-demographics, pedestrian networks, and transport facilities, on pedestrian crash frequencies in areas surrounding metro stations.

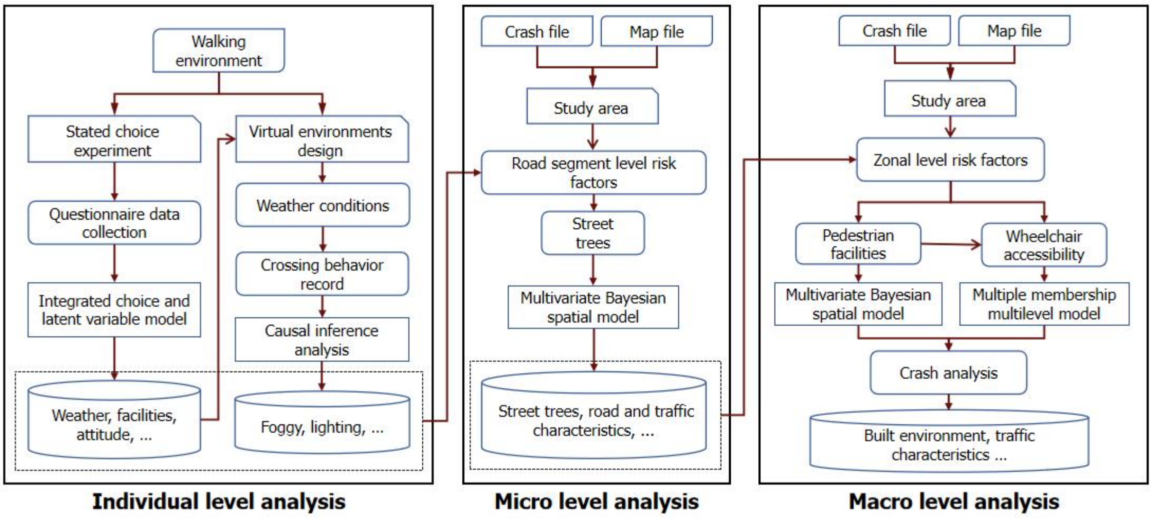


Figure 1.2 Research framework of pedestrian walking behaviour and safety

1.4 Thesis organization

Chapter 2 presents the literature on various aspects of walking behaviour and pedestrian safety studies, including pedestrian walking behaviour, influencing factors of pedestrian safety, and methods for walking behaviours and pedestrian safety.

Chapter 3 illustrates the roles of the environment and individual perception in pedestrian path choice by analyzing the relationships between the built environment, traffic conditions, individual perceptions, and walking path choices. The study assesses the walkability of Transit-Oriented Developments through stated preference experiments. Additionally, the effects of individual heterogeneity on decision-making are examined using an integrated choice and latent variable model.

Chapter 4 presents the impact of weather conditions, such as rain, fog, and low visibility, along with environmental factors on pedestrian risk perception at mid-block crossings, utilizing an immersive Cave Automatic Virtual Environment (CAVE) experiment. The study employs a propensity score method to estimate the causal effects of weather on safety perceptions, while inverse probability of treatment weighting is used to address the influence of multi-level data.

Chapter 5 unveils the impact of road geometric design, traffic facilities, and urban greenery on pedestrian crash risk at the microscopic level for individual streets. Pedestrian crash exposure is assessed using comprehensive pedestrian count data. A multivariate Bayesian spatial analysis method is applied to analyze spatial dependency and correlation in pedestrian casualty counts across different injury severity levels. Finally, how pedestrian crashes at the segment level are influenced by tree density and canopy coverage is discussed.

Chapter 6 illustrates pedestrian networks and facilities at a macroscopic level, with a focus on the impact of footbridges and underpasses on pedestrian crashes. Three-dimensional digital maps are utilized to estimate the connectivity and accessibility of pedestrian networks. Data are aggregated into a grid format. A multivariate Poisson log-normal regression model is employed to analyze fatal and severe injury and slight injury pedestrian, while accounting for unobserved heterogeneity, spatial correlation, and the interdependence of crashes counts.

Section 7 provides the impact of walking accessibility to the metro system on pedestrian safety. Walking accessibility for individuals with and without physical disabilities is considered. The multiple membership multilevel modeling approach is adopted, accounting for the effects of hierarchical data structure and spatial correlation on the association measure of pedestrian crash risk. Additionally, the section explores temporal instability in parameter estimation.

Chapter 8 concludes the study with a summary of the findings, implications, limitations, and future research directions.

Chapter 2 Literature review

This chapter presents the literature on walking behaviour and pedestrian safety analysis from several aspects. Section 2.1 reviews the literature on risk perception and influencing factors of pedestrian walking behaviours. Section 2.2 discusses the influencing factors of pedestrian safety, with a focus on the effect of built environments, traffic characteristics and socioeconomic and demographic factors. Section 2.3 reviews the literature with respect to analytic methods and critical methodological issues relating to pedestrian safety and walking behaviour analysis.

2.1 Pedestrian walking behaviours

2.1.1 Influencing factors on pedestrian walking choices

Beyond the behaviour of pedestrians crossing streets, it is crucial to understand pedestrian travel preferences during their journeys. When selecting walking routes, pedestrians do not strictly adhere to the shortest path. Although walking distance and travel time are key determinants of route choice, their significance is influenced by various other route characteristics (Sevtsuk et al., 2021; Zhu et al., 2023a). Pedestrians often prefer routes that are safer, more comfortable, or more aesthetically pleasing, as long as the detour remains within an acceptable range (Basu et al., 2023). Previous research indicates that pedestrian walking behaviour is significantly influenced by various attributes of the walking environment. These attributes can be categorized into three main types. First, neighborhood-level attributes impact the walking experience, including factors such as land use patterns, the distribution of points of interest, walking accessibility, the characteristics of the road network, and the socioeconomic characteristics of the local population (Liu et al., 2020; Liang et al., Sevtsuk, et al.,2021; 2023; Zhu et al., 2023b). Second, street-level attributes directly impact walking behaviour and encompass elements such as pedestrian crossing facilities, traffic volume, street greenery, street lighting, sidewalk width, and slope (Basu and Sevtsuk, 2022; Liu et al., 2024 Sevtsuk et al., 2021; Zhu et al., 2023a). Third, other exogenous and uncontrollable factors, such as weather conditions and weather, also play a role (Liu et al., 2015; Zhu et al., 2023a).

Current research on pedestrian walking preferences has identified several key factors influencing walking behaviour (Gupta et al., 2022; Paydar et al., 2020; Sun et al., 2016). The walking behaviour of metro passengers is primarily influenced by walking distance and time, as well as their interactions with environmental factors (Paydar et al., 2020). Studies indicate that when selecting walking routes, passengers prioritize minimizing walking distance, followed by safety considerations (Gupta et al., 2022; Sun et al., 2016). Although there are regional variations in walking distance and time, these distances generally fall within acceptable ranges, with the average acceptable walking time and distance being less than eight minutes and half a mile respectively (Kim, 2015; Sun et al., 2016). Additionally, factors such as connectivity, mixed land use, and pedestrian-friendly designs in the walking environment are crucial in facilitating walking behaviour (Gupta et al., 2022; Paydar et al., 2020). These elements enhance the convenience and attractiveness of walking, thereby influencing pedestrian walking behaviour. Furthermore, confounding factors including individual demographics, socioeconomic, and travel purpose that affect the underlying relationship between possible attributes and walking behaviour of transit passengers should be explored.

2.1.2 Safety perception and crossing behaviour

Pedestrians are among the most vulnerable road users, accounting for a significant share of road traffic fatalities. The majority of pedestrian crashes occur during road crossings, with urban areas posing the greatest risk. Consequently, understanding pedestrians' safety perception is essential for analyzing their crossing behaviour. Safety perception is a critical field of study due to its substantial influence on the behaviour and decision-making of road users in uncertain conditions, thereby directly or indirectly affecting road safety attitudes. Individuals with heightened safety perception are more likely to engage in cautious behaviour. Previous research has examined the impact of safety perception on walking behaviour, revealing a positive correlation between pedestrians' safety perception and their walking activity (Elias and Shiftan, 2012; Nehme et al., 2016; Rankavat and Tiwari, 2016). This suggests that when pedestrians perceive their environment as safe, they are more likely to engage in walking, highlighting the importance of fostering a sense of safety to promote pedestrian activity.

Several factors that influence pedestrian crossing behaviour and risk perception have been identified (Hou et al., 2022; Kwon et al., 2022; Li et al., 2022; Papadimitriou et al., 2016). These factors encompass pedestrian characteristics, such as age and gender (Hou et al., 2022; Pala et al., 2021). For example, older pedestrians often exhibit increased caution due to declines in cognitive and physical abilities (Pala et al., 2021; Wilmut and Purcell, 2022). Besides, crashes caused by the elderly are more frequent than those caused by the younger population, with a narrower safety margin and a slower pace when crossing the road (Pala et al., 2021). In contrast, male pedestrians generally perceive lower risk and tend to prefer taking risks (Morgenroth et al., 2018).

Additionally, various road and traffic characteristics, such as the number of lanes, road width, traffic signals, traffic volume, speed limits, and road infrastructure, as well as vehicle types, significantly influence pedestrian crossing behaviour (Kwon et al., 2022; Rankavat and Tiwari, 2016). For instance, previous research indicates that pedestrians are more likely to cross mid-block when traffic is light or absent, compared to when it is heavy or congested (Papadimitriou et al., 2016). Minor roads are more frequently chosen for mid-block crossings compared to major roads (Papadimitriou et al., 2016). Pedestrians are more sensitive to increased waiting times at signalized intersections than to the additional walking time required by pedestrian overpasses and underpasses (Zhu et al., 2023a). Studies also suggest that due to the generally larger mass of heavy vehicles, the risk of severe road crashes is relatively higher, leading pedestrians to avoid gaps closed by large vehicles (Kadali et al., 2015).

Environmental factors, such as the presence of street trees, roadside parking, pavement signs, and street lighting (Kwon et al., 2022; Rankavat and Tiwari, 2016), along with social and psychological factors like group behaviour and distraction (Aghabayk et al., 2021; Hou et al., 2022; Tian et al., 2022), significantly influence pedestrian crossing behaviour. Weather conditions also play a crucial role in altering these behaviours. Research indicates that adverse weather conditions lead to an increase in jaywalking incidents among pedestrians (Zafri et al., 2020; Zhai et al., 2019b). Under such conditions, pedestrians are more likely to engage in dangerous and noncompliant crossing behaviours (Zhai et al., 2019b). Moreover, pedestrians tend to cross streets more quickly in rainy conditions compared to normal weather (Bargegol et al., 2022). However, there is limited research on how safety perception mediates the relationship between road environments, traffic characteristics, and pedestrian crossing behaviour. It is crucial to identify the factors that influence pedestrians' safety perception.

Weather significantly influences pedestrian behaviour. For instance, pedestrians tend to exhibit more aggressive and risk-taking behaviours in adverse weather conditions, leading to an increased propensity for jaywalking (Ansariyar and Jeihani, 2023; Zafri et al., 2020). Additionally, pedestrians walk faster when crossing roads in rainy weather compared to clear conditions (Bargegol et al., 2022). Weather also affects pedestrians' perception of vehicular speed. In rainy conditions, pedestrians tend to underestimate vehicle approach speeds by over 20% (Sun et al., 2015). Conversely, in foggy weather, especially with the presence of street trees and road facilities, pedestrians often overestimate vehicle speeds (Sudkamp and Souto, 2023).

2.2 Influencing factors of pedestrian safety

Pedestrians are particularly vulnerable road users, exposed to numerous physical variables in their environment. Their fatality rate is higher than that of car occupants and other road users (Sze et al., 2019). The severity of pedestrian injuries in the event of a crash is influenced by a range of factors, including the demographics of both drivers and pedestrians (Liu et al., 2019; Morgenroth et al, 2018; Papadimitriou et al., 2016), road design and traffic characteristics (Damsere-Derry et al., 2019; Osama and Sayed, 2017;

Zhu et al., 2023b), the specific circumstances of the crash (Alhajyaseen et al., 2013; Prato et al., 2019), land use (Zhu at al., 2023b), physical environment(Hu et al., 2020; Xu et al., 2020), as well as weather conditions (Zhai et al., 2019b).

2.2.1 Effect of built environments

Studies have investigated the relationship between various influencing factors and the frequency of pedestrian crashes within geographical units such as counties, census tracts, and traffic analysis zones (Cai et al., 2016; Hu et al., 2020; Su et al., 2021b). At a macroscopic level, factors related to the built environment that influence pedestrian safety have been considered, including road network characteristics (Osama and Sayed, 2017; Wang et al., 2016), land use (Su et al., 2021b; Zhu et al., 2023b), points of interest (Su et al., 2021b), and transport facilities (Chimba et al., 2018; Lee et al., 2020; Zhu et al., 2023b). For example, pedestrian crash rates in commercial and industrial areas are significantly higher than in residential areas (Lee et al., 2020; Wong et al., 2007), largely due to the frequency of roadside pickup and drop-off activities (Kraidi and Evdorides, 2020). Conversely, pedestrian crashes tend to decrease as the proportion of green areas increases (Ryan et al., 2018; Zhu et al., 2024). Additionally, pedestrian crash risk is positively associated with road width and the number of lanes (Koh et al., 2014; Zhao et al., 2020). Furthermore, the presence of bus stops and metro exits is linked to an increase in pedestrian crashes (Chen and Zhou, 2016; Su et al., 2021b).

At a microscopic level, studies have assessed pedestrian crash risk for specific entities such as road segments, intersections, and crosswalks (Stipancic et al., 2020; Zhu et al., 2022a). The presence of schools, bus stops, transit stations, and on-street parking has been found to increase pedestrian crash risk (Kim, 2019; Kraidi and Evdorides, 2020; Zhu et al, 2022). Regarding the safety impacts of geometric and intersection characteristics, features such as three-way intersections, raised medians, roundabouts, curb extensions, and exclusive left-turn lanes have been shown to reduce pedestrian crash injuries (Kim, 2019; Vignali et al., 2020; Zafri et al., 2020). Researchers have also identified that road safety measures, such as raised medians and crosswalk markings, contribute to reducing pedestrian injuries by minimizing potential traffic conflicts between pedestrians and vehicles (Stipancic et al., 2020; Vignali et al., 2020). However, certain factors at road segments, including the total number of lanes, street trees, street lighting, park recreational land use, and commercial entrances, have been associated with an increased risk of pedestrian crashes (Zhang et al., 2017; Zhu et al., 2022a). Additionally, physical features such as median barriers and verges within road segment characteristics have been shown to reduce the number of pedestrian crashes (Zhu et al., 2022b).

2.2.2 Effect of traffic characteristics

Regarding the effect of traffic characteristics, vehicle speed and speed variation are one of the most important crash factors. Some studies suggest that average speed is negatively correlated with road crashes, while speed variation is positively correlated with crashes (Quddus, 2013; Xu et al., 2016). In addition, the effects of speed and speed variation were proved to be related to other traffic variables, such as flow (Choudhary et al., 2018; Xu et al., 2016). Additionally, several studies have evaluated the association between the pedestrian crashes and the type of vehicles (Choudhary et al., 2018; Hu and Cicchino, 2022; Molan et al., 2020). Large vehicles have a relatively high risk of serious road crashes (Kadali et al., 2015; Yannis et al., 2013). For instance, light truck vehicles were more likely involved in fatal crashes at or near intersections when compared with cars and light truck vehicles were also associated with increased odds of walking-along-roadway crashes (Hu and Cicchino, 2022).

Regarding traffic control characteristics, pedestrian crash risk decreases with the implementation of measures such as stop controls, exclusive pedestrian (green signal) phases, permissive right-turn signals (in left-hand drive contexts), pedestrian islands, and colored pavements (Kim, 2019; Stipancic et al., 2020; Vignali et al., 2020; Zafri et al., 2020). Conversely, pedestrian crash risk increases with higher traffic volumes (Zhu at al., 2022). Therefore, it is crucial to implement local area traffic management and traffic calming measures, such as low-speed limit zones and pedestrian priority traffic signals. These interventions can effectively reduce pedestrian injury risk at hotspots where pedestrian-vehicle conflicts are prevalent (Zhang et al., 2017; Zafri et al., 2020).

2.2.3 Effects of other factors

With regard to socioeconomic and demographic factors, areas with higher employment density, population density were positively correlated with the number of pedestrian crashes (Chimba et al., 2018; Hu et al., 2020). Besides, the population of neighborhoods commuting to work by walking, population of neighborhoods of housing units with no vehicles and population had a positive relation with the number of pedestrian crashes (Chimba et al., 2018). In addition, some studies showed that less female than male pedestrians in general were found to violate traffic rules, which indicates a higher risk tendency of the male pedestrians (Hidayati et al., 2020). Previous studies also found that age of the pedestrians is one of the factors influencing pedestrian safety. For instance, younger pedestrians were more likely to violate rules and elderly pedestrians are vulnerable and are at great risk of injury or death, when involved in a crash (Kim, 2019).

Studies have examined the effects of network characteristics on road safety (Clifton et al., 2009; Guo et al., 2017; Marshall and Garrick, 2011). Road crash is positively associated with network connectivity (Marshall and Garrick, 2011; Osama and Sayed, 2017). Crash rate of lollipop network with limited access is lower than that of grid network (Sun and Lovegrove, 2013). However, it is not the case for pedestrian crashes (Guo et al., 2017). Pedestrian crash increases with intersection density (Guo et al., 2017) number of links (Osama and Sayed, 2017), and node-to-link ratio (Guerra, et al., 2020). It is crucial to measure the association between pedestrian network configuration and pedestrian safety.

Weather and visual conditions significantly impact the severity of pedestrian injuries. Increased rainfall intensity can lead to reduced road roughness and visibility, thereby elevating the potential risk of crashes (Malin et al., 2019). The risk of pedestrian injury rises during rainy and snowy weather, largely due to reckless driving behaviours under adverse conditions (Li et al., 2017; Zafri et al., 2020; Zhai et al., 2019b). There is also a negative correlation between road lighting and the likelihood of severe pedestrian crashes, indicating that better lighting reduces crash severity (Li et al., 2017).

2.3 Methodological approaches for walking behaviours and pedestrian safety studies

2.3.1 Data acquisition for pedestrian studies

Attitudinal survey is commonly adopted for the understanding on choice decision and associated factors in transport studies (Liang et al., 2023; Liu et al., 2023). For example, revealed and stated choice experiments can be applied (Arellana et al., 2023). The former examines the underlying preferences based on observed or self-reported behaviour. Revealed preference study is relatively straightforward but may be limited to the observable choices. Potential choices and dynamic changes in the preferences over time may not be considered (Liang et al., 2023). To gain a comprehensive understanding on the travel behaviour, stated choice experiments, with which hypothetical scenarios and a wide range of attributes and levels are included, can be adopted (Basu et al., 2023; Chen et al., 2022; Liu et al., 2023). For instance, trade-offs between attributes like walking time and distance, visual attractiveness, safety and security, and level of comfort can be measured using hypothetical choice scenarios for pedestrian studies.

In recent years, emerging technologies like virtual reality are also adopted for the examination of pedestrian behaviours (Kwon et al., 2022; Pala et al., 2021). Compared to empirical surveys, virtual reality offers an efficient and cost-effective way to study pedestrian behaviours in a controlled manner. Furthermore, immersive CAVE automatic virtual environment is also adopted for the study of pedestrian crossing behaviour, with which the risk of simulator sickness of participants is mitigated (Mallaro et al., 2017; Pala et al., 2021). In addition to built environment, traffic control and personal characteristics, influences of visual and cognitive distractions on the pedestrian crossing behaviours are also explored using the immersive CAVE experiments (Tian et al., 2022).

2.3.2 Walking behaviour analysis

(1) Discrete choice models

In conventional transport studies, econometric methods like multinomial, ordered, and binary logit and probit regression models are adopted to measure the association between possible attributes and choice decision (Chen et al., 2021; Guo et al., 2023; Huang et al., 2019). Essentially, the integrated choice and latent variable model combines a latent variable model to enhance the explanatory power of the classical choice model to account for the effects of unobserved heterogeneity attributed to subjective perception (Chen et al., 2023; Guo et al., 2023; Wang and Song, 2024). The latent variable model captures the causal relationship between exogenous variables and latent factors, requiring a measurement model that represents the hypothesized relationship between the latent factors and attitudinal indicators.

(2) Causal inference approaches

Causal inference approaches like propensity score method are often adopted for the effectiveness evaluation of road safety interventions in empirical studies, with which the effects of possible confounding factors are controlled for (Li et al., 2020b; Zhang et al., 2021). Propensity score refers to the conditional probability of an entity being exposed to a "treatment" (or "intervention"), given a set of observed covariates (Rosenbaum and Rubin, 1983). The propensity score method balances the distribution of observed covariates between treatment and control groups by adjusting the balance values, with which the confounding factors and potential counterfactuals are accounted for. Otherwise, it would result in bias and imprecision of treatment effect estimates (Graham, 2022).

There are four common propensity score methods for covariate adjustment, namely regression, stratification, matching and weighting (Fuentes et al., 2022). In particular, propensity score is used to balance the pseudo-population by weighting each individual entity in accordance with the inverse probability of receiving its exposure (Fuentes et al., 2022; Zhang et al., 2023). It is effective in assessing the balance between entities with and without "treatment" for all observed covariates. Despite that, very few studies have adopted propensity score method for the matching of multi-level entities (Fuentes et al., 2022). For example, individual entities are nested within clusters in conventional safety studies. Furthermore, it is rare that the propensity score method is generalized to multiple treatment scenarios (Li et al., 2020b).

2.3.3 Pedestrian safety analysis

(1) Conventional models

To measure the association between crash frequency and influencing factors, count data models like Poisson, Poisson-gamma and Poisson-lognormal regression models are commonly used (Lee and Mannering, 2002; Lord and Mannering, 2010; Washington et al., 2020). However, issues like excessive zero observation and imbalanced crash data can be prevalent for disaggregate crash frequency model (Lord et al. 2005, 2007; Pei et al., 2016). In addition, accounting for the effect of unobserved heterogeneity (because of unknown or omitted variables) among the observation units, random parameters approach can be applied (Barua et al., 2016; Chen et al., 2021; Mannering et al., 2016).

To distinguish between the effects of influencing factors on different types of crashes, separate univariate models are estimated for the subsets of crash data with respect to crash type, transport mode, and injury severity (Lee and Mannering 2002; Qin et al. 2005; Wong et al., 2007). Alternately, joint probability model can be adopted, accounting for the correlation between crash counts of different types for an observation unit (Bhowmik et al., 2018; Pei et al., 2011; Su et al., 2021b). Furthermore, as the location of crash and other covariates are involved in the analysis, issues including spatial correlation between neighboring units and spatial heterogeneity should be considered using Bayesian model with conditional autoregressive (CAR) prior (Barua et al., 2014; Huang et al., 2019; Quddus, 2008).

(2) Multivariate models

In pedestrian safety analysis, it is often used to model specific types of pedestrian crash counts, such as crash severity (e.g., fatal, serious, minor). The application of univariate regression models separately ignores the fact that the number of crashes of one particular type cannot be independent of the number of crashes of other types. In other words, they are not independent of each other and they are correlated. This is a common problem in studies involving multivariable when using univariate statistical methods rather than multivariable statistical methods. Thus, multivariate regression models have been widely used for road safety analysis over the last decades, considering the unobserved effects and dependency across multiple crash counts (Aguero-Valverde, 2013; Ma et al., 2008; Sacchia and El-Basyouny, 2018).

(3) Multilevel model

Multilevel data structures often exist for built environment, traffic, population, and safety data in spatial crash analysis (Kim et al., 2014; Zhou and Zhang, 2019). For example, traffic and crash count of individual road entities like street links and intersections (individual-level) are nested within geographical units like street blocks, census tracts, and traffic analysis zones (group-level) (Zhao et al., 2020; Zhu et al., 2022a; Zhu et al., 2022b). In contrast, land use, population socio-demographics, and road network characteristics data are often aggregated at the group level (Cho et al., 2009; Hu et al., 2020; Wang et al., 2016; Zhu et al., 2023). Additionally, there are often repeated measurements for traffic flow and crash over time at each road entity (Huang and Abdel-Aty, 2010). It is necessary to account for both unstructured and structured disturbances, attributed to hierarchical and temporal data structures, in parameter estimation (Cai et al., 2018; Lee et al., 2017). To this end, Bayesian hierarchical and spatial models were adopted for the prediction of crash hotspots, accounting for the within-group and between-group disturbances in the estimation (Fawcett et al., 2017; Huang et al., 2016). Nevertheless, multi-level modeling approach was also proposed to explore the variability of intrinsic process for hierarchical data structure (Dupont et al., 2013).

2.4 Concluding remarks

This chapter presents the findings from a literature survey on pedestrian walking behaviour and safety assessment studies. Several research gaps have been identified in the existing literature, which are outlined as follows.

Firstly, while significant attributes influencing perceived walkability have been identified, their roles in the decision-making processes of urban transit passengers remain underexplored. Therefore, it is essential to investigate confounding factors, including individual demographics, socioeconomic status, and travel purpose, that affect the underlying relationship between these attributes and the walking behaviour of transit passengers.

Secondly, although several factors influencing pedestrian crossing behaviour and risk perception have been identified, the impact of weather conditions, which is a significant contributory factor to crashes, on pedestrian safety perception remains underexamined. Therefore, it is crucial to explore pedestrian perceptions and crossing behaviours under varying weather conditions.

Thirdly, while studies have explored the effects of urban street trees on road user perception, travel behaviour, and traffic safety in general, the specific relationship between street trees and pedestrian safety is seldom examined. Consequently, it is essential to investigate the effects of road geometric design, transport facilities, and urban street trees on pedestrian crash risk at the microscopic level for individual streets.

Fourthly, most studies have concentrated on the network connectivity and accessibility of cities with limited footbridges or underpasses. Therefore, it is crucial to consider topographical features, such as elevation and gradient, when evaluating the connectivity and accessibility of pedestrian networks. Additionally, data on land use, road networks, street environments, traffic characteristics, pedestrian crashes, and population socio-demographics are typically aggregated at varying spatial scales. To address this, a multiple membership multilevel modeling approach is employed, which accounts for the effects of hierarchical data structures and spatial correlations on the assessment of pedestrian crash risk at both microscopic and macroscopic levels.

Chapter 3 Effect of walking environment and perception on pedestrian path choice

3.1 Introduction

Transit-Oriented Development (TOD) has been implemented as a pivotal urban planning strategy in metropolitan cities like Nanjing (Nanjing Natural Resources Bureau, 2023), with special emphasis on integrated housing and commercial development around transit stations (Singh et al., 2017). TOD encourages the development of a compact neighborhood with a mix of various urban functions that are easily accessible by public transportation. An integrated metro system and public transport network often forms the backbone of an efficient transportation system of a transit-oriented city (Su et al., 2021a). This could then stimulate the modal shift from private cars to public transport, addressing the problems of car reliance, traffic congestion and carbon emission. Therefore, sustainable urban transport development can be promoted. In 2023, the average daily passenger trip made by metro in Nanjing City was 2.76 million. This constituted two-thirds of overall public transport trips in the city (Nanjing Transport, 2024a). In addition, walking has been the primary means of access for housing, study, work, shopping, leisure, and public transportation in a transit-oriented city (Singh et al., 2017; Su et al., 2021a). It is crucial to address the needs of pedestrian-friendly design for the "first mile and last mile" travel to and from the transit stations. To this end, it is necessary to understand the underlying relationship between pedestrian planning, walkability, and walking behaviour of pedestrians.

As aforementioned, TOD focuses on integrated development around transit stations. There are often seamless connections between indoor and outdoor spaces, with abundant natural lighting, green vegetation, amenities, crosswalks, and accessible design for person with disabilities (Chan et al., 2022). In Nanjing City, pedestrian friendly design is adopted at 134 metro stations (56.8% of overall). All these 134 stations are connected with nearby building development through grade-separated walkways (Nanjing Transport, 2024b). An early study indicated that provision of accessible design at the underground transit stations can increase transit use (Chan et al., 2022). However, the relationship between accessible design and walking path choice accessing the transit station is less explored. Furthermore, interference of pedestrian perception on the association between walking behaviour and possible attributes should be considered. In preceding studies, objective measures like connectivity, integration, and accessibility of pedestrian network were adopted to examine the relationship between walking behaviour and possible attributes using the space syntax method (Serra-Coch et al., 2018). However, influences of subject feelings including visual attractiveness, perceived safety, and level of comfort on the choice decision and behaviour of pedestrians are less studied. Hence, this study aims to examine the relationship between physical environment, traffic characteristics, subjective perception, and walking path choice of pedestrians for TOD through the stated choice experiments in Nanjing City. Contribution of this study is twofold. First, what roles do physical environment and subjective perception play in the walking behaviour are examined. In particular, influences of urban design, streetscape, weather, visual attractiveness, traffic dynamics, and connections between indoor and outdoor spaces around the metro stations on the choice decision are considered. Second, a hybrid approach of integrated choice and latent variable model is adopted, with which the influences of individual heterogeneity and subjective perception on the association between walking choice and other observed attributes are incorporated.

The remainder of this chapter is structured as follows. Stated choice experiment and analysis method are described in Section 3.2 and Section 3.3, respectively. Section 3.4 presents the estimation results and their policy implications. Finally, concluding remarks are given in Section 3.5.

3.2 Stated choice experiment

In this study, an attitudinal survey is conducted to measure the trade-offs between different attributes for the preferred walking path of pedestrians accessing urban rail transit stations. The questionnaire consists of three parts. First, information on gender, age, education and income of individuals is gathered. Second, importance of possible attributes that affect the perceived comfort and safety of pedestrians are measured. Third, hypothetical scenarios of stated choice are presented.

3.2.1 Perceived comfort and safety

In this study, two latent variables that indicate the effects of perceived comfort and safety on the choice preference of pedestrians are established. Table 1 illustrates the specification of latent variables. As shown in Table 1, attributes that affect the perceived level of comfort are quality of pedestrian facilities, pedestrian volume, and sidewalk width. On the other hand, attributes that affect the perceived safety are traffic flow volume, level of familiarity, and lighting (Basu and Sevtsuk, 2022; Sevtsuk et al., 2021; Zhu et al., 2023). For instance, the five-point Likert scale approach (with 1 implies strongly disagree and 5 implies strongly agree) is adopted for the estimation of relative importance. As also shown in Table 3.1, perceived level of comfort increases for the streets with better pedestrian facilities (average of 4.34 out of 5), fewer pedestrians (3.63), and wider sidewalks (4.20). On the other hand, perceived safety increases for the street with lower traffic volume (4.17), higher familiarity (4.37), and adequate lighting (4.41).

Table 3.1 Specification of latent variables

Scope of work	Description	Mean	Standard deviation
Perceived Comfort	C1: Street with better pedestrian facilities is preferred	4.34	0.79
	C2: Street with fewer pedestrians is preferred	3.63	1.07
	C3: Street with wider sidewalks is preferred	4.20	0.84
Perceived Safety	S1: Street with fewer vehicles is preferred	4.17	0.94
	S2: Street with higher familiarity is preferred	4.37	0.80
	S3: Street with lighting is preferred	4.41	0.76

3.2.2 Stated preference design

In this study, scenarios of possible walking path choices from a transit station to specific destinations are generated. For example, travel purposes including work, leisure, and back home are considered. In each choice scenario, two options are presented. Table 3.2 summarizes the attributes and levels considered in the stated choice experiments.

Table 3.2 Variables and attribute levels for the stated choice experiment

Variable	Attribute level	
Walking time	1	Short: 8 minutes
	2	Medium: 15 minutes
	3	Long: 25 minutes
Proportion of indoor link	1	Low: 10%
	2	Medium: 25%
	3	High: 40%
Connection between indoor and outdoor spaces	1	Easy: No difference in vertical levels
	2	Medium: Connected with elevators and lifts
	3	Difficult: Connected with staircases
Number of crosswalks	1	No: Zero
	2	Less: Two
	3	More: Five
Weather	1	Fine
	2	Hot
	3	Rainy
Proportion of sky view	1	Low: 10%
	2	Medium: 25%
	3	High: 40%
Proportion of green view	1	Low: 10%
	2	Medium: 25%
	3	High: 40%

As shown in Table 3.2, attributes including walking time, proportion of indoor link, connection between indoor and outdoor spaces, number of crosswalks, weather, and proportions of sky and green view from pedestrian perspective are included. Additionally, each attribute has three levels. If all possible combinations of attributes and levels were adopted, there would be $3^7 = 2,187$ options in the choice set. To improve the efficiency of estimation, a fractional factorial design is often adopted to examine the main and interaction effects with a minimum number of trials (Zhu et al., 2023). Furthermore, a D-efficient design approach can be adopted to increase the precision of estimation and minimize the standard errors (Chen et al., 2022). In this study, 24 choice scenarios are generated using the D-efficient approach with STATA package. Finally, the scenarios are divided into four blocks, each with six scenarios, to reduce the burden of individual participant. To enhance the presentation of choice scenarios and understanding of participant, illustrations based on the actual scenes in Nanjing City are provided (as shown in Figure 3.1).

	Option A	Option B
Work trip (select one ☑):	☐	☐
Leisure trip (select one ☑):	☐	☐
Home trip (select one ☑):	☐	☐
Weather	Hot	Rainy
Walking time	8 minutes	25 minutes
Proportion of indoor link	Low	Medium
Connection between outdoor and indoor links	Medium	Easy
Number of crossings	3	0
Proportion of sky view	 Medium	 Low
Proportion of green view	 Low	 High

Figure 3.1 An example of stated choice experiment (English translation)

3.2.3 Attitudinal survey

The stated preference survey was conducted in Nanjing City during the period between April and May 2024. Participants were recruited through an online survey platform (www.powercx.com). Inclusion criteria of participants are (i) lived in Nanjing City for not less than 12 months, (ii) aged not less than 18 years; and (iii) used Nanjing Metro in preceding 12 months. Informed consent was sought prior to the survey. Overall, a sample of 600 participants (with 600 x 6 = 3600 observations of choice scenarios) was collected. Table 3.3 summarizes the characteristics of participants. As shown in Table 3.3, 41.7% of participants were male, about half (54.3%) were young adult of age between 26 and 35 years, and majority (78.2%) attained tertiary education. Furthermore, the majority earned between 5,000 and 19,999 RMB (i.e., 703 to 2,812 USD) per month.

Table 3.3 Summary statistics of the sample

Variable	Attribute	Count	Proportion
Gender	Male	250	41.7 %
	Female	350	58.3 %
Age	18 – 25 years	81	13.5 %
	26 – 35 years	326	54.3 %
	36 – 45 years	166	27.7 %
	Above 45 years	27	4.5 %
Education level	Secondary education or below	131	21.8 %
	Tertiary education or above	469	78.2 %
Employment status	Full-time employment	530	88.3 %
	Self-employed	25	4.2 %
	Student	25	4.2 %
	Other	20	3.3 %
Monthly income	Less than 5,000 RMB	74	12.3 %
	5,000 – 9,999 RMB	222	37.0 %
	10,000 - 19,999 RMB	232	38.7 %
	20,000RMB or above	72	12.0 %

Note: Number of responses: 600

3.3 Method of analysis

In conventional transport studies, econometric methods like multinomial, ordered, and binary logit and probit regression models are adopted to measure the association between possible attributes and choice decision. To account for the effects of unobserved heterogeneity attributed to subjective perception, an integrated choice and latent variable model is adopted in this study (Chen et al., 2023; Guo et al., 2023; Wang and Song, 2024).

Figure 3.2 illustrates the framework of integrated choice and latent variable model proposed. As shown in Figure 3.2, a measurement model is adopted to measure the relationship between latent variables (i.e., perceived comfort and safety) and observed attributes like quality of pedestrian facilities, pedestrian volume, sidewalk width, traffic flow, familiarity, and street lighting. Then, a choice model is established to examine both the direct and indirect effects of pedestrian socio-demographics, stated choice attributes (i.e., walking time, weather, proportion of indoor link, connection between indoor and outdoor spaces, and proportions of sky and green views), and latent variables on the choice decision using random utility model. Table 3.4 summarizes the variables and attribute levels considered in the proposed integrated choice and latent variable model.

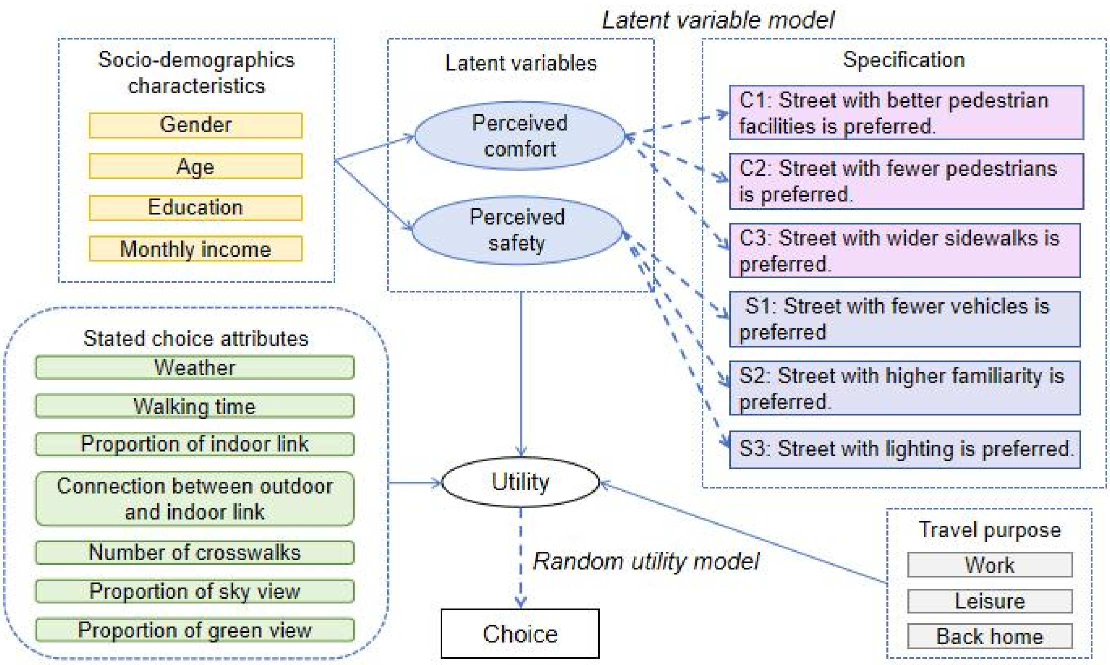


Figure 3.2 Framework of the proposed integrated choice and latent variable model

Table 3.4 Variables considered in the proposed model

Scope of work	Variable	Attribute
Socio-demographics	Gender	1: Male; 0: Female
	Age	1: 35 years or below; 0: Otherwise
	Education level	1: Tertiary or above; 0: Secondary or below
	Monthly income	1: Less than 10,000 RMB; 0: 10,000 RMB or above
Latent variable	Perceived comfort	Minimum: 1; Maximum: 5
	Perceived safety	Minimum: 1; Maximum: 5
Weather	Hot weather	1: Yes; 0: No
	Rainy weather	1: Yes; 0: No
Route attribute	Walking time	Minimum: 8; Maximum: 25
	Proportion of indoor links	Minimum: 0.1; Maximum: 0.4
	Connection with lift	1: Yes; 0: No
	Connection with staircases	1: Yes; 0: No
	Number of crossings	Minimum: 0; Maximum: 5
Street view	Proportion of sky view	Minimum: 0.1; Maximum: 0.4
	Proportion of green view	Minimum: 0.1; Maximum: 0.4

3.3.1 Latent variable model

The latent variable model consists of two components: (1) a structural model for the association between pedestrian socio-demographics and latent variables, and (2) a measurement model for the relationship between observed attributes and latent variables. For instance, the structural model for latent variable *k* of individual *i* is specified by,

$$x_{ik}^{*} = \delta_k + \beta_k u_i + \phi_k^i \sigma_{\phi_k} \qquad (Eq.\ 1)$$

where u_i denotes the vector of personal characteristics of individual i, β_k is the vector of corresponding parameters, ϕ_k^i denotes the vector of standard normally distributed random error terms, and σ_{ϕ_k} is the scale parameter.

Then, the conditional probability is specified by,

$$P(x_{ik}^{*}|u_i) = \psi\left(\frac{x_{ik}^{*} - \beta_k u_i}{\sigma_{\phi_k}}\right) \qquad (Eq.\ 2)$$

where ψ is the standard normal density function.

On the other hand, the measurement model that links the latent variables and observed attribute y^{i*}_{ko} (o = *C1*, *C2*, *C3*, …, and *S3* in this study) can be given by (Bouscasse, 2018; Wang and Song, 2024),

$$y^{i*}_{ko} = \theta_{ko} + \beta_{ko} x^{*}_{ik} + \eta^{i}_{ko}\sigma_{\eta_o} \qquad (Eq.\ 3)$$

where θ_{ko} is the intercept, β_{ko} is the parameter for attribute o, η^{i}_{ko} is the standard normally distributed random error terms, and σ_{η_o} is the scale parameter.

As aforementioned, five-point Likert scale approach is adopted for the observed attributes, the probability function can be specified using ordered probit regression method as,

$$y^{i}_{ko} = \begin{cases} 1 & y^{i^*}_{ko} < \tau_1 \\ 2 & \tau_1 \leq y^{i^*}_{ko} < \tau_2 \\ \vdots & \vdots \\ m & \tau_{m-1} \leq y^{i^*}_{ko} \end{cases} \qquad (Eq.\ 4)$$

where y^{i}_{ko} is the observed response, $\tau_1, \tau_2, \ldots, \tau_{m-1}$ are thresholds, and m = 5 respectively.

Furthermore, two positive parameters δ_1 and δ_2 are defined, considering the symmetrical nature of the thresholds. Hence, the thresholds are specified as,

$$\begin{aligned} \tau_1 &= -\delta_1 - \delta_2 \\ \tau_2 &= -\delta_1 \\ \tau_3 &= \delta_1 \\ \tau_4 &= \delta_1 + \delta_2 \end{aligned} \qquad (Eq.\ 5)$$

Finally, the probability of observed responses can be written as,

$$P(y_{ko}^{i}|x_{ik}^{*}) = \prod_{no}\left(\Phi\left(\frac{\tau_n-(\theta_{ko}+\beta_{ko}x_{ik}^{*})}{\sigma_{\eta_o}}\right) - \Phi\left(\frac{\tau_{n-1}-(\theta_{ko}+\beta_{ko}x_{ik}^{*})}{\sigma_{\eta_o}}\right)\right) \qquad (Eq.\ 6)$$

where Φ is the standard normal cumulative distribution function, and n = 1, 2, 3 and 4.

3.3.2 Random utility model

In this study, the binary logit regression approach is adopted to model the preferred walking path with the utility function given by,

$$v_i = \alpha w_i + \gamma x_i^{*} + \varepsilon_i \qquad (Eq.\ 7)$$

where w_i and x_i are the observed and latent variables of observation i, α and γ are corresponding parameters, and ε_i is the independent and identically extreme value distributed error term.

Then, the probability is given by,

$$P(Z = 1) = \frac{e^{v}}{1+e^{v}} \qquad (Eq.\ 8)$$

To model the joint probability, the integrated choice and latent variable model is given by,

$$P(z_i, y_{ko}^{i}|x_i^{*}, w_i) = \int_{x_i^{*}} P(z_i = 1|w_i, x_i^{*}) \bullet P(y_{ko}^{i}|x_i^{*}) \bullet P(x_i^{*}|w_i) dx_i^{*} \qquad (Eq.\ 9)$$

Nevertheless, effects of unobserved heterogeneity and panel data are also accounted using mixed approach.

3.4 Results and discussion

3.4.1 Latent variables

Table 3.5 presents the parameter estimation results for the structural model of perceived comfort and safety. Personal attributes including gender, age, education level, and monthly income are considered. As shown in Table 3.5(a) and Table 3.5(b), there is no significant difference in parameter estimates among travel purposes, i.e., work, leisure, and back home.

For perceived comfort, as shown in Table 3.5(a), perceived comfort is higher for pedestrians of age 35 or below. This is because younger adults tend to prioritize the options with higher levels of comfort in travel choice (Olsson et al., 2020). Additionally, there are positive associations between perceived comfort, education level and monthly income perceived comfort. Such a finding is intrinsic as people with higher education level and income tend to prioritize options with better quality. Nevertheless, there is no significant effect for gender on perceived comfort.

For perceived safety, as shown in Table 3.5(b), effects of gender, age, education level, and income are significant. For instance, perceived safety is lower for male and pedestrians of age 35 or below. Such findings are consistent with those in previous traffic psychology studies. Male and younger adults tend to be more risk-taking. They are less sensitive to road hazards (Rišová and Madajová, 2020; Salducco et al., 2022). In contrast, perceived safety is higher for pedestrians with high education level and monthly income. This justifies the effectiveness of education in enhancing road safety awareness and promoting the compliance of road traffic rules (Cordellieri et al., 2016). Furthermore, it is intrinsic that people with higher income tend to have higher safety awareness. Also, they could have been more risk averse (Heydari et al, 2019).

Table 3.5 Results of parameter estimation for the structural model

(a) Perceived comfort

Variable	Work trip		Leisure trip		Home trip	
	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error
Male	-0.003	0.15	-0.005	0.21	-0.004	0.19
Age of 35 years or below	0.031*	0.04	0.034*	0.03	0.033*	0.05
Tertiary education or above	0.075*	0.08	0.081**	0.11	0.080**	0.13
Monthly income more than 10,000 RMB	0.051*	0.07	0.048*	0.08	0.047*	0.09

** Significant at the 5% level*

*** Significant at the 1% level*

(b) Perceived safety

Variable	Work trip		Leisure trip		Home trip	
	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error
Male	-0.071*	0.06	-0.062*	0.05	-0.065*	0.05
Age of 35 years or below	-0.048*	0.04	-0.061*	0.06	-0.055*	0.06
Tertiary education or above	0.083**	0.15	0.094**	0.19	0.086**	0.12
Monthly income more than 10,000 RMB	0.55*	0.02	0.57*	0.05	0.53*	0.08

** Significant at the 5% level*

*** Significant at the 1% level*

Table 3.6 presents the parameter estimation results for the measurement model. As shown in Table 3.6, all parameters (β) for perceived comfort and perceived safety are statistically significant, regardless of the travel purpose. Furthermore, thresholds for the ordered model are also estimated.

Table 3.6 Results of parameter estimation for the measurement model

Variable		Work trip					Leisure trip					Home trip				
		$\beta_{l,k}$	τ_1	τ_2	τ_3	τ_4	$\beta_{l,k}$	τ_1	τ_2	τ_3	τ_4	$\beta_{l,k}$	τ_1	τ_2	τ_3	τ_4
Perceived comfort - C_1	Parameter	0.568*	-1.055	-0.357	0.698	1.055	0.689*	-1.314	-0.513	0.801	1.314	0.614*	-1.321	-0.527	0.794	1.321
	Standard error	0.022					0.018					0.033				
Perceived comfort - C_2	Parameter	0.891*	-1.822	-0.639	1.183	1.822	0.879*	-1.838	-0.701	1.137	1.838	0.793*	-1.512	-0.584	0.928	1.512
	Standard error	0.054					0.061					0.039				
Perceived comfort - C_3	Parameter	0.788*	-1.412	-0.433	0.979	1.412	0.533*	-1.01	-0.308	0.702	1.01	0.739*	-1.659	-0.579	1.08	1.659
	Standard error	0.047					0.042					0.041				
Perceived safety - S_1	Parameter	0.639*	-1.478	-0.496	0.982	1.478	0.708*	-1.512	-0.537	0.975	1.512	0.703*	-1.551	-0.521	1.03	1.551
	Standard error	0.028					0.021					0.028				
Perceived safety - S_2	Parameter	0.482*	-0.919	-0.236	0.683	0.919	0.656*	-1.386	-0.487	0.899	1.386	0.526*	-1.298	-0.457	0.841	1.298
	Standard error	0.027					0.033					0.039				
Perceived safety - S_3	Parameter	0.954*	-2.278	-0.796	1.482	2.278	0.841*	-1.76	-0.609	1.151	1.76	0.896*	-1.846	-0.634	1.212	1.846
	Standard error	0.081					0.071					0.069				

** Significant at the 5% level ; ** Significant at the 1% level*

3.4.2 Walking path choice

Table 3.7 presents the parameter estimation results for the integrated choice and latent variable model. There is no major difference in parameter estimates among the models for different travel purposes.

For the effects of socio-demographics of pedestrians, as shown in Table 3.7, factors including gender (Work: -0.351; Leisure: -0.014; Back home: -0.017), age (0.004; -0.042; -0.047) and monthly income (0.807; 0.211; 0.181) all significantly affect the choice of pedestrians, regardless of the travel purpose, at the 5% level. Nevertheless, effects of education level (-0.079; -0.473; -0.314) on walking path choices are marginal. For the effects of pedestrian perception, pedestrians tend to choose the walking paths that have higher level of perceived comfort (0.7335; 0.748; 0.969) and perceived safety (0.801; 0.778; 0.978), all at the 5% level.

For the effects of weather condition, as shown in Table 3.7. Both hot weather and rainy weather are associated with expected negative coefficients, suggesting that pedestrians are less inclined to travel during adverse weather conditions. Furthermore, the parameter for rainy weather is higher (-0.377; -0.881; -0.283) than that for hot weather (-0.294; -0.754; -0.042), indicating that different weather conditions have varying impacts on walking decisions. Additionally, metro passengers' perceived walkability for leisure purposes is more significantly affected by weather conditions than other travel purposes. This justifies that pedestrians are sensitive to the weather conditions in walking path choice. Adverse weather conditions like rain and extreme high temperatures can modify the relationship between possible factors and utilities of specific walking path (Liu et al., 2015).

For the effects of route attributes, as shown in Table 3.7, it is intrinsic that paths with longer walking time (Work: -0.036; Back home: -0.002) are less preferred, for work and back home trips, at the 5% level (Chen et al., 2023). Paths with longer walking time might be preferred for leisure trips (0.023), even if the effect is marginal. In addition, paths with higher proportions of indoor link (work: 0.001, leisure: 0.007, home: 0.002) are more preferred, regardless of the travel purpose, all at the 5% level. This is because indoor links usually have level surfaces, shops and amenities. They are often considered as safe, comfortable, and pedestrian-friendly since possible hazards like road traffic, air pollutants, adverse weather, injuries, and crimes can be avoided (Sun et al., 2016; Zhu et al., 2024). Furthermore, walking paths that are connected by lift (0.065; 0.035; 0.106) are preferred, regardless of the travel purpose, all at the 5% level. In contrast, walking paths that are not equipped with an accessible design (i.e., connection with staircases only) are less preferred (-0.104; -0.361; -0.080), at the 5% level. Last but not least, walking paths that have more crosswalks are less preferred (-0.032; -0.018; -0.020), regardless of the travel purpose. Such finding is consistent with that of our previous study (Zhu et al., 2023).

For the effects of street view from pedestrians' perspectives, as shown in Table 3.7, walking paths that have more sky view (0.008; 0.011; 0.003) are preferred, regardless of the travel purposes, all at the 1% level. It is because of the positive association between open sky and pleasant feeling (Liu et al., 2024). Just, the favorable effects of green view are less significant, compared to that of sky view. As also shown in Table 3.7, there is significant association between green view (0.006) and utility for leisure trip only at the 5% level. This is because of the effectiveness of greenery in alleviating the anxiety and depression symptoms (Nordfjærn et al., 2014).

Table 3.7 Results of parameter estimation for the choice model

Variable	Work trip		Leisure trip		Home trip	
	Parameter	t-statistics	Parameter	t-statistics	Parameter	t-statistics
Constant	0.944*	2.08	1.213*	1.96	1.458*	2.03
Gender	-0.351**	-2.73	-0.014*	-1.99	-0.017*	-2.15
Age	0.004*	1.99	-0.042*	1.96	-0.047*	1.99
Education level	-0.079^	-1.93	-0.473^	-1.94	-0.314^	-1.94
Monthly income below 10000 RMB	0.807*	1.99	0.211^	1.85	0.181^	1.95
Perceived comfort	0.735**	2.82	0.748**	2.65	0.969*	2.47
Perceived safety	0.801**	2.69	0.778*	2.37	0.978*	2.31
Hot weather	-0.249**	-4.87	-0.754**	-3.96	-0.042**	-2.98
Rainy weather	-0.377**	-7.35	-0.881**	-10.39	-0.283**	-3.69
Walking time	-0.036**	-11.85	0.023^	1.84	-0.002**	-2.84
Proportion of indoor link	0.001*	1.99	0.007*	2.31	0.002*	2.55
Connection with lift	0.065*	1.99	0.035*	2.01	0.106*	2.34
Connection with staircases	-0.104*	-2.06	-0.361*	-2.27	-0.080**	-2.62
Number of crossings	-0.032**	-2.60	-0.018*	-2.36	-0.020**	-2.87
Proportion of sky view	0.008**	6.22	0.011**	4.68	0.003**	3.54
Proportion of green view	0.002	1.62	0.006*	1.96	0.002^	1.79

^ *Significant at the 10% level*
* *Significant at the 5% level*
** *Significant at the 1% level*

3.5 Concluding remarks

There has been concern for rapid urbanization in many developing countries. Urban agglomeration often results in problems like traffic congestion, air pollution, noise, and road injuries. To this end, transit-oriented development (TOD) is increasingly implemented to resolve the problem of unsustainable urban development. With the integration of housing development and urban rail transit system, modal shift to public transport and walkability are promoted. Studies have explored the relationship between TOD and walkability, based on the metrics like connectivity, integration, and accessibility of pedestrian networks. However, the moderation effect of pedestrian perception on the association between physical environment and walking behaviour of pedestrians is less considered. Furthermore, pedestrians' preference on the indoor environment, vertical access, and visual perspective in the decision-making process is rarely explored. In this study, a stated choice experiment is established to gauge the trade-off of pedestrians among different physical environment attributes in walking path choice. Additionally, perceived comfort and safety of the walking path are also considered. Furthermore, an integrated choice and latent variable model is adopted for the parameter estimation. Results indicate that route attributes like walking time, proportion of indoor link, vertical access, and sky and green views significantly affect the path choice of pedestrians for work, leisure, and back home trips from the metro stations. For instance, shorter routes, more indoor links, better vertical access, and more sky view are preferred. Nevertheless, perceived safety and comfort, socio-demographics, and weather can also modify the relationship between route attributes and walking path choice.

Findings are indicative to future pedestrian planning and urban design strategies. For example, perceived walkability can be enhanced when more environmental-friendly design including covered walkway, accessible design including ramps, elevators and movable walkways, and open space and sky view are provided. Nevertheless, this study also has limitations. First, effects of spatial dependency and panel data could be accommodated using advanced econometric methods. Second, effects of spatial-temporal dynamics of real-time traffic and pedestrian flow on the walking behaviour of pedestrians could be explored using advanced microscopic traffic simulation model. Third, effects of walking experience on the walking behaviour could have been explored using virtual reality simulation and field observation.

In our recruitment of survey respondents, we primarily utilized online questionnaires. This method may have unintentionally biased our sample towards younger and middle-aged individuals. Older adults might have been less likely to participate due to potential unfamiliarity with online platforms or limited exposure to areas where these surveys are typically advertised. To address this issue in future research, we can design targeted surveys specifically for the elderly population.

Chapter 4 Effect of weather and traffic conditions on pedestrian safety perception at mid-block crossing

4.1 Introduction

Pedestrians are vulnerable to fatal and severe injuries in road crashes. About a quarter of road fatalities around the world were pedestrians in 2023 (World Health Organization, 2023). Hong Kong is a densely populated city. Walking is the primary mean of access to public transport services. However, the majority of road deaths (65%) are pedestrians. Inattentiveness and reckless crossing of pedestrians are the major contributory factors to road crashes involving pedestrians (Hong Kong Police Force, 2023; Zhu et al., 2024). It is necessary to identify the possible factors that affect the perceived safety risk, and therefore, likelihood of reckless crossing behaviour of pedestrians (Hou et al., 2022; Rupp et al., 2016; Zhu et al., 2021), particularly at the accident-prone locations like mid-block crossings (Siddiqui et al., 2006).

Weather is recognized as a crucial factor that affects road user behaviour and traffic safety. Adverse weather conditions like rain and fog have significant impacts on driver and pedestrian behaviour (Liu et al., 2015; McCann and Fontain, 2016). For example, cognitive performance of drivers and pedestrians could have been impaired in the low visibility condition since the capabilities of visual and auditory cognitions to the environment are reduced (Ingold, 2005; Malin et al., 2019; Półrolniczak and Kolendowicz, 2023). However, previous studies mainly focus on the impairment of driver behaviour. Associations between weather, safety perception and crossing behaviour of pedestrians are less explored (Druta et al., 2020; Zhai et al., 2019b). To this end, it is crucial to examine the interdependence between pedestrian safety perception, weather, and other possible confounding factors.

In this study, influences of weather conditions on pedestrian safety perception at the mid-block crossing are examined using the immersive CAVE experiment. For instance, pedestrian safety perceptions in different weather conditions are compared using a causal inference model. Furthermore, effects of multilevel data for multiple treatments are accounted using inverse probability of treatment weighting. The contribution of this study is twofold. First, associations between weather, other possible factors and pedestrian safety perceptions are measured. Second, the effects of multiple treatments on the causal inference are accounted for using advanced statistical methods.

The remainder of this chapter is structured as follows. Methods of data collection and analysis are described in Section 4.2 and Section 4.3, respectively. Section 4.4 summarizes the results of causal inference. Finally, concluding remarks are given in Section 4.5.

4.2 Data collection

4.2.1 Study design

In this study, the 3D model of a typical mid-block crossing in Hong Kong is developed. The selected site is near a metro station – Sha Tin Wai. As shown in Figure 4.1, the crossing is at a one-way single lane local street. Pedestrian footpaths are available on both sides of the street. To provide more realistic experience to the participants, design and layout of road features like road barriers, road markings, traffic signs, and street lighting are similar to those in Hong Kong. In the experiment, a participant would “stand” at the kerbsides. Vehicles with varying gap sizes are approaching from the right-hand side, and the participant would be asked whether a suitable gap exists for him or her to cross safely.

Figure 4.1 3D virtual reality model of the study site

In this study, factors including vehicle speed, gap size, weather, and lighting are considered. A gap refers to the time difference between the arrival of the rear bumper of a leading vehicle and the front bumper of a following vehicle. Gap acceptance can be affected by factors including demographics, personal attitude, walking speed, and perception-reaction time of pedestrians (Feldstein, 2019; Soares et al., 2021; Stafford et al., 2019). For crosswalks on single-lane roads, the acceptable gap typically ranges from 2 to 5 seconds. Gap acceptance is generally not sensitive to gap sizes smaller than 2 seconds or larger than 5 seconds (Tian et al., 2022). Therefore, this study considers a gap size range of 1 to 5 seconds. As shown in Table 4.1, there are two levels for vehicular speed, five levels for vehicle gap, three levels for weather, and two levels for lighting, respectively.

Table 4.1 Factor attributes considered in the experiment

Factor	Attributes
Vehicle speed	30 km/h, 50 km/h
Gap	1 second, 2 second, 3 second, 4 second, 5 second
Weather	Fine weather, rain, light fog, heavy fog
Lighting	Daytime, dusk

However, there could have been 80 = 2 x 5 x 4 x 2 experiment scenarios if all possible combinations were considered. To improve the efficiency of experiments, three schemes of approaching traffic with varying gap sizes (see Figure 4.2) and five scenarios of weather and lighting conditions (see Figure 4.3), i.e. (I) daytime – fine weather; (II) daytime – rain; (III) dusk – rain; (IV) daytime – light fog; and (V) daytime – heavy fog, respectively, would be presented. In each scheme, as shown in Figure 4.2, there are eleven gaps with size ranging from 1 to 5 seconds. To this end, there are 30 = 2 (vehicle speed) x 3 (scheme of vehicle gaps) x 5 (weather and light conditions) trials for the experiments. Order of the 30 trials would be randomized for each participant to avoid the learning effect.

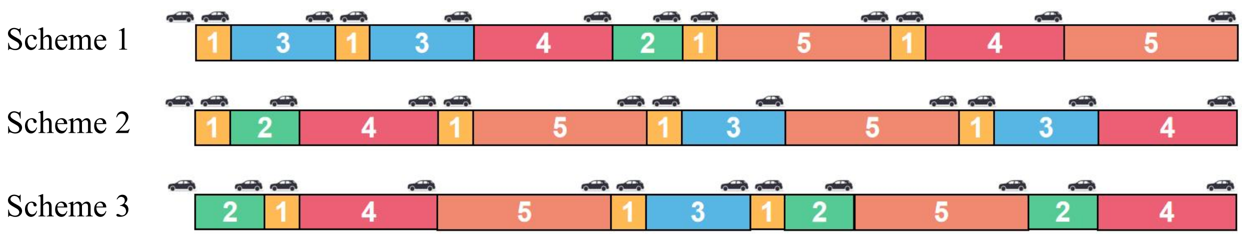


Figure 4.2 Gap sizes (in seconds) in different experimental schemes

(a) Daytime – Fine weather

(b) Daytime - Rain

(c) Dusk - Rain

(d) Daytime – Light fog

(e) Daytime – Heavy fog

Figure 4.3 Illustrations of different weather conditions

Figure 4.4 illustrates the instrument used in this study. The immersive CAVE has four screens, with the size of 2.2 metre high x 3.2 metre wide x 2.6 metre deep. As shown in Figure 4.4, participants would stand in the middle of the CAVE and wear a pair of active stereo shutter glasses. This is to avoid the genlock problem for the synchronized signal.

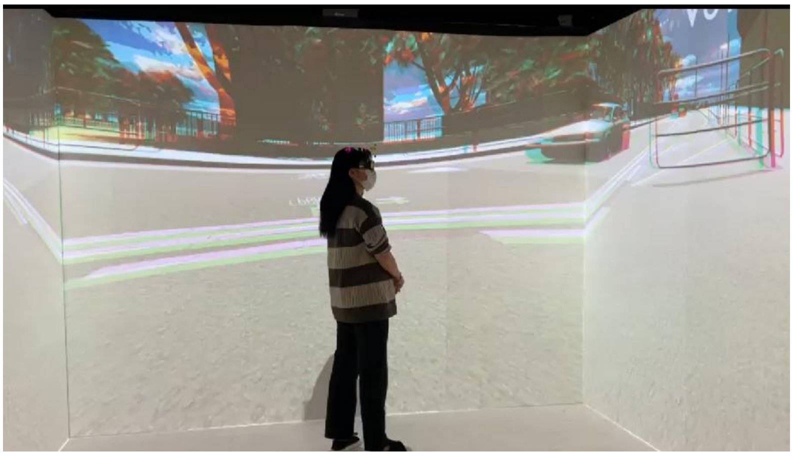


Figure 4.4 CAVE used in this study

4.2.2 Study procedures

A power analysis is conducted to determine the necessary sample size (Cohen, 2013). For example, assuming an effect size of 0.15, a statistical power of 0.9, and a significant level of 0.05, the required sample size is 47. Therefore, 50 participants are recruited for the experiments. The inclusion criteria include age of 18 years or above, lived in Hong Kong for more than 12 months, good physical health, normal or corrected-to-normal full-colour vision, capable for walking, and with no hearing problem. Mean age of the participants is

31.6 years (range: 18 years to 60 years). 25 are males and 25 are females respectively. No simulation sickness occurs in the experiments. Research ethics approval was obtained from the Human Subjects Ethics Sub-committee of the Hong Kong Polytechnic University. Written consent for participation was sought. Also, an honorarium of HKD 100 would be given for each participant.

For each participant, the duration of the experiment is about 60 minutes. First, a briefing session would be given for the introduction of study purpose, experiment procedures, and safety precaution. Also, a survey on personal characteristics like gender, age, and travel habits would be conducted and informed consent would be sought. Second, a practice session would be given to help familiarize the participants with the operation of instrument and experiment procedures. Third, each participant would be asked to complete 30 trials of gap acceptance tests. A five-minute break would be given after every ten trials. Lastly, a perceptional survey would be conducted to measure the participants' attitude towards the experiments. Overall, there are 1,500 observations (50 participants x 30 trials).

As mentioned, eleven vehicle gaps, with varying gap sizes, would be presented to the participant in each trial. For each gap presented, the participant must indicate whether the gap is "acceptable" for safe crossing, by raising his or her hand. Number of approaching vehicles and total waiting time are not known to the participant in each trial. Also, a participant would be asked to give a rating, indicating the likelihood of crash if he or she had crossed the road with the accepted gap, using the 10-point Likert scale (1 refers to very unlikely, 10 refers to very likely), after each trial. Lastly, upon the completion of all 30 trials, each participant is required to answer two questions for the measurement of (i) Rashness ("I behaved more recklessly in the experiments, compared to the real life", 1 refers to strongly disagree, 10 refers to strongly agree), (ii) hesitation ("It was easier for me to decide whether to cross or not in the experiments, compared to the real life", 1 refers to strongly disagree, 10 refers to strongly agree), again using 10-point Likert scale.

4.3 Method of analysis

4.3.1 Propensity score method

In the propensity score framework, treatment and corresponding control entities have similar characteristics. In this study, the sample of 1,500 observations (*trials*) are nested within 50 clusters (*participants*). Let i_{mn} denotes individual observation, with m = 1, 2, …, and 50 and n = 1, 2, …, and 30. Weather and light conditions are the treatments under investigation in this study. Let $T_i = j$ denotes the treatment assigned to i, with j = 0, 1, 2, 3 and 4. Also, Y_i (T_i) denotes the outcome, i.e., safety perception, of observation i when assigned treatment T_i. Hence, individual causal effect (ICE) can be given by,

$$\varphi_i = Y_i(j) - Y_i(k) \qquad \textit{(Eq. 1)}$$

where $j \neq k$.

Furthermore, assumptions for causal inference should be modified for multiple treatments as follow.

ASSUMPTION 1 - Weak unconfoundedness: Treatment assignment is weakly unconfounded when,

$$Y_i(j) \perp 1(T_i = j) | X_i, \forall j \in \{0,1,2,3,4\} \qquad \textit{(Eq. 2)}$$

ASSUMPTION 2 - Sufficient overlap or positivity: For all x and j , probability of treatment assignment is bounded away from zero as,

$$\pi_j(x) > 0, \forall x \text{ in support of } X_i \text{ and } \forall j \in \{0,1,2,3,4\} \qquad \textit{(Eq. 3)}$$

4.3.2 Multilevel multinomial logit model

In general practice, propensity scores are estimated using empirical data. Additionally, it is necessary to consider multilevel data structure for the estimation (Fuentes, et al., 2022).

To this end, random-intercept multilevel multinomial logit model is adopted for propensity score estimation given by,

$$\eta_i^{(j)} = \alpha^{(j)} + \beta^{(j)} X_i + \xi_m^{(j)} + \delta_i^{(j)} \qquad \textit{(Eq. 4)}$$

where $\alpha^{(j)}$ and $\beta^{(j)}$ have specific parameters, and $\xi_m^{(j)}$ and $\delta_i^{(j)}$ are independent error terms with $\xi'_m \sim N\left(0, \Sigma_\xi\right)$ and $\delta'_m \sim N(0, \Sigma_\delta)$.

Furthermore, the response variable follows a multinomial distribution and $j = 0$ is the reference (with all parameters and random errors set as zero). Hence, the conditional probability of response variable $Y_i(j)$ can be given by,

$$1 \Big/ \left(1 + \sum_{j=1}^{4} exp\left[\eta_i^{(j)}\right]\right) \qquad \textit{(Eq. 5)}$$

Propensity score, i.e., conditional probability for treatment exposure, has been an effective summary measure of covariate. For multiple treatments, it can be extended to generalized propensity score given by (Imbens, 2000),

$$\eta_i^{(j)} = logit\left[\pi_i^{(j)}\right] \qquad \textit{(Eq. 6)}$$

$$\pi_i^{(j)} = Pr\left(Y_i = j \middle| X_i, \xi_m, \delta_i\right) = \frac{exp\left\{\eta_i^{(j)}\right\}}{1 + \sum_{j=1}^{4} exp\left\{\eta_i^{(j)}\right\}} \qquad \textit{(Eq. 7)}$$

4.3.3 Inverse probability of treatment weightings

In this study, inverse probability of treatment weightings (*IPW*) is adopted to balance the pseudo-population. For instance, individuals with higher probability receiving the "treatment" are assigned small weights, and vice versa. Then, treatment assignment and distribution of covariates for propensity score estimation are independent. Therefore, the average treatment effect can be estimated, with which the weights of individuals with and without treatment are reallocated. For example, the weights for average treatment effect estimation are given by,

$$\omega_{IPW_i} = \begin{cases} \dfrac{1}{\pi_i^{(j)}} = \dfrac{1}{Pr\left(Y_i = j \middle| X_i, \xi_m, \delta_i\right)} & \text{, for treatment group} \\ \dfrac{1}{1-\pi_i^{(j)}} = \dfrac{1}{1 - Pr\left(Y_i = j \middle| X_i, \xi_m, \delta_i\right)} & \text{, for control group} \end{cases} \qquad \textit{(Eq. 8)}$$

Then, the weighted mean estimate for treatment *j* is given by,

$$\lambda_j = \frac{\sum_{m=1}^{M}\sum_{i=1}^{MN}\omega_i\, T_i(j)\, Y_i}{\sum_{m=1}^{M}\sum_{i=1}^{MN}\omega_i\, T_i\,(j)} \qquad \textit{(Eq. 9)}$$

Finally, the average treatment effect (*ATE*), which is the expectation across all ICEs integrated over all *x* with respect to *IPW,* is given by,

$$\varphi_{ATE} = E[Y_i(j) - Y_i(k)] = \lambda_j - \lambda_k \qquad \textit{(Eq. 10)}$$

4.3.4 Covariates

In this study, the primary objective is to examine the effects of weather conditions on the association between pedestrian safety perception and other possible factors. Therefore, observations are assigned to different groups in accordance with the following Table 4.2.

Table 4.2 Assignment of treatment and control group

Group	Weather
Control (T_0)	Daytime – Fine weather
Treatment 1 (T_1)	Daytime – Rain
Treatment 2 (T_2)	Dusk - Rain
Treatment 3 (T_3)	Daytime – Light fog
Treatment 4 (T_4)	Daytime – Heavy fog

In this study, the Propensity score method is employed to account for the effects of confounding factors. This approach balanced the distributions of observed attributes among treatment and control groups, allowing for more precise estimates of treatment effects and reducing bias attributed to possible confounding factors. Table 4.3 summarizes the covariates considered for the propensity score estimation. As shown in Table 4.3, four covariates including pedestrian age, gender, rashness, and hesitation are at the participant level and another four including vehicles passed, waiting time, gap accepted, and vehicle speed are at the observation level, respectively.

Table 4.3 Covariates considered in the proposed model

Scope of work	Covariate	Description	Covariate type
Dependent variable	Pedestrian safety perception	Anticipated crash risk if gap is accepted	Ordinal: 10 refers to very likely, 1 refers to very unlikely
Participant level	Age	Age of participant	Continuous
	Gender	Gender of participant	Categorical: 1 refers to male, 0 refers to female
	Rashness	Participant behaved more recklessly in the experiments, compared to the real life	Ordinal: 10 refers to strongly agree, 1 refers to strongly disagree
	Hesitation	Participant considered easier to decide whether to cross or not in the experiments, compared to the real life	Ordinal: 10 refers to strongly agree, 1 refers to strongly disagree
Observation level	Vehicles passed	Number of vehicles passed until the participant starts crossing	Count
	Waiting time	Waiting time until the participant starts crossing	Continuous
	Gap accepted	Size of gap accepted by the participant	Categorical: Not accepted, 2 second, 3 second, 4 second, 5 second
	Vehicle speed	Speed of approaching vehicle	Categorical: 30 km/h, 50 km/h

Last but not least, balance of covariate is assessed using standardized mean difference (SMD). SMD refers to the standardized difference in means for each covariate among treatment groups. A smaller SMD implies better balance of covariate.

4.4 Results and discussion

4.4.1 Standardized mean difference for covariate balance

Figure 4.5 illustrates the Love plot of the SMD before and after propensity score weighting for all covariates. Positive SMD implies the over-representation of corresponding covariate in the treatment group. As shown in Figure 4.5, a threshold of 0.1 is established for the covariate balance prior to propensity score weighting. As also shown in Figure 4.5, values of SMD are below 0.1 for all covariates after propensity score weighting. This implies a satisfactory balance is achieved.

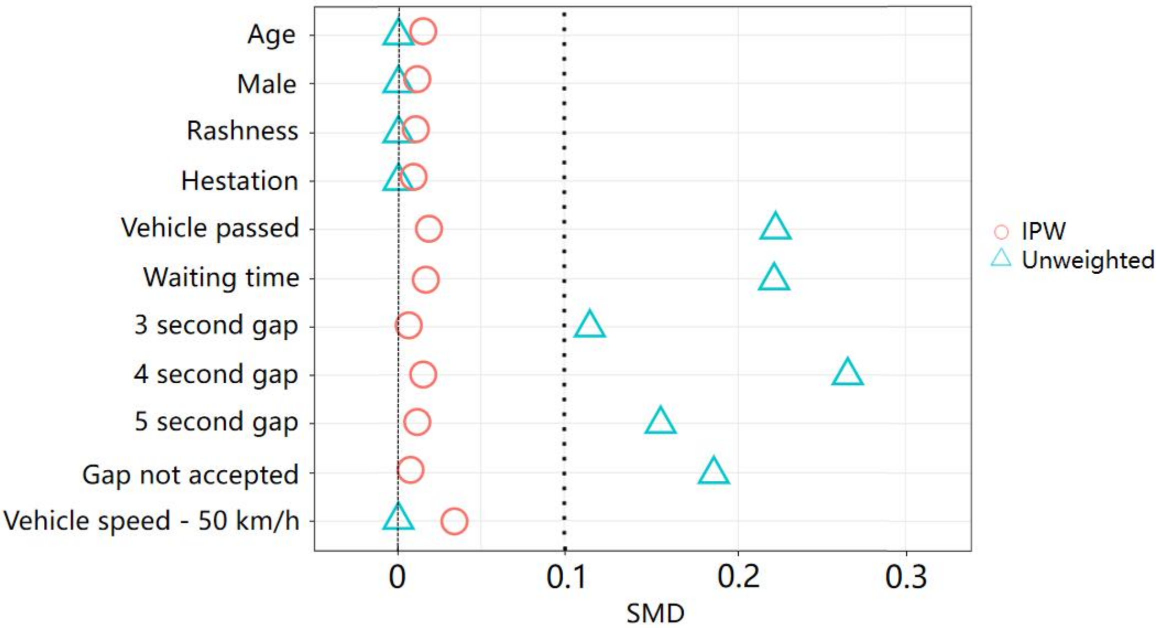


Figure 4.5 Standardized mean difference before and after weighting

4.4.2 Adjustment by inverse probability of treatment weighting

Overall, there are 1,500 observations in this study. For instance, they are evenly allocated to the five treatment and control groups given in Table 4.2 in previous Section 4.3. Table 4.4 presents the descriptive statistics and SMD estimates for the treatment and control groups, before and after propensity score weighting. As shown in Table 4.4, there are noticeable imbalances for covariates like vehicle passed (SMD = 0.118), waiting time (0.120), and gap acceptance (0.238), before propensity score weighting. In contrast, no significant imbalance can be observed for gender, age, rashness, hesitation, and vehicle speed. Nevertheless, there is also remarkable imbalance for pedestrian risk perception (0.441). To sum up, this justifies the need to account for confounding factors using the proposed inverse probability of treatment weighting. As also shown in Table 4.4, values of SMD are less than 0.1 for all covariates, after propensity score weighting. This implies that between-group differences in covariates are eliminated, and the differences in outcomes are surely attributed to the "treatment". There is remarkable imbalance for pedestrian risk perception (0.455). This justifies that weather significantly affects pedestrian risk perception.

Table 4.4 Descriptive statistics before and after propensity score weighting

Covariate		Unweighted						Weighted					
		T_0	T_1	T_2	T_3	T_4	SMD	T_0	T_1	T_2	T_3	T_4	SMD
Observation		300	300	300	300	300	N/A	299.67	299.73	300.11	297.87	300.46	N/A
Age	Mean	31.60	31.60	31.60	31.60	31.60	<0.001	31.62	31.62	31.64	31.49	31.65	0.006
	SD	11.30	11.30	11.30	11.30	11.30		11.16	11.37	11.38	11.14	11.42	
Male	Count	150	150	150	150	150	<0.001	148.48	150.14	150.38	149.23	149.95	0.005
	%	50.00	50.00	50.00	50.00	50.00		49.55	50.09	50.11	50.10	49.91	
Rashness	Mean	4.36	4.36	4.36	4.36	4.36	<0.001	4.36	4.36	4.35	4.37	4.35	0.005
	SD	1.77	1.77	1.77	1.77	1.77		1.77	1.76	1.76	1.77	1.78	
Hesitation	Mean	4.38	4.38	4.38	4.38	4.38	<0.001	4.39	4.38	4.38	4.38	4.38	0.004
	SD	1.83	1.83	1.83	1.83	1.83		1.83	1.84	1.83	1.83	1.85	
Vehicle passed	Mean	5.04	5.56	5.38	5.06	5.76	0.118	5.32	5.37	5.36	5.39	5.38	0.006
	SD	3.15	3.37	3.43	3.29	3.39		3.37	3.31	3.41	3.42	3.21	
Waiting time	Mean	10.61	12.25	11.72	10.81	12.85	0.120	11.57	11.67	11.64	11.73	11.63	0.006
	SD	9.02	10.10	10.10	9.67	10.36		9.81	9.90	10.00	10.07	9.74	
2 second gap	Count	1	2	2	0	6	0.238	1.88	2.18	2.37	0.00	2.21	0.056
	%	0.33	0.67	0.67	0.00	2.00		0.63	0.73	0.79	0.00	0.73	
3 second gap	Count	36	31	28	39	37		34.27	34.17	34.06	34.26	34.05	
	%	12.00	10.33	9.33	13.00	12.33		11.44	11.40	11.35	11.50	11.33	
4 second gap	Count	113	104	120	129	90		111.35	110.50	111.20	111.00	112.38	
	%	37.67	34.67	40.00	43.00	30.00		37.16	36.87	37.05)	37.27	37.40	
5 second gap	Count	122	122	110	99	120		114.58	115.03	114.70	114.68	114.18	
	%	40.67	40.67	36.67	33.00	40.00		38.24	38.38	38.22	38.50	38.00	
Gap not	Count	28	41	40	33	47		37.58	37.84	37.77	37.92	37.64	

accepted	%	9.33	13.67	13.33	11.00	15.67		12.54	12.63	12.59	12.73	12.53	
50 km/h speed	Count	150	150	150	150	150	<0.001	149.22	151.66	150.74	147.26	146.95	0.017
	%	50.00	50.00	50.00	50.00	50.00		49.80	50.60	50.23	49.44	48.91	
Risk Perception	Median	3.00	5.00	5.00	5.00	7.00	0.441	3.00	5.00	5.00	5.00	7.00	0.455
	IQR	[2.00, 5.00]	[3.00, 6.00]	[4.00, 7.00]	[3.00, 6.00]	[4.00, 8.00]		[2.00, 5.00]	[3.00, 6.00]	[4.00, 7.00]	[3.00, 6.00]	[4.00, 8.00]	

Note: IQR refers to Interquartile range

4.4.3 Weather effect on pedestrian safety perception

Table 4.5 presents the results of parameter estimation for the association between pedestrian safety perception and possible factors. As shown in Table 4.5, perceived risk of pedestrians significantly increases with age (coefficient = 0.05), at the 5% level. Such a finding is consistent with that of previous studies. Older pedestrians tend to be more cautious given the reduced cognitive and physical capabilities (Pala et al., 2021; Wilmut and Purcell, 2022). In contrast, male pedestrians tend to have lower perceived risk (-0.36), at the 5% level of significance. This could be because males are more risk-taking (Morgenroth et al., 2018). For the effects of personal attitudes, perceived risk increases significantly with the degree of rashness (0.26) and hesitation (0.24), respectively, both at the 5% level. It is intrinsic that risk-averse pedestrians (with higher level of hesitation) tend to be more cautious. Hence, perceived risk increases. Just, it may be controversial that reckless pedestrians also have higher perceived risk. This could be attributed to the sensation seeking for risky behaviour (Dinh et al., 2020). For the effects of traffic characteristics, perceived risk of pedestrians significantly decreases with number of vehicles passed (-0.20) and waiting time (-0.15), both at the 5% level. This is because pedestrians may become less tolerant after waiting for long (Tian et al., 2023). Additionally, it is intrinsic that perceived risk also significantly decreases with vehicle gap size (-1.41 for 3 second gap, -2.09 for 4 second gap, and -2.70 for 5 second gap), but increases with vehicle speed (0.05) at the 5% level. Such findings are consistent with that of previous studies (Luque et al., 2024; Tian et al., 2023). Last but not least, for the effects of weather conditions, perceived risk of pedestrians significantly increase in adverse weather condition (0.89 for daytime – rain, 1.43 for dusk – rain, 0.89 for daytime – light fog, and 2.39 for daytime – heavy fog), all at the 1% level. This justifies that pedestrians tend to be more risk-averse in adverse weather conditions. This could be because of the compensatory strategies of road users for the offset of anticipated risk (Bargegol et al., 2022; Chen et al., 2021). Such phenomenon could be more prevalent in low visibility conditions like heavy fog and dusk time, where the increases in perceived risk are magnified (Wu et al., 2018).

Table 4.5 Results of parameter estimation for weather effect on pedestrian safety perception

Covariate	Coefficient	Standard error	95% confidence interval
Intercept	3.78**	0.25	(3.29, 4.27)
Age	0.05*	0.02	(0.01, 0.09)
Male	-0.36*	0.21	(-0.73, -0.08)
Rashness	0.26*	0.10	(0.05, 0.47)
Hesitation	0.24*	0.11	(0.02, 0.47)
Vehicle passed	-0.20*	0.12	(-0.47, -0.09)
Waiting time	-0.15*	0.06	(-0.33, -0.05)
3 second gap	-1.41**	0.63	(-2.58, -0.04)
4 second gap	-2.09**	0.64	(-3.39, -0.80)
5 second gap	-2.70**	0.57	(-3.86, -1.53)
Gap not accepted	-3.90**	0.78	(-5.48, -2.33)
Vehicle speed - 50 km/h	0.05*	0.18	(0.01, 0.07)
Daytime – Rain (T_1)	0.89**	0.19	(0.51, 1.26)
Dusk – Rain (T_2)	1.43**	0.20	(1.02, 1.84)
Daytime – Light fog (T_3)	0.89**	0.15	(0.58, 1.19)
Daytime – Heavy fog (T_4)	2.39**	0.33	(1.73, 3.04)

** Significant at the 5% level; ** Significant at the 1% level*

4.5 Concluding remarks

Weather significantly affects the travel behaviour and safety risk especially for active transport modes like walking. However, the relationship between weather and pedestrian safety perception is less explored. In this study, pedestrian gap acceptance behaviour and safety perception at the mid-block crossing is examined using the CAVE experiments. In addition to weather condition, confounding factors including pedestrian socio-demographics, safety attitude, and traffic characteristics are also accounted for using propensity score method. Furthermore, effects of multiple treatment and multilevel data structure are also considered using the inverse probability of treatment weighting method. Results indicate that pedestrian risk perception significantly increases in the adverse weather conditions like rain and fog. Such increases were even more remarkable in poor visibility conditions like dusk time and heavy fog. Additionally, there are noticeable association between pedestrian age, safety attitude, vehicle speed, waiting time and risk perception. Finding should shed light on the development and implementation of local area traffic management and adaptive traffic control that can mitigate the pedestrian crash risk at accident-prone locations in adverse weather conditions.

Nevertheless, this study has some limitations. First, a one-way single-lane street, which presents a less complex traffic environment compared to two-way or multi-lane streets, is simulated. To enhance the generalizability of the results, future studies could include additional experiments in varied geometric designs and traffic settings. Second, participants only verbally indicated their intent to cross or not in the simulated scenarios. It would be worth exploring the discrepancies between actual crossing behaviour in real-world settings and self-reported intentions in future research, such as through naturalistic walking studies. Third, participants might anticipate changes in gaps after repeated experiments and their decision-making process could have been affected. In future research, capturing physiological signals such as eye movement, gaze patterns, and EEG, could provide insights into the interaction between physiological state, safety perception, and gap acceptance behaviour.

Chapter 5 Effect of urban street landscape on pedestrian safety

5.1 Introduction

Walking is the primary mean of access to essential resources, activities, and services in urban areas. Pedestrians are vulnerable road users. They constitute 23% of road deaths around the world (World Health Organization, 2018; World Health Organization, 2023). Thus, it is necessary to create pleasant and safe walking environment with effective urban planning and development strategies (Sze and Christensen, 2017). Urban street trees play an important role in the shaping of urban landscape and promotion of walkability. Environmental, economic, and social benefits of urban street trees are recognized (Choi et al., 2016; Hamim et al., 2024). Increase in the proportion of street tree canopy can improve the walking environment, and encourage walking (Guzman et al., 2022; Herrmann et al., 2017; Larsen et al., 2009; Nehme et al., 2016). In addition, street trees can help reduce stress by relieving anxiety and depression. It can improve the mental health and quality of life among inhabitants (Henderson et al., 2016; Li and Sullivan, 2016).

Many cities have recognized the importance of urban forestry in the past decade. In 2012, Melbourne City Council has initiated an Urban Forest Strategy, aiming to increase the tree coverage, diversify the urban ecosystem, improve the tree health, and mitigate the urban heat island problem (City of Melbourne, 2012). In the early 2010s, there were about 70,000 trees and 22% of tree canopy cover in the public areas of Melbourne. In accordance with the Urban Forest Strategy, tree canopy cover should be increased to 40% by 2040 (City of Melbourne, 2012). In addition, priorities for urban space allocation should be given to walking, cycling, and public transport, in accordance with Melbourne's Transport Strategy 2030 (City of Melbourne, 2020a). For example, footpaths in Central Melbourne should be widened. Also, tree planting and other climate change adaptation measures would be integrated with urban streetscape projects. These are crucial for the improvement of safety, accessibility, and sustainability of urban areas

(Chen et al., 2020).

However, trees were considered roadside hazards in the past decades. They may reduce the visibility on roadways. Street trees were removed to provide clear zones and reduce crashes associated with fixed-objects (Budzynski et al., 2016). Previous studies have examined the relationship between urban street trees, driving behaviour, and traffic safety (Cai et al., 2022; Harvey and Aultman-Hall, 2015; Marshall et al., 2018; Naderi, et al., 2008). For example, urban street trees can create perceived edges and introduce visual complexities, thereby enhancing drivers' attention and alertness. Consequently, driving speed may be reduced, and drivers' braking reaction times can be affected (Naderi et al., 2008; Wang et al., 2024). In addition, urban street trees can form a visual wall, separating the roads from the buildings and other infrastructures. This can provide a sense of familiarity and security and increase the safety perception of drivers (Cai et al., 2022; Harvey et al., 2015; Naderi et al., 2008). Furthermore, the enclosure of urban streetscapes by tree canopy is negatively associated with the risk of road injury and fatality (Harvey and Aultman-Hall, 2015; Marshall et al., 2018). However, the effect of urban street trees on pedestrian safety is rarely investigated. Therefore, it is important to identify the factors that affect the risk of pedestrian crashes and injuries.

In previous studies, pedestrian crash exposure at the zonal level was estimated using the metrics including population, population density, and trip data (Ferenchak and Marshall, 2019;Sze et al., 2019; Su et al., 2021b; Wang et al., 2016). It was rare that pedestrian crash exposure at the microscopic level (e.g., road segment, intersection, and crosswalk) using pedestrian counts was estimated. Furthermore, research has yet to consider factors that could influence findings on pedestrian crash exposure such as unobserved heterogeneity, spatial dependency, and correlation among different crash types. Thus, effects of the factors including urban street trees, geometric design, traffic characteristics and time period on pedestrian injury at the street level will be evaluated using Poisson lognormal regression method. Density and canopy of urban street trees will be considered for the effect of urban forestry on pedestrian safety. More importantly, pedestrian crash

exposure will be measured using comprehensive pedestrian count data by space and time. For example, hourly pedestrian count data of individual road segments will be adopted.
The remainder of this chapter is structured as follows. Illustration of data collection and statistical model are described in Section 5.2 and Section 5.3, respectively. Section 5.4 summarizes the estimation results and discusses the policy implications. Finally, concluding remarks are given in Section 5.5.

5.2 Data

5.2.1 Study data

Data was collected in a state in Australia. Melbourne city is busy, with approximately one million people using the streets every day, as pedestrians, cyclists, drivers, and motorcycle riders. To illustrate, walking constitutes 33-36% of total trips per day (Victorian Integrated Survey of Travel and Activity (VISTA); Victorian State Government, 2018). During 2014-2018, 19% of pedestrians sustained road injury and 30% of crashes resulted in fatality (VicRoads, 2020).

Pedestrian counting system has been installed in Central Melbourne since 2009, collecting the hourly pedestrian counts across the area. In this study, pedestrian, traffic, and injury data of 38 road segments that have pedestrian sensors in the period between 2014 and 2018 are modeled. Figure 5.1 illustrates the road segments, with the length ranging from 65 to 265 metres, under investigation. In this study, pedestrian injury of a road link between two intersections is modeled.

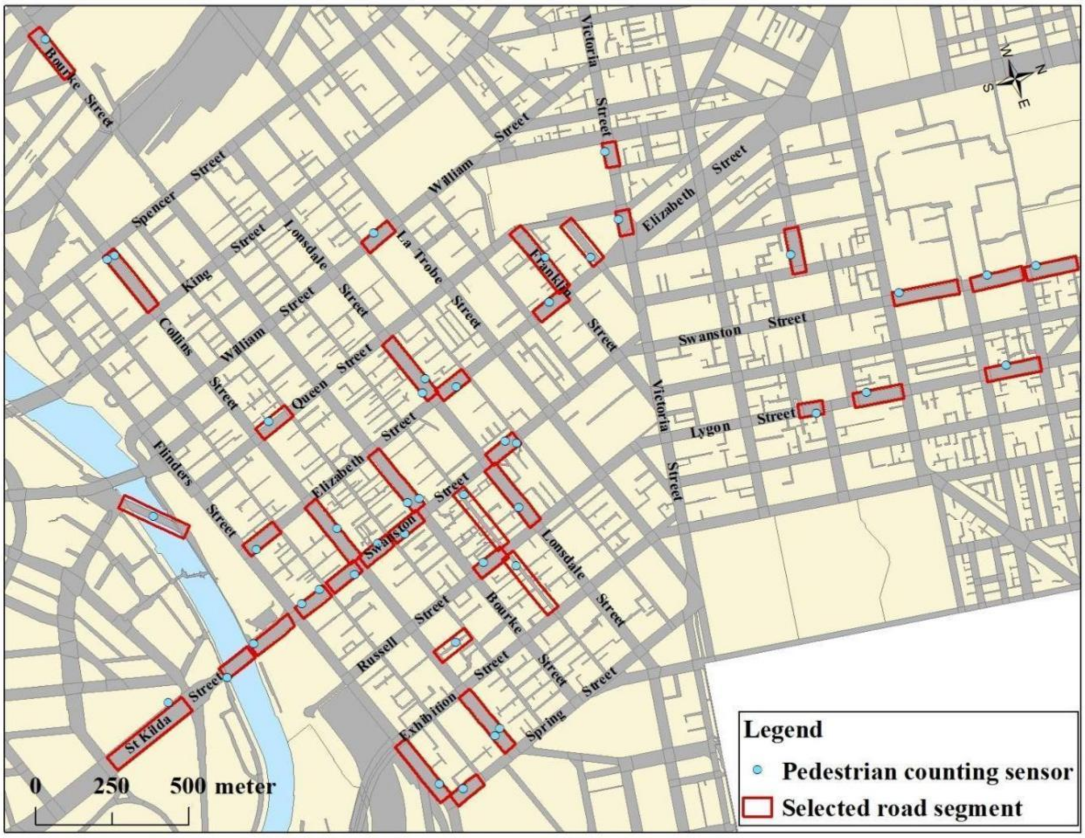


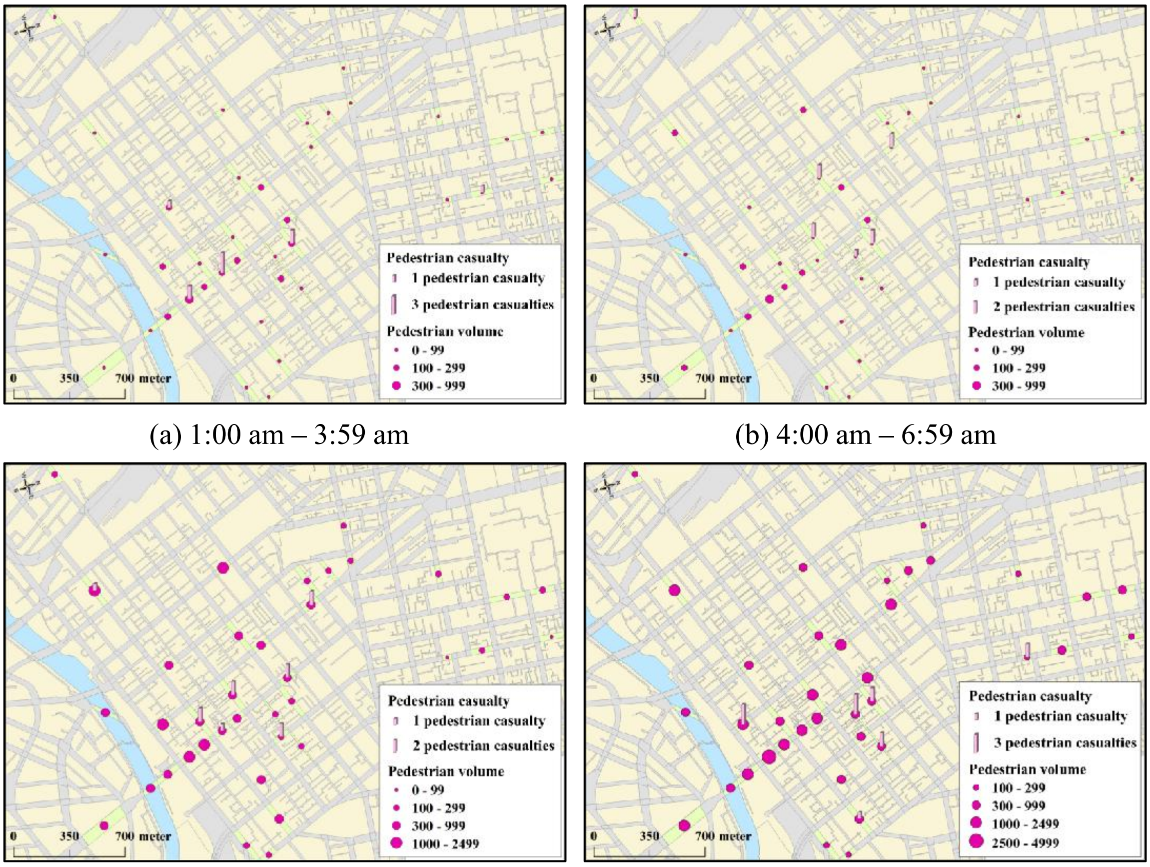
Figure 5.1 Road segments under investigation

5.2.2 Traffic and crash data

In this study, crash data was obtained from the Road Crash Information Database of Victorian State Government (VicRoads, 2020). The database contains information on crash time and location, gender and age of road user, vehicle type, crash circumstances, and road and weather conditions of every crash reported to the police. There were 2,018 pedestrian casualties at the selected road segments in the observation period. For instance, pedestrian casualties were classified into three categories by injury severity: (i) fatality (died within 30 days after crash), (ii) severe injury (required hospital admission), and (iii) slight injury. In this study, fatal and severe injuries are combined into one class in the model to avoid the bias attributed to imbalanced crash data, considering the extremely low count of fatal injury (Chen et al., 2022; Ding et al., 2022).

In this study, traffic and pedestrian count data are obtained from the Traffic Count Vehicle

Classification and Pedestrian Counting System of Melbourne City Council (City of Melbourne, 2020b, 2020c). For the former, information on the number of vehicles, vehicle class, average speed, maximum speed, and 85^{th} percentile speed for each hour can be obtained (City of Melbourne, 2020b). For the latter, number of pedestrians passing a sensor for each direction and hour is measured (City of Melbourne, 2020c). In this study, crash and traffic data were aggregated at 3-hour intervals, avoiding the bias associated with excessive zero observations and imbalanced crash data (Chen et al., 2022; Ding et al., 2022). Figure 5.2 presents the distribution of pedestrian counts and casualties of selected road segments in different time intervals.

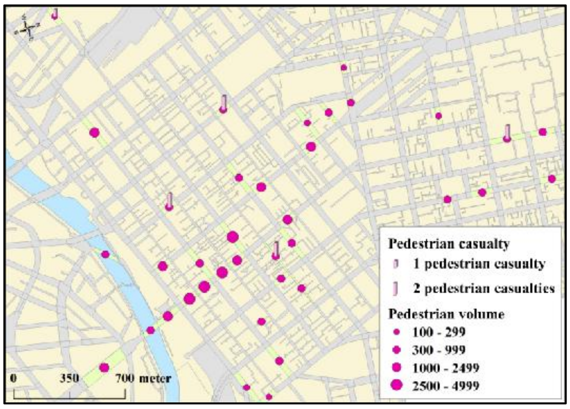


(a) 1:00 am – 3:59 am

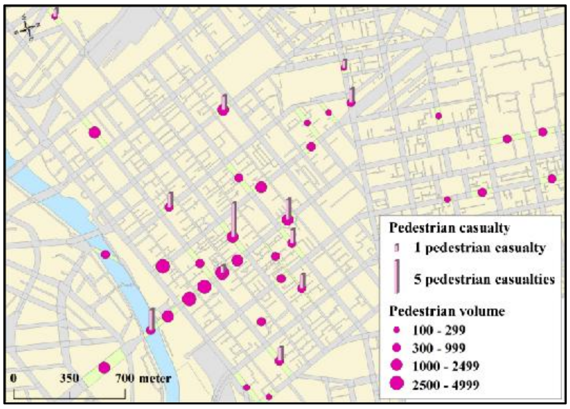
(b) 4:00 am – 6:59 am

(c) 7:00 am – 9:59 am

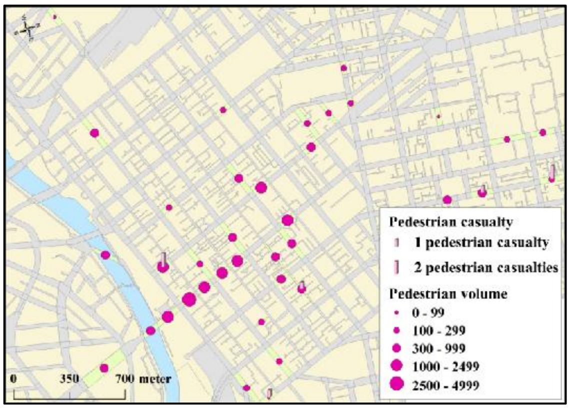
(d) 10:00 am – 12:59 pm



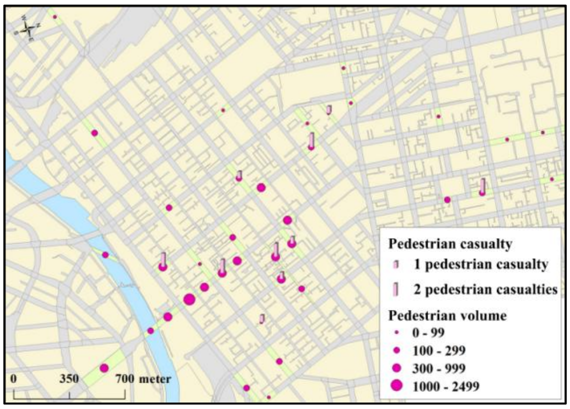
(e) 1:00 pm – 3:59 pm



(f) 4:00 pm – 6:59 pm



(g) 7:00 pm – 9:59 pm



(h) 10:00 pm – 12:59 am

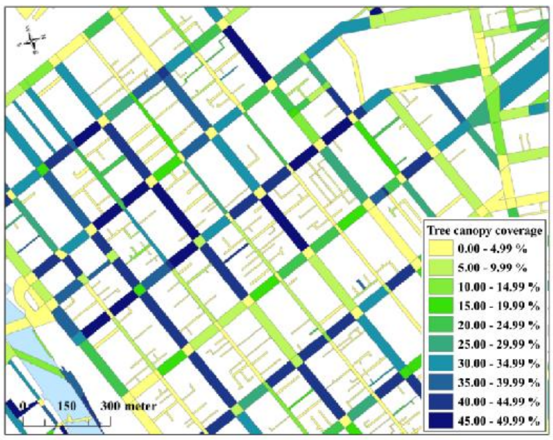
Figure 5.2 Pedestrian counts and casualties in different time intervals

5.2.3 Tree data

Effects of tree density and tree canopy cover on pedestrian safety were investigated. Location and canopy of each tree, measured by aerial photography and LiDAR techniques, were obtained from the open data portal of Melbourne City Council (City of Melbourne, 2020d). Then, street network data (planimetric edge of the road) was integrated with the tree data using geographical information system (GIS) technique. As shown in Figure 5.3, the proportion of road area (pavement and footpath) that is covered by tree canopy was estimated. There were more than ten percentage point changes (both gain and loss) in tree canopy cover for the sampled road segments in the study period (Hurley et al., 2019). Figure 5.4 illustrates the distribution of tree canopy cover of Inner Melbourne for each year in 2014-2018. As shown in Figure 5.4, variations in tree canopy cover over the years and across the road segments are considerable.

Figure 5.3 Illustration of tree location and canopy cover

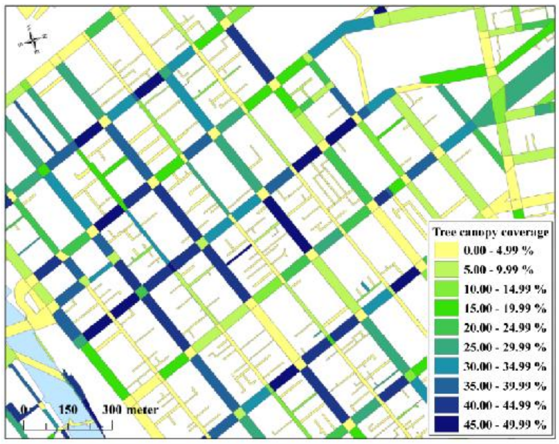
(a) 2014



(b) 2015

(c) 2016

(d) 2017



(e) 2018

Figure 5.4 Spatial distribution of tree canopy in 2014-2018

5.2.4 Road network and traffic characteristics

The effects of road geometry and transport facilities were considered. Information on road length and road width were obtained from the public road profile of Melbourne City Council (City of Melbourne, 2021). In addition, information on the locations of bus stop, tram station, and on-street parking spaces were obtained from Google Street View observation. The sample size was 1,160, for annual average 3-hour crash, pedestrian, and traffic counts of selected road segments in 2014-2018. Table 5.1 summarizes the sample.

Table 5.1 Summary statistics of the sample

Scope of work	Variable	Mean	Std. Dev.	Min.	Max.
Pedestrian casualty	Slight injury	0.09	0.38	0.00	3.00
	Fatal and severe injury	0.02	0.12	0.00	1.00
Exposure	Ln (Pedestrian count)	2.39	0.62	0.78	3.67
	Ln (Vehicle-kilometre)	2.74	0.97	0.19	5.48
Street tree	Tree density (per 100 m)	9.83	8.29	0.00	34.73
	Tree canopy (percentage)	12.95	8.83	0.00	42.87
Road and Traffic characteristics	Presence of Crosswalk (1: Yes; 0: No)	0.29	0.46	0.00	1.00
	Presence of bus stop (1: Yes; 0: No)	0.17	0.38	0.00	1.00
	Presence of tram station (1: Yes; 0: No)	0.22	0.41	0.00	1.00
	Presence of on-street parking (1: Yes; 0: No)	0.57	0.50	0.00	1.00
	Road width (m)	17.99	4.95	5.00	27.58
	85^{th} percentile speed (kph)	34.42	7.48	21.52	57.14
Time period	7:00 am – 9:59 am	0.13	0.35	0.00	1.00
	10:00 am – 12:59 pm	0.13	0.35	0.00	1.00
	1:00 pm – 3:59 pm	0.13	0.35	0.00	1.00
	4:00 pm – 6:59 pm	0.13	0.35	0.00	1.00
	7:00 pm – 9:59 pm	0.13	0.35	0.00	1.00
	10:00 pm – 12:59 am	0.13	0.35	0.00	1.00
	1:00 am – 3:59 am	0.13	0.35	0.00	1.00
	4:00 am – 6:59 am	0.13	0.35	0.00	1.00

5.3 Method of analysis

5.3.1 Poisson lognormal regression

The dependent variable was pedestrian crash frequency. Poisson lognormal regression approach was adopted based on the distribution given as follows,

$$y_i^k \sim Poisson(\lambda_i^k) \quad (1)$$

where y_i^k is the observed number of pedestrian casualties of severity level k at road segment i, and λ_i^k is the Poisson parameter given as follows,

$$ln\left(\lambda_i^k\right) = a^k + b^k X_i' + U_i^k + S_i^k \quad (2)$$

where X_i is the vector of covariates, a^k is the intercept, b^k is the vector of parameters, U_i^k is the unstructured random term for overdispersion, and S_i^k is the structured random term for spatial dependency.

To account for the effects of unobserved heterogeneity among the observation units, random parameters b_i^k can be specified as,

$$b_i^k = b^k + \delta_i^k \tag{3}$$

where b^k is the fixed parameter and δ_i^k is the randomly distributed error term that follows the normal distribution with the mean of zero and variance of σ^2.

To account for the effects of spatial dependency, conditional autoregressive (CAR) prior given as follows would be adopted,

$$S_i^k | S_{-i}^k \sim N\left(\overline{S_i^k}, \sigma_{Sk}^2 / n_i\right) \tag{4}$$

where $\overline{S_i^k} = \sum_{j \neq i} S_j^k \times \omega_{i,j} \big/ n_i$ with $\omega_{i,j}$ representing the spatial weight, $\omega_{i,j} = 1$ when road segment i and j are adjacent and 0 otherwise, n_i refers to the number of neighboring units adjacent to i, and the hyperparameter σ_{Sk}^2 follows the Gamma distribution given by,

$$\sigma_{Sk}^{-2} \sim Gamma(0.01，0.001) \tag{5}$$

5.3.2 Multivariate model

A multivariate model was adopted to consider the correlation between the counts of different injury severity levels, m. The random parameters can be specified as,

$$b_{mi}^k = b_m + \delta_{mi}^k \tag{6}$$

where b_m is the fixed parameter for multivariate and δ_{mi}^k is the normally distributed random term.

In addition, the unstructured random term, following a multivariate normal distribution, can be written as,

$$U_i \sim M\,N(\mu_i, \Sigma_\mu) \tag{7}$$

where μ_i denotes the vector of zeroes, and Σ_μ is the covariance matrix estimated using the Wishart distribution given by,

$$\Sigma_\mu{}^{-1} \sim W\,ishart(R_\mu, F) \tag{8}$$

where R_μ is the scale matrix for precision matrix and F is the degrees of freedom (K = 2 in this study).

For instance, the non-informative prior for R_μ is set as (Aguero-Valverde, 2013),

$$R_\mu = \begin{bmatrix} 0.1 & 0.005 \\ 0.005 & 0.1 \end{bmatrix} \tag{9}$$

Furthermore, the multivariate CAR prior can be specified as,

$$S_i \middle| \left(S_{-i}^1, S_{-i}^2\right) \sim MN\left(\overline{S_i}, \Sigma_s/n_i\right) \tag{10}$$

where $\overline{S_i} = \left(\sum_{j\neq i} S_j^1 \times \omega_{i,j}/n_i\,, \sum_{j\neq i} S_j^2 \times \omega_{i,j}/n_i\right)^T$ and Σ_s is a 2×2 covariance matrix.

Univariate and multivariate random parameters Poisson-lognormal models were estimated using the Bayesian framework with Markov chain Monte Carlo simulation, with the first 10,000 iterations being discarded as a burn-in and the further 20,000 iterations run for each chain. Credibility of the variables considered were assessed using the 95% Bayesian Credible Intervals (BCIs). To assess the model fit, Akaike Information Criterion (AIC) is commonly used. In addition, generalized performance metrics like

Watanabe-Akaike Information Criterion (WAIC) and Deviance Information Criterion (DIC) have been proposed to account for model complexity and avoid overfitting. Despite that Bayesian measures like WAIC may be superior to point estimates, DIC is adopted considering the computational efficiency (Kitali et al., 2022; Li et al., 2021). In this study, DIC would be estimated using the following (Spiegelhalter et al., 2002),

$$DIC = Dbar + pD \tag{11}$$

where $Dbar$ is the posterior mean of deviance and pD is the number of effective parameters.

DIC considers both the predictive performance ($Dbar$) and model complexity (pD). Model with the lower DIC, that indicates superior model fit, is preferred.

5.4 Results and Discussion

Table 5.2 summarizes the model fit of univariate and multivariate random parameters Poisson lognormal regression models for pedestrian casualties. As shown in Table 5.2, the multivariate model (DIC = 342.34) outperforms the univariate model (DIC = 398.65). Hence, the multivariate model was adopted.

Table 5.2 Goodness-of-fit assessment of multivariate and univariate Poisson-lognormal models

Parameter	Multivariate Poisson-lognormal model	Univariate Poisson-lognormal model
Dbar	263.59	304.38
Dhat	184.85	210.71
pD	78.74	93.97
DIC	342.34	398.65

Table 5.3 presents the results of parameter estimation of both multivariate and univariate models. A variable is considered significant when the MC error is less than 0.05 and the 95% BCIs do not overlap with zero. As shown in Table 5.3, parameter estimates between

multivariate and univariate models are similar. Hence, results of multivariate model would be discussed in detail as follows.

For the exposure, pedestrian count (slight injury, β = 0.92; fatal and severe injury, β = 0.93), and vehicle-kilometre (slight injury, 0.37; fatal and severe injury, 0.39) are positively associated with pedestrian casualties, at the 95% BCIs. For the effect of street tree, both tree density (slight injury, -0.42; fatal and severe injury, -0.43) and tree canopy (slight injury, -0.35; fatal and severe injury, -0.39) are negatively associated with pedestrian casualties, at the 95% BCIs. For the effects of road and traffic characteristics, presence of bus stop (slight injury, 1.01; fatal and severe injury, 1.22), presence of tram station (slight injury, 0.13; fatal and severe injury, 0.15), presence of on-street parking (slight injury, 0.99; fatal and severe injury, 1.02), road width (slight injury, 0.43; fatal and severe injury, 0.45), and 85th percentile speed (slight injury, 0.38; fatal and severe injury, 0.46) are positively associated with pedestrian casualties. In contrast, presence of crosswalk (slight injury, -0.36) is negatively associated with pedestrian casualties, all at the 95% BCIs. For the time effect, pedestrian casualty risk is higher in the morning peak (i.e., 7:00 am – 9:59 am; slight injury, 0.13; fatal and severe injury, 0.13) and afternoon peak (i.e., 4:00 pm – 6:59 pm; slight injury, 0.11; fatal and severe injury, 0.12) periods. However, pedestrian casualty risk is lower in the nighttime (i.e., 7:00 pm – 9:59 pm; slight injury, -0.15; fatal and severe injury, -0.17).

As also shown in Table 5.3, effects of tree density, tree canopy, presence of bus stop, presence of tram station, presence of on-street parking and road width are random. This implies that effects of these variables may vary across individual road segments, known as unobserved heterogeneity. Furthermore, spatial effects are significant (slight injury: 0.26; Fatal and severe injury: 0.27). This justifies the correlation in pedestrian casualties of the road segments that are in close proximity (Quddus, 2008).

Table 5.3 Results of parameter estimation of multivariate and univariate Poisson-lognormal models

Scope of work	Variable		Multivariate Poisson-lognormal model				Univariate Poisson-lognormal model			
			Slight injury		Fatal and severe injury		Slight injury		Fatal and severe injury	
			Mean	(95% BCI)	Mean	(95% BCI)	Mean	(95% BCI)	Mean	(95% BCI)
Intercept			3.08*	(0.93, 5.49)	3.21*	(1.12, 5.32)	3.43*	(1.79,5.28)	3.51	(1.61, 5.57)
Exposure	Ln (Pedestrian count)		0.92*	(0.46, 1.27)	0.93*	(0.64, 1.35)	0.91*	(0.81,0.98)	0.93*	(0.65,1.17)
	Ln (Vehicle-kilometre)		0.37*	(0.11, 0.51)	0.39*	(0.09, 0.53)	0.34*	(0.10,0.49)	0.38*	(0.08,0.55)
Street tree	Tree density	Mean	-0.42*	(-0.78, -0.10)	-0.43*	(-0.81, -0.14)	-0.41*	(-0.64, -0.18)	-0.43*	(-0.75, -0.18)
		SD	0.31*	(0.07, 0.88)	0.25*	(0.09, 0.55)	0.29*	(0.05,0.81)	0.21*	(0.05,0.39)
	Tree canopy	Mean	-0.35*	(-0.52, -0.10)	-0.39*	(-0.72, -0.11)	-0.30*	(-0.75, -0.05)	-0.34*	(-0.68, -0.08)
		SD	0.27*	(0.08, 0.43)	0.32*	(0.11, 0.62)	0.26*	(0.058,0.87)	0.34*	(0.22,0.48)
Road and traffic characteristics	Presence of Crosswalk		-0.36*	(-0.52, -0.17)	-0.38	(-0.58, -0.07)	-0.32*	(-0.51, -0.09)	-0.32	(-0.54, -0.13)
	Presence of bus stop	Mean	1.01*	(0.69, 1.33)	1.22*	(0.51, 1.98)	1.07*	(0.73,1.57)	1.19*	(0.88,1.56)
		SD	0.27*	(0.06, 0.51)	0.35*	(0.18, 0.67)	0.33*	(0.05,0.75)	0.30*	(0.10,0.49)
	Presence of tram station	Mean	0.13*	(0.06, 0.30)	0.15*	(0.07, 0.31)	0.09*	(0.05,0.19)	0.08*	(0.04,0.16)
		SD	0.23*	(0.06, 0.49)	0.26*	(0.04, 0.77)	0.22*	(0.10,0.43)	0.24*	(0.04,0.51)
	Presence of on-street parking	Mean	0.99*	(0.53, 1.55)	1.02*	(0.71, 1.41)	1.11*	(0.93,1.59)	1.06*	(0.52,1.50)
		SD	0.33*	(0.10, 0.46)	0.38*	(0.26, 0.48)	0.44*	(0.17,0.68)	0.46*	(0.31,0.62)
	Road width	Mean	0.43*	(0.10, 0.72)	0.45*	(0.13, 0.81)	0.45*	(0.21,0.78)	0.48*	(0.23,0.57)
		SD	0.39*	(0.09, 0.63)	0.40*	(0.08, 0.71)	0.37*	(0.17,0.51)	0.37*	(0.07,0.77)
	85th percentile speed		0.38*	(0.18, 0.49)	0.46*	(0.22, 0.67)	0.37*	((0.27,0.46)	0.33*	(0.08,0.52)
Time period	7:00 am - 9:59 am		0.13*	(0.07, 0.18)	0.13*	(0.05, 0.19)	0.12*	(0.05, 0.25)	0.14*	(0.07, 0.32)
	4:00 pm - 6:59 pm		0.11*	(0.08, 0.18)	0.12*	(0.06, 0.20)	0.14*	(0.09, 0.23)	0.16*	(0.09, 0.23)
	7:00 pm - 9:59 pm		-0.15*	(-0.31, -0.03)	-0.17*	(-0.34, -0.03)	-0.16*	(-0.31, 0.01)	-0.20*	(-0.34, -0.10)

Unobserved effects	Unstructured effect		0.19	(0.07, 0.28)	0.23*	(0.09, 0.37)	0.18	(0.06, 0.25)	0.20	(0.07,0.34)
	Spatial effect		0.26*	(0.08, 0.61)	0.27*	(0.05, 0.71)	0.29*	(0.09, 0.75)	0.29*	(0.07,0.77)

** Significant at the 95% BCI*

Table 4.4 presents the correlation between the random effects. As shown in Table 4, correlation between the total random effects is remarkable (Mean = 0.90; S.D. = 0.14) at the 95% BCI and the correlation between unstructured random effects is significant (Mean = 0.92; S.D. = 0.11).

Table 5.4 Correlation between the random effects for the multivariate models

	Mean	S.D.	(95% BCI)
Unstructured random effect	0.92	0.11	(0.63, 0.99)
Structured random term for spatial dependency	0.50	0.27	(-0.01, 0.96)
Total random effect	0.90	0.14	(0.47, 0.99)

5.4.1 Pedestrian crash exposure

The results of the study found that pedestrian count was positively associated with pedestrian casualties. This is consistent to the finding of previous study in Florida (United States) that used the household travel survey data to proxy the pedestrian crash exposure (Lee and Abdel-Aty, 2005). This study also found that pedestrian casualties increased less than proportionately with pedestrian count (coefficient of logarithmically transformed pedestrian count being less than 1). This finding justifies the existence of safety-in-numbers effect. In other word, when the number of pedestrians increases, marginal increase in that of pedestrian casualties would diminish. In support, research has found an increase in driver awareness when there are more pedestrians on the roads (Elvik and Bjørnskau, 2017). This is indicative to the policy measures including pedestrian streets, traffic calming, and low speed limit zones, prioritizing the right-of-way of pedestrians in the urban cities like London and Hong Kong (Department for Transport, 2017; Transport Department, 2019). However, information on the pedestrian characteristics like gender, age, and travel purpose, which can affect the safety perception, walking behaviour, and related crash risk, is not available in the pedestrian count data (Su et al., 2021b; Zhu et al., 2021). It is worth exploring the relationship between crash involvement rate and walking trips for each pedestrian group when comprehensive information on socio-demographics and travel behaviour of pedestrians is available in the future study.

This study found that pedestrian casualties increase with vehicle kilometre. This could be because of the increase in pedestrian-vehicle conflicts, particularly in the central business districts (Wong et al., 2007; Zhang et al., 2017). This finding suggests that the implementation of local area traffic management and traffic calming measures that can reduce the traffic flow, increase the driver awareness, and channelize the pedestrian and vehicular traffic (Bertulis and Dulaski, 2014; Damsere-Derry et al., 2019). Therefore, risk of pedestrian-vehicle conflicts can be reduced (Chen et al., 2020). In accordance with the Walking Plan 2014-2017 and Transport Strategy 2030 of Melbourne, safe and walkable street design should be implemented. For example, more space should be allocated for walking, traffic signal operation should be optimized to reduce pedestrian delay, and street network should be redesigned to optimize the pedestrian and traffic flow. Hence, proportion of through-traffic in Central Melbourne would be reduced from 43% in 2020 to 21% in 2030 (City of Melbourne, 2014; 2020a).

5.4.2 Urban street trees

For the effect of urban street trees, results indicate that pedestrian injury is negatively associated with tree density and tree canopy cover. Urban street trees can increase the driver awareness and driving safety by modifying the visual perception of drivers (Naderi, et al., 2008; Wang et al., 2024) and pedestrian safety perception can be improved when street tree cover increases (Ryan et al., 2018); thus, this finding supports strategies focused on urban street trees. In support, the Transport Strategy 2030 of Melbourne states that more physical protections including trees and other street furniture to be installed to separate between pedestrians and vehicles (City of Melbourne, 2020a). Nevertheless, it is worth exploring the factors including pedestrian socio-economics, safety attitude, and social norms that can affect the trade-off between efficiency and safety of pedestrians when the scarce urban space is allocated for urban greening (Chen et al., 2020; Sanganaikar and Mulangi, 2023; Zhu et al., 2021). Moreover, moderating effect by urban streetscape, built environment, and weather conditions on the association between urban street tree, pedestrian crossing behaviour, and pedestrian safety can be investigated using virtual experiment and field observation (Naderi et al., 2008; Zhai et al., 2019b; Zhu et al., 2022b). Nevertheless, effects of tree density and tree canopy on pedestrian injury are random. This could be because of the unobserved effects of seasonal changes in tree canopy cover and moderating effect by the weather condition on the association between tree canopy, walking behaviour and pedestrian safety (Hurley et al., 2019). It is worth exploring the effects of seasonal changes in tree density and canopy on pedestrian safety when comprehensive weather and tree data is available in the future.

5.4.3 Road and traffic characteristics

For the effect of road geometry, pedestrian casualty is positively associated with road width. As revealed in previous study, road width is positively correlated with pedestrian crossing distance. Hence, pedestrian may have higher likelihood to involve in a crash (Manuel et al., 2014). This is indicative to effective road design and traffic control measures like traffic calming that can reduce the pedestrian crashes at high risk locations. As indicated in current results, pedestrian casualty rate is lower when there is a crosswalk. Optimal design and planning of crosswalks, particularly in the areas with high development density and pedestrian activity would be essential (Su and Sze, 2022; Sze and Wong, 2007; Zegeer et al., 2001; Zhu et al., 2022a). In addition, pedestrian injuries increase when bus stop, tram station, or on-street parking is present. This finding suggests that the frequent pickup and drop-off activities at the kerbside, frequent pedestrian crossing activities near the bus stops and tram stations, and visual obstruction of pedestrians and drivers by the parked vehicles, buses, and trams (City of Melbourne, 2020a; Hosseinpour et al., 2014; Kraidi and Evdorides, 2020; Sze and Wong, 2007; Wong et al., 2007). Such findings are indicative to the street design and traffic calming measures in Central Melbourne. For example, road space should be allocated for walking by reducing the road width, removing the on-street parking, and widening the footpath, accessibility can be improved (especially for individuals with disability) by removing the road kerbs, and crossing distances can be reduced (Chen et al., 2020; Sze and Christensen, 2017). However, effects of bus stop, tram station, and on-street parking on pedestrian safety are random. This could be because of the unobserved heterogeneity of crossing behaviours among individuals. To this end, it is worth exploring the effects of safety perception, socio-demographics, and social norms on the crossing behaviours of pedestrians in the future study (Zhu et al., 2021). Furthermore, positive association between pedestrian injury and traffic speed (85^{th} percentile speed) can be expected (Bertulis and Dulaski, 2014). Thus, pedestrian-priority and low speed limit zones can be introduced (City of Melbourne, 2020a; Li et al., 2020b; Transport for London, 2001). Therefore, walking environment can be improved, and overall pedestrian safety can be enhanced in the long run (Su et al., 2021b).

5.4.4 Time period

Last but not least, time effect on pedestrian safety is also considered. For example, pedestrian casualty rates are higher in the morning peak and afternoon peak periods. Such finding is consistent to that of previous studies (Gu and Peng, 2021; Katanalp and Eren, 2021). This could be because of the poor light conditions and aggressive crossing behaviours of pedestrians in these periods (Gårder, 2004; Gu and Peng, 2021; Makarova et al., 2019). In contrast, pedestrian casualty rate is lower in the nighttime. This may be because drivers are usually not in a hurry, and would drive more cautiously (Cai et al., 2007). To sum up, these are indicative to the implementation of better street design and road management, e.g., streetlights, road barriers, and warning signs, that can increase the safety awareness of pedestrians and therefore reduce the pedestrian injury risk (Zhu et al., 2022a).

5.5 Concluding remarks

Urban street tree plays an important role in improving walking environment (Choi et al., 2016; Larsen et al., 2009; Sze et al., 2019). However, it is rare that the relationship between urban tree street and pedestrian safety is examined (Marshall et al., 2018). In this study, effects of tree density and tree canopy cover, based on the data obtained using

LiDAR technique, on pedestrian casualty at the microscopic level are evaluated. For instance, pedestrian crash exposure is measured using disaggregate pedestrian counting data of individual streets at the short time intervals. Then, a multivariate Poisson lognormal regression model is established to measure the association between pedestrian casualty and influencing factors, with which the effects of unobserved heterogeneity, spatial dependency, and correlation between injury counts of different severity levels are controlled.

Results indicate that road width, bus stop, tram station, on-street parking, and traffic speed are positively associated with pedestrian casualty. In contrast, pedestrian casualty would decrease when tree density and tree canopy cover increase. Hence, safety benefit of urban greening for walking is justified (Naderi et al 2008). More importantly, findings are indicative to optimal street design and traffic calming measures like reducing the crossing distance, reducing the speed limit, removing the on-street parking, and introducing the pedestrian-priority zone. Therefore, safe and comfortable walking environment can be provided, and walkability can be enhanced (Harvey et al., 2015).

Nevertheless, this study also has some limitations. First, most of the road segments are located in or close to the CBD. Results of parameter estimation might be limited to the urban area. It is worth exploring the effects of demographic, socioeconomic, built environment, and travel characteristics on the relationship between street tree and pedestrian safety when comprehensive street tree, traffic and safety data in other areas are available (Su et al., 2021b). In addition, this study is limited to the yearly trend of tree canopy cover only. Indeed, 40% of the tree in Melbourne City are deciduous, tree canopy may change more drastically due to seasonal effects. It is worth exploring the moderating effects by the factors including climate, socio-cultural mechanism, and walking behaviour on the association between tree canopy and pedestrian safety when comprehensive information on tree canopy and pedestrian behaviour are available in the empirical survey. Future study can use street view images to capture built environment. Furthermore, crash data used may be subject to missing data and under reporting, especially for slight injury crash. It is worth exploring the effects of under reporting, imbalanced crash data, temporal instability, and correlation between random effects on the parameter estimation using advanced statistical and machine learning modeling framework in the future (Behnood and Mannering, 2019; Ding et al., 2022; Lord and Mannering, 2010; Toran Pour et al., 2017; Toran Pour et al., 2018).

Chapter 6 Effect of pedestrian network and traffic conditions on pedestrian safety

6.1 Introduction

Walkability is one of the key attributes that determine urban vitality. Many metropolitan cities, that have high population density and activity intensity including Hong Kong, London, Melbourne, New York, Seoul, Singapore, Tokyo, and Toronto have been promoting walkability with new city and transport planning framework for pedestrians. Hence, street-level environment, air quality, accessibility, and safety for pedestrians can be improved (Guzman et al., 2022; Hamim and Ukkusuri, 2024; Ng et al., 2012; Transport Department, 2019). In Hong Kong, almost 90% of daily trips are made by public transport. Walking is the primary mean of access for public transport and other essential urban services (Guzman et al., 2022; Sze and Christensen, 2017). In 2021, an overall walkability strategy for Hong Kong was developed to improve the pedestrian environment (Transport Department, 2021). Characteristics of pedestrian facilities including sidewalks, walkways, crosswalks, footbridges and underpasses, landscape and street trees, and public spaces can affect pedestrian route choices. For example, footpaths that are well connected and have more amenities are favored by pedestrians (Anciaes and Jones, 2020). However, pedestrians are also vulnerable to fatality and severe injuries in road crashes. Pedestrians constitute 23% of road deaths round the world. In the Asia-Pacific area, pedestrians represent 14-22% of road deaths (World Health Organization, 2018). In Hong Kong, extremely high proportion (56%) of road deaths are pedestrians (Transport Department, 2022). Hence, it is necessary to consider pedestrian safety for the design of pedestrian network and facilities, and the formulation of traffic management strategy (Marshall and Garrick, 2010; Oviedo-Trespalacios and Scott-Parker, 2017; Sanganaikar and Mulangi, 2023; Zhao et al., 2021).

Road infrastructure plays an important role in road safety, especially for vulnerable road users (Intini et al., 2019; Papadimitriou et al., 2019; Sanganaikar and Mulangi, 2023;

Wegman and Slop, 1998). Over 90 countries have specific design standards for the separation between pedestrians and road traffic, and more than 130 countries have considered pedestrians for the design of crosswalks (World Health Organization, 2018). In Hong Kong, design for all principles have been applied for road curbs, building accesses, walkways, and crosswalks (Planning Department, 2016). To reduce the pedestrian-vehicle conflicts on urban roads, many footbridges and underpasses have been built since the 1980s. In Hong Kong, pedestrians often use footbridges and underpasses to cross the roads. On average, there were 217 rainy days and 18 very hot (with daily maximum temperature above 33 degrees Celsius) days per year in the past three decades (Hong Kong Observatory, 2021). Pedestrians tend to be unwilling to wait at the signalized crossings in adverse weather (Yang et al., 2015). Additionally, footbridges and underpasses are often interconnected with major transport hubs and commercial development and become parts of the elevated and underground walkway systems of the city (Highways Department, 2022). Furthermore, many footbridges and underpasses have been retrofitted with lifts and escalators (Planning Department, 2022). Pedestrians generally prefer footbridges and underpasses to at-grade pedestrian crossings considering the safety, accessibility, and efficiency implications (Soliz and Pérez-López, 2022).

It is challenging to characterize the complex multi-layer pedestrian network in Hong Kong (Chan et al., 2022; Zhao et al., 2021). Hong Kong has extremely high density of building development and transport infrastructures. The urban morphology and spatial hierarchy of three-dimensional pedestrian network are far more complicated, compared to the road network designed for motor vehicles. There are large number of links including staircases, ramps, lifts, escalators, and people movers connecting multi-level path segments and infrastructures in the vertical metropolis (Sanganaikar and Mulangi, 2023; Solomon et al., 2012; Sun et al., 2021). Additionally, it is necessary to consider the effect of the change in vertical level among all interconnected path segments in the pedestrian network on accessibility and safety outcomes. In previous studies, the relationship between characteristics of trafficable road network and pedestrian safety has been explored (Li et al., 2020a; Osama and Sayed, 2017). For example, a global integration index was adopted to characterize the topological structure of road network using space syntax technique (Guo et al., 2017). However, it is rare that safety effects of the characteristics like connectivity and accessibility of pedestrian network are investigated. In this study, a recently developed three-dimensional (3D) digital map of Hong Kong pedestrian network is applied for the data collection, imputation, and analysis of pedestrian network patterns (Lands Department, 2022). For example, the topology of individual walkway links, connectivity of pedestrian network, and accessibility of pedestrian facilities including at-grade crossings, footbridges, and underpasses can be determined. Then, the role of pedestrian network patterns in pedestrian safety can be identified.

The objective of this study is to examine the effects of footbridge and underpass on pedestrian safety. For instance, comprehensive land use, population characteristics, road infrastructures, traffic and crash data are mapped to 379 grids in urban Hong Kong using Geographical Information System (GIS) technique (Su et al., 2021b). Additionally, accessibility to pedestrian facilities including footbridge, underpass, and at-grade crossing is estimated. Furthermore, a multivariate Poisson-lognormal regression model with conditional autoregressive (CAR) prior is developed to measure the association between pedestrian crash and possible influencing factors, with which the effects of spatial correlation, unobserved heterogeneity, and correlation between crash counts are accounted, using the full Bayesian approach (Zhu et al., 2022a). Findings of this study will inform the optimal design, planning and development of pedestrian networks so to improve the accessibility of pedestrian facilities, enhance pedestrian safety, and more importantly, promote walkability in Hong Kong.

The remainder of this chapter is structured as follows. Illustration of data collection and statistical model are described in Section 6.2 and Section 6.3, respectively. Section 6.4 summarizes the estimation results and discusses the policy implications. Finally, concluding remarks are given in Section 6.5.

6.2 Data

6.2.1 Study area

In Hong Kong, about 8% of total land area only can be developed due to the mountainous terrain. City landscape is characterized by dense and high-rise development, limited vegetation and green space, diverse land use, and integrated transport network (Planning Department, 2016). Total length of the pedestrian network in Hong Kong is 8,363 km, 281% longer than that of the trafficable road network. A trafficable road refers to one that is designed for motor vehicles. In addition, number of pedestrian links is 8.5 times higher than that of road link (Sun et al., 2021). As of March 2022, there were 1,560 footbridge (total length of 108.5 km) and underpass (38.4 km) structures in Hong Kong (Highways Department, 2022). The multi-layer pedestrian links are usually interconnected using staircases, ramps, lifts, and escalators. Furthermore, built-up area constitutes 25% of total land area only in Hong Kong (Lands Department, 2022). Hence, the study area covers the urban area (Kowloon and North shore of Hong Kong Island) in Hong Kong only. The study area has high concentration of residential and commercial development, and high activity and travel intensity. Land area of the study area is 69.39 km^2, and population is about 3.15 million in the year 2016 (Census and Statistics Department, 2019).

In Hong Kong, land use and population census data are aggregated to pre-defined geographical units, i.e., Tertiary Planning Unit (TPU), for planning purpose. However, land area of a TPU can range from 0.07 km^2 to 4.8 km^2, which could hinder the assessment and benchmarking of topological characteristics of pedestrian network across units. Therefore, data are mapped to 379 (0.5 km x 0.5 km) grids in this study. Such configuration has considered: (1) amount of activity and travel; (2) both macroscopic- and microscopic-level characteristics of pedestrian network; (3) distributions of at-grade and grade-separated crossings; and (4) pedestrian crash intensity, at the neighborhood level. Other grid dimensions, such as 800 and 200 meters, were contemplated; however, they did not produce satisfactory outcomes. Specifically, the 800-meter radius proved to be excessively spacious for the densely populated pedestrian network of Hong Kong, whereas the 200-meter radius was insufficiently extensive to accommodate certain land use data.

6.2.2 3D digital map of pedestrian network

In this study, pedestrian network characteristics can be determined using the data from the 3D digital map of the Lands Department (Lands Department, 2022). There are 436,900 links (with 27,600 at-grade crosswalk, 7,200 footbridge, and 6,100 underpass links) and 372,500 nodes in total for the Hong Kong network. For instance, information on location (coordinates, street name, and building name), geometry (length, vertical level, and gradient), traffic control (crosswalk, footbridge or underpass, and crossing control), and pedestrian access (indoor or outdoor, covered or not, and escalator, lift, ramp, or wheelchair access) of each footpath link is available. All pedestrian links connecting footbridges, underpasses, transit stations, and commercial development are included in the dataset.

Figure 6.1 illustrates the schematic diagram of the 3D digital map for the pedestrian network. As shown in Figure 1, node refers to the intersecting point of at least two links, and vertex refers to the turning point on a link. In this study, connectivity of the pedestrian network can be reflected by three indicators as follows,

(1) Footpath density: Footpath length per 100 m^2 of land
(2) Node density: Number of nodes per 100 m of footpath
(3) Number of vertices per footpath link

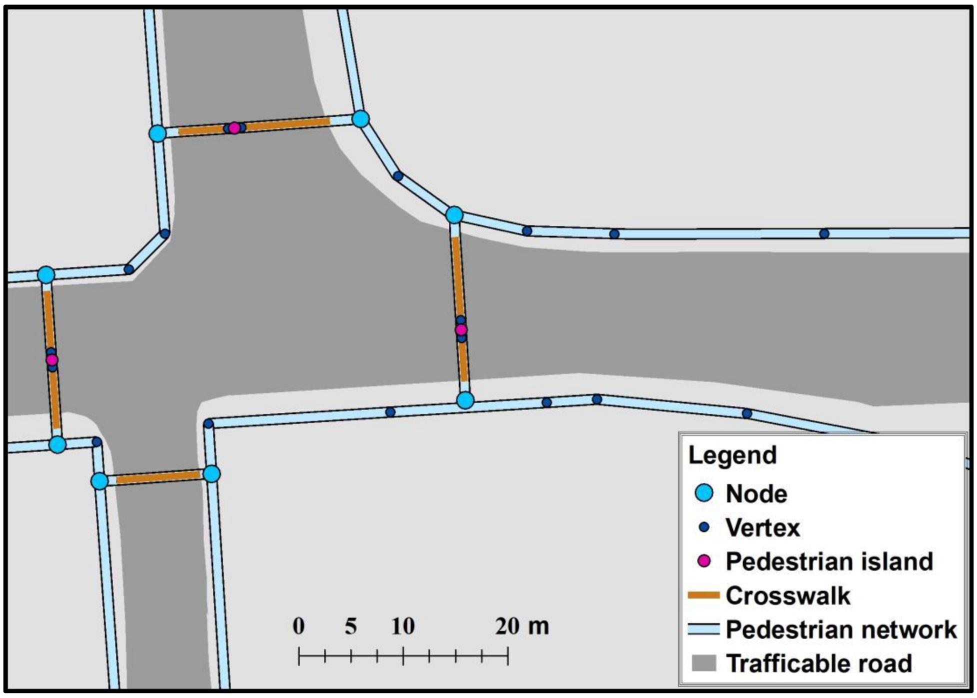


Figure 6.1 Characteristics of pedestrian network

In addition, topographical characteristics of the pedestrian network are also considered given the hilly terrain of Hong Kong. For grid i, average gradient of all footpath links is given by,

$$\overline{m_i} = \frac{\sum_s m_{is} l_{is}}{\sum_s l_{is}} \quad \text{(Eq. 1)}$$

where l_{is} refers to the length of footpath link s of grid i and m_{ij} refers the gradient.

Furthermore, as the focus of this study is to evaluate the influence of grade-separated crossing on pedestrian safety, accessibility to at-grade crossings, footbridges, and underpasses are estimated. For instance, factors including detour distance, difference in vertical level, and effective crosswalk distance that could affect the choice of pedestrians are considered when estimating accessibility. Figure 6.2 illustrates the parameters used for the estimation of accessibility for grade-separated crossings, i.e., footbridges and underpasses. As shown in Figure 6.2, l_{ik} refers to the length of crossing facility (footbridge or underpass) k, l'_{ik} refer to the effective crossing distance (i.e., width of the trafficable road), and d_{ik} refer to the detour distance, respectively. Thus, the impedance function that indicates the travel cost saving (i.e., total waiting time for all at-grade crossings avoided) for crossing facility k can be given by,

$$E_{ik} = e^{-\frac{c_{ik}}{2n_k}} \quad \text{(Eq. 2)}$$

where $c_{ik} = \frac{d_k}{d_0}$ when $d_k \leq d_0$, and $c_{ik} = 1$ when $d_k > d_0$, n_k refers to the number of at-grade crossings avoided when crossing facility k is used, and d_0 refers to the acceptable detour distance of pedestrian. In this study, d_0 is set at 100 m (Arellana et al., 2022).

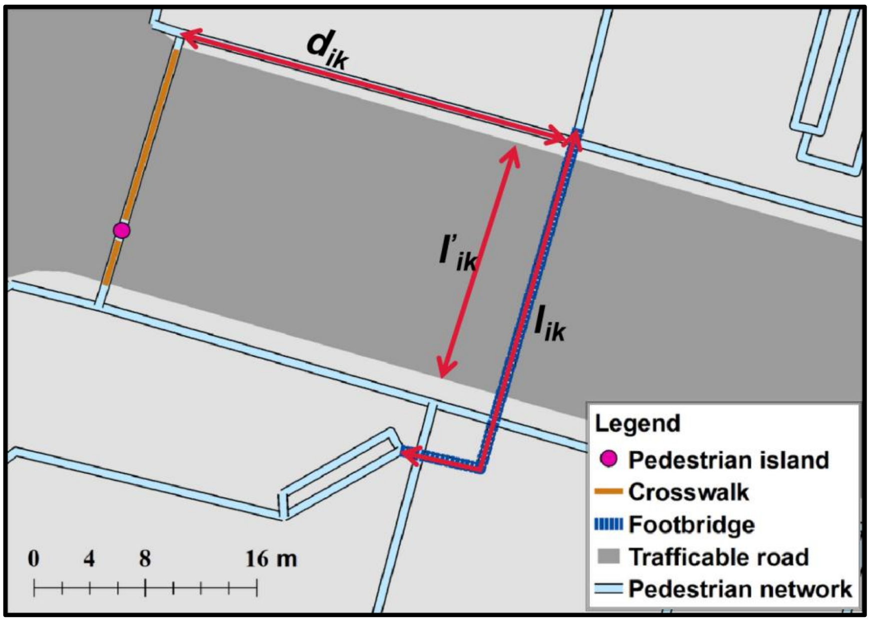


Figure 6.2 Parameters for the estimation of accessibility of grade-separated crossing

Impedance function that reflects the difference in vertical level of crossing facility k can be given by,

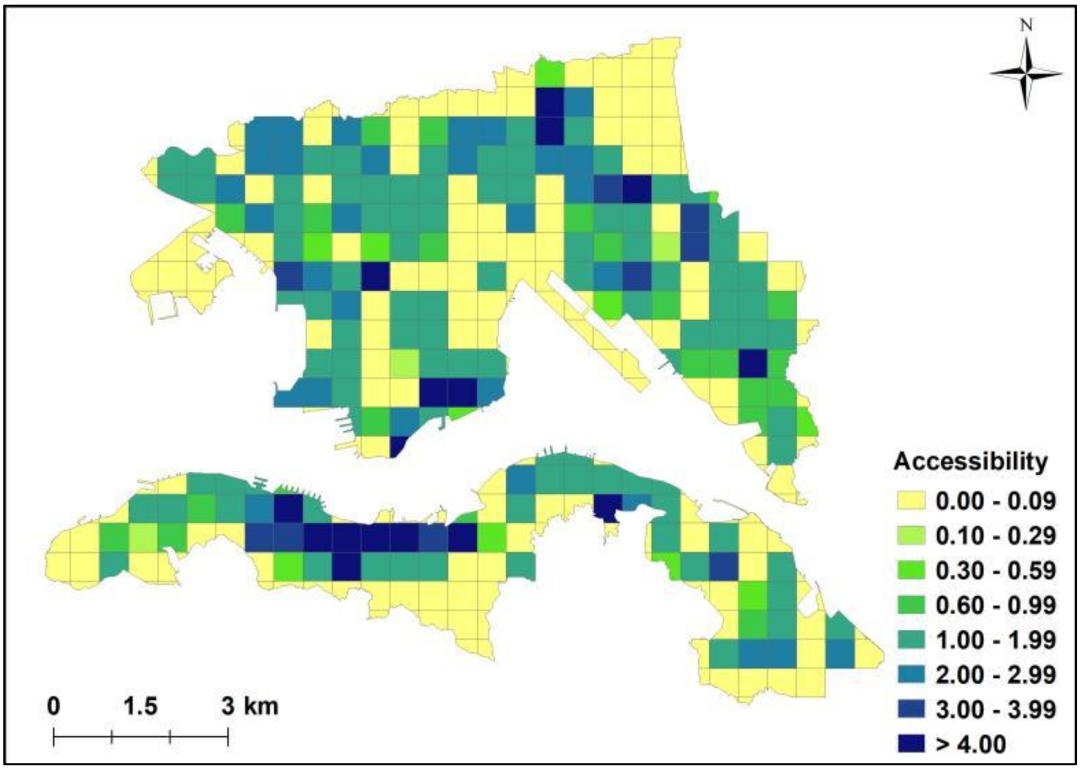
$$G_{ik} = e^{-\frac{c_{ik} \times \Delta h_{ik}}{2}} \quad \text{(Eq. 3)}$$

where $\Delta h_{ik}$is difference in vertical level between k and ground surface.

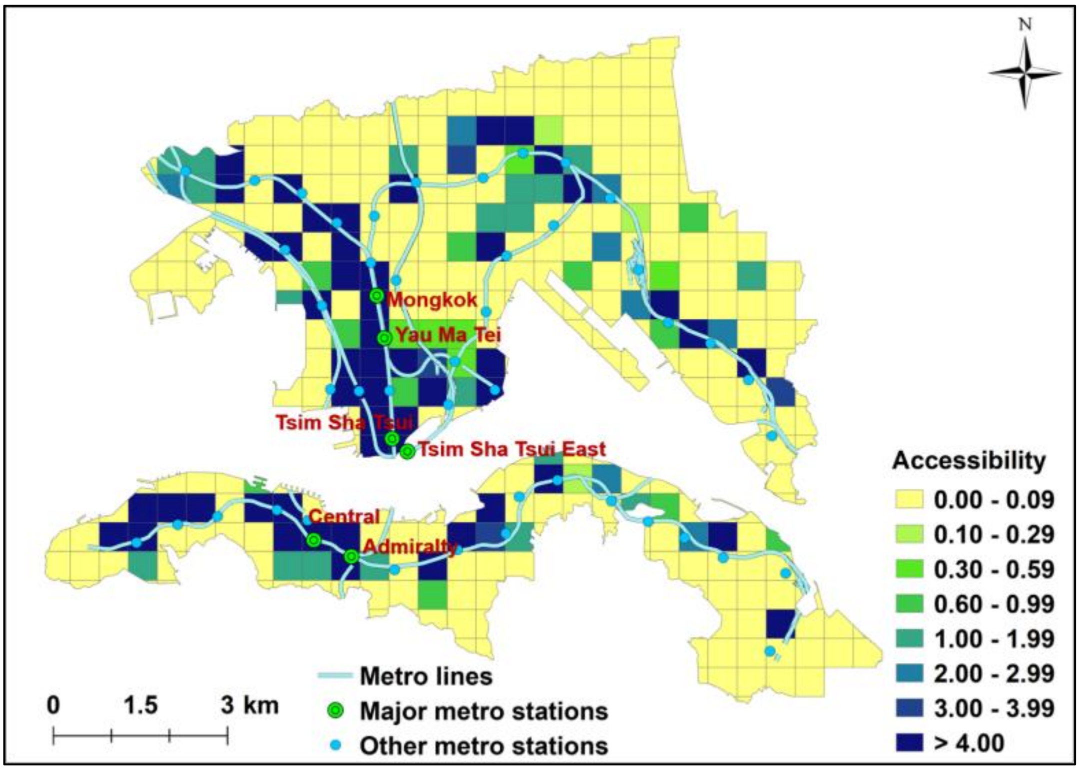
Hence, overall accessibility of all grade-separated crossings of grid i can be given by,

$$A_i = \sum_k E_{ik} \frac{1}{\frac{l_{ik} G_{ik}}{l_{ik}^{'}}} \qquad \text{(Eq. 4)}$$

As shown in Eq. (4), accessibility of footbridges and underpasses is directly proportional to the travel cost saving and inversely proportional to the difference in vertical level, considering the acceptable detour distance of pedestrians. Figure 6.3 illustrates the spatial distribution of accessibility for footbridges (Figure 3(a)) and underpasses (Figure 3(b)) of the study area. As shown in Figure 3(a), accessibility of footbridges is generally high for the majority of observation units. This could be attributed to the development of massive elevated walkway system in the past four decades (Highways Department, 2022). In contrast, accessibility of underpasses is generally low, except for in the central business districts which have major underground transit stations.



(a) Footbridge



(b) Underpass

Figure 6.3 Distribution of accessibilities of footbridge and underpass in the study area

For the at-grade crossings, accessibility can be given by,

$$A_i = \frac{C_i}{R_i} \quad \text{(Eq. 5)}$$

where C_i is the number of at-grade crossing of grid i and R_i is the number of trafficable road link.

6.2.3 Built environment, traffic, and crash data

In this study, effects of land use and transport facilities on pedestrian safety are considered. Land use data is obtained from the two-dimensional digital map of Planning Department, which allows estimations for the proportions of residential area, commercial area, government and utility area, and green space for each grid. Additionally, location of bus stops and metro exits was obtained from the 3D digital map from the Lands Department.

To evaluate the effect of exposure on pedestrian safety, comprehensive traffic count data was obtained from the Annual Traffic Census (ATC) report of Transport Department. This report includes the annual average daily traffic (AADT) of about 1,600 road segments (Transport Department, 2019-2021). To estimate the walking trip frequency, household travel data was obtained from the Travel Characteristics Survey (TCS) report (Transport Department, 2014). Information on the origin, destination, departure time, and walking time of every walking trip leg was available. Furthermore, population and household characteristic data was obtained from the Census and Statistics Department database (Census and Statistics Department, 2019-2021).

Crash data was obtained from the Traffic Information System (TIS). In this study, only motor vehicle crashes that involve pedestrians are included. Information on the location, date and time, and injury severity (e.g., fatality, severe injury, and slight injury) of pedestrians for each crash was obtained. In 2017-2019, there were 4,768 pedestrian-vehicle crashes in the study area. Fatal and severe injury crashes constituted 21.9% of the sample.

In this study, land use, transport facilities, pedestrian network characteristics, crossing facilities, traffic and pedestrian crash data were mapped to the 379 grids using the GIS technique. Analysis focused on the association between frequencies of slight injury crash and fatal and severe injury (FSI) crashes, as well as possible influencing factors at the grid level. Table 6.1 summarizes the data. Correlation between explanatory variable has been checked prior to parameter estimation. For instances, values of variance inflation factor (VIF) are less than five for all explanatory variables.

Table 6.1 Summary statistics of the sample

Scope of work	Variable	Mean	Max.	Min.	S.D.
Pedestrian crash	Slight injury crash	9.81	134.00	0.00	16.97
	Fatal and severe injury (FSI) crash	2.77	30.00	0.00	4.79
Exposure	Ln (Annual average daily traffic)	9.66	11.77	6.54	1.01
	Ln (Population density)	10.28	12.32	6.77	1.37
	Ln (Daily walking trip)	8.30	11.32	0.75	1.98
Pedestrian network characteristics	Footpath density (m per 100 m^2)	3.90	21.98	0.00	2.70
	Node density (per 100 m)	3.56	20.70	0.00	2.34
	Number of vertices per footpath link	6.32	138.63	0.00	16.46
	Average gradient	8.16	37.78	0.00	9.55
Crossing facilities	Accessibility of footbridge	1.01	12.24	0.00	1.71
	Accessibility of underpass	2.14	52.59	0.00	6.43
	Number of at-grade crossings per road segment	0.53	2.00	0.00	0.57
Land use	Proportion of residential area	19.47	99.74	0.00	20.47
	Proportion of commercial area	3.00	58.83	0.00	8.02
	Proportion of government and utility area	10.98	65.93	0.00	11.89
	Proportion of green area	19.73	100.00	0.00	30.98
Transport facilities	Number of bus stop	4.30	22.00	0.00	4.90
	Number of metro exit	1.00	17.00	0.00	2.53

6.3 Method of analysis

Poisson lognormal regression approach was adopted to model the association between pedestrian crash and possible influencing factors, given that the dependent variable is over-dispersed and heavy-tail distributed (Sohn, 1994; Miranda-Moreno et al., 2005), using the following,

$$y_i^p \sim Poisson(\lambda_i^p) \quad \text{(Eq. 6)}$$

where y_i^p is the observed number of pedestrian crashes of injury severity level *p* at grid *i*, and λ_i^p is the Poisson parameter given as follows,

$$ln\left(\lambda_i^p\right) = a^p + b^p X_i^{'} + U_i^p + S_i^p \quad \text{(Eq. 7)}$$

where a^p is the intercept, $X_i^{'}$ is the matrix of covariates, b^p is a column vector of corresponding coefficients, U_i^p is the unstructured random term for overdispersion, and S_i^p is the spatially structured random term for spatial autocorrelation respectively.

Considering the effect of spatial dependency, conditional autoregressive (CAR) prior given as follows is adopted,

$$S_i^p \middle| S_{-i}^p \sim N\left(\overline{S_i^p}, \sigma_{Sp}^2 / n_i\right) \quad \text{(Eq. 9)}$$

where S_{-i}^p refers to all the elements except S_i^p, $\overline{S_i^p} = \sum_{j \neq i} S_j^p \times \omega_{i,j} / n_i$ with $\omega_{i,j}$ representing the spatial weight ($\omega_{i,j} = 1$ if grid i and j are adjacent and 0 otherwise), n_i is the number of units that are adjacent to grid i, and the hyperparameters follow the Gamma distribution.

To account for the possible correlation between crash counts of different injury severity level, multivariate approach was adopted. For instance, the unstructured random term that follows multivariate normal distribution is written as,

$$U_i \sim MN\left(\mu_i, \Sigma_\mu\right) \quad \text{(Eq. 10)}$$

where μ_i is the vector of zeroes and Σ_μ is the covariance matrix estimated by the Wishart distribution,

$$\Sigma_\mu^{-1} \sim Wishart\left(R_\mu, P\right) \quad \text{(Eq. 11)}$$

where R_μ is a scale matrix for precision and P is degree of freedom ($P = 2$).

For instance, the non-informative prior for R_μ is set as (Aguero-Valverde, 2013),

$$R_\mu = \begin{bmatrix} 0.1 & 0.005 \\ 0.005 & 0.1 \end{bmatrix} \quad \text{(Eq. 12)}$$

Furthermore, the multivariate CAR prior can be expressed as,

$$S_i \left| \left(S_{-i}^1, S_{-i}^2\right) \sim MN\left(\overline{S_i}, \Sigma_s/n_i\right) \right. \quad \text{(Eq. 13)}$$

where $\overline{S_i}$ is the mean vector, $\overline{S_i} = \left(\sum_{j\neq i} S_j^1 \times \omega_{i,j}/n_i, \sum_{j\neq i} S_j^2 \times \omega_{i,j}/n_i\right)^T$ and Σ_s is a 2×2 covariance matrix. Similar to the specification of Σ_μ, the same approach was adopted to determine Σ_s.

Multivariate Poisson lognormal model assumes the multivariate normal distribution with mean vector zero and unrestricted variance-covariance matrix. Correlation can be positive or negative, depending on the sign of the element of variance-covariance matrix (Chib and Winkelmann, 2001; El-Basyouny and Sayed, 2009; Ma et al., 2008). Positive element indicates positive correlation, and vice versa. In addition, diagonal element of the unrestricted variance-covariance matrix can be positive. Hence, overdispersion can be accounted (Aguero-Valverde, 2013; Chib and Winkelmann, 2001; Ma et al., 2008).

To assess the goodness of fit of the models, Watanabe-Akaike Information Criterion (WAIC) is adopted. Not only the predictive power, but also the model complexity and overfitting are considered (Ali et al., 2021; Kitali et al., 2022).

WAIC is a Bayesian approach that utilizes the posterior distribution for the estimation of out-of-sample expectation (Li et al., 2021; Bakhshi and Ahmed,2021). In this study, WAIC would be estimated using the following (Watanabe and Opper, 2010),

$$WAIC = -2lppd + 2p_{WAIC} \quad \text{(Eq. 14)}$$

where *lppd* is log posterior predictive density, p_{WAIC} is effective number of parameters.

Model with smaller WAIC is preferred. In this study, Markov Chain Monte Carlo (MCMC) based full Bayesian approach was used to estimate the proposed multivariate Poisson-lognormal model. For instance, the first 10,000 samples were discarded as burn-in, and 20,000 further iterations was run for each chain. Convergence of the models was assessed using autocorrelation plots.

6.4 Results and Discussion

This study examines the effects of built environment, pedestrian network, crossing facilities, and transport facilities on pedestrian crash frequency using a multivariate Poisson-lognormal regression model. For instance, a 3D digital map is applied to assess the connectivity and accessibility of pedestrian network of Hong Kong.

In this study, value of WAIC (2,032.16) of multivariate Poisson-lognormal model is less than that of univariate model (2,901.33). Hence, the multivariate model is adopted. Table 6.2 shows the parameter estimation results of both multivariate and univariate models. Bayesian credible interval (BCI) specifies the probability range of posterior distribution of parameter. A variable is considered significant if the MC error is less than 0.05 and 95% Bayesian credible interval (BCI) does not contain the null effect (i.e., zero) (Sameen and Pradhan, 2017). In addition, backward stepwise technique is adopted to identify significant variables. Results of parameter estimation of multivariate and univariate models are comparable. Hence, results of the multivariate model are discussed in detail in the following.

As shown in Table 6.2, for the exposure, pedestrian crash was positively associated with annual average daily traffic (FSI, β = 0.092), population density (slight injury, 0.425; FSI, 0.493), and daily walking trip (slight injury, 0.573; FSI, 0.623). For the pedestrian network, pedestrian crash was positively associated with footpath density (slight injury, 0.099; FSI, 0.106), node density (slight injury, 0.267; FSI, 0.279), and number of vertices per footpath links (slight injury, 0.042; FSI, 0.044). In contrast, pedestrian crash was negatively associated with average gradient (slight injury, -0.039; FSI, -0.044). For the crossing facilities, pedestrian crash was negatively associated with accessibility of footbridges (slight injury, -0.287; FSI, -0.322), accessibility of underpasses (slight injury, -0.006; FSI, -0.007), and number of at-grade crossings per road segments (FSI, -0.010). For the land use and transport facilities, pedestrian crashes increases with the proportions of residential areas (slight injury, 0.329; FSI, 0.348), commercial area (slight injury, 0.118; FSI, 0.130), government and utility areas (slight injury, 0.046; FSI, 0.049), number of bus stops (slight injury, 0.047; FSI, 0.050) and number of metro exits (slight injury, 0.034; FSI, 0.036); but decreased with the proportion of green areas (slight injury, -0.073; FSI, -0.069). Furthermore, both the unstructured effect (slight injury, 0.474; FSI: 0.430) and spatial effect were significant (slight injury, 0.530; FSI: 0.571).

Table 6.2 Results of parameter estimation of multivariate and univariate Poisson-lognormal models

Scope of work	Variable	Multivariate Poisson-lognormal model				Univariate Poisson-lognormal model			
		Mean	S.D.	MC error	(95% BCI)	Mean	S.D.	MC error	(95% BCI)
Slight injury crash									
	Intercept	-9.891*	0.584	0.023	(-11.080, -8.857)	-9.987	0.685	0.071	(-11.103, -8.298)
Exposure	Ln (Annual average daily traffic)	0.076	0.010	0.002	(0.055, 0.093)	0.079*	0.013	<0.001	(0.057, 0.101)
	Ln (Population density)	0.425*	0.094	0.003	(0.255, 0.592)	0.401*	0.085	0.003	(0.249, 0.568)
	Ln (Daily walking trip)	0.573*	0.081	0.003	(0.374, 0.724)	0.545*	0.089	0.002	(0.354, 0.714)
Pedestrian network characteristics	Footpath density	0.099*	0.079	0.003	(0.005, 0.282)	0.087*	0.076	0.003	(0.011, 0.220)
	Node density	0.267*	0.038	0.001	(0.186, 0.333)	0.222*	0.054	0.001	(0.185, 0.375)
	Number of vertices per footpath link	0.042*	0.023	0.001	(0.004, 0.093)	0.041*	0.021	0.001	(0.012, 0.074)
	Average gradient	-0.039*	0.022	0.001	(-0.088, -0.004)	-0.031*	0.031	0.001	(-0.075, -0.001)
Crossing facilities	Accessibility of footbridge	-0.287*	0.134	0.004	(-0.599, -0.051)	-0.252*	0.068	0.001	(-0.380, -0.127)
	Accessibility of underpass	-0.006*	0.003	<0.001	(-0.014, -0.001)	-0.007*	0.005	<0.001	(-0.014, -0.001)
	Number of at-grade crossings per road segment	-0.008	0.009	0.001	(-0.025, 0.009)	-0.010	0.015	<0.001	(-0.045, 0.015)
Land use	Proportion of residential area	0.329*	0.069	0.002	(0.203, 0.457)	0.325	0.017	0.001	(0.293, 0.346)
	Proportion of commercial area	0.118*	0.048	0.001	(0.016, 0.209)	0.106*	0.031	0.001	(0.041, 0.164)
	Proportion of government and utility area	0.046*	0.027	0.001	(0.011, 0.136)	0.043*	0.018	<0.001	(0.024, 0.075)
	Proportion of green area	-0.073*	0.024	0.001	(-0.119, -0.026)	-0.075*	0.021	0.001	(-0.133, -0.020)
Transport facilities	Number of bus stop	0.047*	0.012	<0.001	(0.027, 0.071)	0.045*	0.017	<0.001	(0.007, 0.087)
	Number of metro exit	0.034*	0.014	<0.001	(0.006, 0.061)	0.035*	0.017	<0.001	(0.005, 0.068)
Unobserved effects	Unstructured effect	0.474*	0.064	0.003	(0.358, 0.583)	0.468*	0.068	0.003	(0.341, 0.603)
	Spatial effect	0.530*	0.152	0.006	(0.160, 0.730)	0.522*	0.115	0.004	(0.282, 0.744)

FSI crash									
	Intercept	-10.020*	1.216	0.060	(-11.840, -6.769)	-11.480*	1.352	0.055	(-14.010, -9.074)
Exposure	Ln (Annual average daily traffic)	0.092*	0.035	0.001	(0.033, 0.162)	0.087*	0.053	0.001	(0.038, 0.157)
	Ln (Population density)	0.493*	0.063	0.002	(0.360, 0.611)	0.518*	0.110	0.004	(0.342, 0.731)
	Ln (Daily walking trip)	0.623*	0.176	0.008	(0.312, 0.926)	0.655*	0.097	0.003	(0.493, 0.812)
Pedestrian network characteristics	Footpath density	0.106*	0.044	0.002	(0.019, 0.185)	0.090*	0.085	0.004	(0.029, 0.183)
	Node density	0.279*	0.040	0.002	(0.1895, 0.3503)	0.189*	0.067	0.002	(0.083, 0.274)
	Number of vertices per footpath link	0.044*	0.023	0.002	(0.006, 0.094)	0.045*	0.043	0.001	(0.014, 0.075)
	Average gradient	-0.044*	0.016	<0.001	(-0.075, -0.013)	-0.037*	0.021	0.001	(-0.085, -0.003)
Crossing facilities	Accessibility of footbridge	-0.322*	0.055	0.002	(-0.455, -0.236)	-0.378*	0.074	0.002	(-0.469, -0.237)
	Accessibility of underpass	-0.007*	0.003	<0.001	(-0.014, -0.001)	-0.009*	0.004	<0.001	(-0.019, -0.001)
	Number of at-grade crossings per road segment	-0.010*	0.004	<0.001	(-0.019, -0.002)	-0.016*	0.005	<0.001	(-0.041, -0.003)
Land use	Proportion of residential area	0.348*	0.025	0.001	(0.311, 0.395)	0.358*	0.032	0.001	(0.281, 0.501)
	Proportion of commercial area	0.130*	0.017	<0.001	(0.102, 0.163)	0.128*	0.035	0.001	(0.065, 0.193)
	Proportion of government and utility area	0.049*	0.021	<0.001	(0.022, 0.114)	0.044*	0.019	<0.001	(0.022, 0.106)
	Proportion of green area	-0.069*	0.025	0.001	(-0.116, -0.019)	-0.076*	0.025	0.001	(-0.137, -0.018)
Transport facilities	Number of bus stop	0.050*	0.011	<0.001	(0.030, 0.071)	0.050*	0.018	<0.001	(0.019, 0.084)
	Number of metro exit	0.036*	0.013	<0.001	(0.011, 0.062)	0.039*	0.015	<0.001	(0.010, 0.065)
Unobserved effects	Unstructured effect	0.430*	0.042	0.002	(0.336, 0.510)	0.423*	0.094	0.002	(0.255, 0.592)
	Spatial effect	0.571*	0.081	0.004	(0.374, 0.724)	0.554*	0.135	0.005	(0.282, 0.801)

** Significant at the 95% Bayesian credible intervals*

Table 6.3 presents the correlation between crash types. Mean, standard deviation, and 95% BCI of posterior distribution of correlation are reported. As shown in Table 6.3, correlation of unstructured random effect is significant (Mean = 0.597; S.D. = 0.082). This implies that slight injury crash is positively correlated to FSI crash, and justifies that multivariate model is appropriate. Additionally, correlation of spatial effects is significant (Mean = 0.843; S.D. = 0.100). This implies strong spatial dependency between crash counts of different types across geographical units (i.e., grids). Furthermore, correlation of total random effect is significant (Mean = 0.701; S.D. = 0.095). This generally aligns with that of previous studies (Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009; Ma et al., 2008).

Table 6.3 Correlation of the random effects for multivariate model

	Mean	S.D.	(95% BCI)
Unstructured random effect	0.597*	0.082	(0.438, 0.701)
Structured random term for spatial dependency	0.843*	0.100	(0.674, 0.972)
Total random effect	0.701*	0.095	(0.608, 0.859)

** Significant at the 95% Bayesian credible intervals*

6.4.1 Pedestrian network characteristics

Results indicated that pedestrian crashes increased with footpath density, node density, and number of vertices per footpath links. It was found that more integrated and complex footpath networks, with more intersecting and turning points, worsened pedestrian safety. This finding suggests that intersecting points (nodes) and turning points (vertices) like road curves, building accesses, and roadside drop-off, pick-up and loading areas are vehicle-pedestrian conflict hotspots, which increase the crash exposure of pedestrians (Guo et al., 2017; Osama and Sayed, 2017). In contrast, pedestrian crashes decreased with the gradient of footpath. This finding suggests that drivers may be more cautious when they drive along sloping roads, which reduces pedestrian crash risk (Chen and Zhou, 2016). However, detailed information on traffic flow and speed is not available in this study. It is worth exploring the relationship between gradient, traffic volume, vehicular speed, and pedestrian crash when comprehensive traffic count data is available in future research.

For the crossing facilities, these findings suggest that pedestrian safety could be improved if footbridges, underpasses, and crosswalks are made more accessible. This action could be achieved if footbridges and underpasses are installed at strategic locations that have high pedestrian and traffic volumes. In support, research has found that pedestrian-vehicle conflicts are reduced with grade-separated crossings (Oviedo-Trespalacios and Scott-Parker, 2017). This is particularly true for transit-oriented city likes Hong Kong (and other cities like London and Tokyo). To illustrate, massive elevated and underground walkway systems have been developed to provide access to rail transit system in Hong Kong. Such systems ensure that pedestrians walking to the rail transit stations are well separated from the road traffic (Cui et al., 2013; Transport Department, 2020).

6.4.2 Traffic characteristics and pedestrian exposures

This study found that pedestrian crashes increased with population density and daily walking trip. Consistent with previous research, this finding suggests a “safety-in-number” effect, whereby an increase in pedestrian crashes is less than proportionate to the increase in daily walking trips (Elvik and Bjørnskau, 2017; Su et al., 2021b). This finding supports the implementation of overall walkability strategy in metropolitan cities like Hong Kong, London, and Melbourne (City of Melbourne, 2014; Department for Transport, 2017; Transport Department, 2021). For example, more space should be allocated for pedestrian streets. Furthermore, FSI pedestrian crashes increased with traffic volume. This finding suggests it is crucial to implement local area traffic management and traffic calming measures like low-speed limit zones and pedestrian priority traffic signals. These actions have the potential to reduce pedestrian injury risk at the hotspots of pedestrian-vehicle conflicts (Zhang et al., 2017; Zegeer and Bushell, 2012).

6.4.3 Built environment and transport facilities

Consistent with previous research, this study found that pedestrian crashes increased when the proportions of residential, commercial, and government and utility area increased (Effati and Saheli, 2022; Jermprapai and Srinivasan, 2014). In contrast, pedestrian crashes decreased when the proportion of green area increased. This finding suggests that the roads in green area usually have more trees and green vegetation, which could increase the awareness of drivers and safety perception of pedestrians (Hamim and Ukkusuri, 2024; Naderi et al., 2008; Ryan et al., 2018). In support, research has found that pedestrian crashes are reduced with an increase in tree density and canopy cover (Zhu et al., 2022a). Furthermore, pedestrian crashes increased with the number of bus stop and metro exits. This finding suggests that that pedestrian crashes may be the result of frequent roadside pickup and drop-off activities and reckless crossing behaviours near the bus stop and metro exits. Hence, design of road facilities like on-street parking, road barriers, central median, and crosswalks should be improved (Sze and Christensen, 2017).

6.5 Concluding remarks

To improve the pedestrian environment and reduce the pedestrian-vehicle conflicts, facilities like footbridges, underpasses, and elevated and underground walkways have been installed in Hong Kong in the past decades. However, it is rare that influences of pedestrian network characteristics on pedestrian safety are investigated. In this study, a 3D digital map is used to evaluate the topology, connectivity, and accessibility of pedestrian network. Then, association between pedestrian crash, pedestrian network characteristics and other possible influencing factors is measured using the multivariate Poisson lognormal approach, based on multi-source data on traffic flow, walking trip, pedestrian network characteristics, crossing facilities, land use, and transport facilities of 379 grids.

Results indicate that pedestrian crash increases with population density, traffic flow, walking trip, footpath density, node density, number of vertices, residential area, commercial area, government and utility area, bus stop, and metro exit. In contrast, pedestrian crash decreases with average gradient, and accessibility of footbridge, underpass, and at-grade crossing. This justifies the development of elevated and underground walkway system. Moreover, findings should shed light to the implementation of optimal traffic control and management strategy. Therefore, safe and accessible walking environment can be developed, and walkability can be improved (Cui et al., 2013; Oviedo-Trespalacios and Scott-Parker, 2017).

Nevertheless, there are some limitations for this study. First, pedestrian crash data is obtained from the Police. Problem of under reporting and missing data is prevalent. It is worth exploring the use of deep learning and data generation approaches for imbalanced crash data problem (Ding et al., 2022). Furthermore, it is necessary to account for the effect of temporal instability when multiple year data is used (Behnood and Mannering, 2019).

Chapter 7 Effect of walking accessibility for metro system on pedestrian safety

7.1 Introduction

In the past decades, many compact cities around the world have adopted transit-oriented development strategies, aiming to increase public transport use, reduce car dependence, optimize urban space allocation, and promote sustainable urban growth. In Hong Kong, the first metro line was opened in 1979. In the late 1990s, the transit-oriented development policy was initiated. Since then, mixed-use development integrating residential, commercial, leisure and community use with metro stations was widely adopted. As of 2023, there are 10 metro lines and 98 stations (Mass Transit Railway Corporation, 2023). This has reshaped the activity and travel patterns of the citizens. 34% of passenger trips are made by metro in Hong Kong (Sze et al., 2019). To further increase public transport use, it is necessary to improve the level of public transport service, walking environment and accessibility (Park and Chowdhury, 2018; Tiznado-Aitken et al., 2020). In a compact city likes Hong Kong, it is challenging to optimize the allocation of scarce urban space for housing development, road traffic and pedestrians, especially metro stations are often located in high-density mixed-use areas. Efficiency, safety, and well-being of all road users should be considered (Chen et al., 2020).

Walking accessibility refers to the opportunity for a pedestrian to reach potential goods and services from a specific location (Papa et al., 2018; Van der Vlugt et al., 2022). As aforementioned, walking accessibility plays an important role in public transport use. However, same as other developed societies, Hong Kong is facing the problem of aging population. Additionally, over 320 thousand people in Hong Kong (4.5% of the population) are physically impaired (Sze and Christensen, 2017). It is necessary to consider the needs of low mobility groups in urban transport planning. To this end, concepts like design for all and barrier-free access should be adopted in building design, addressing the accessibility problems for individuals with disability (World Physical Therapy Confederation, 2019). In

Hong Kong, barrier-free facilities, including elevators, escalators and ramps, are increasingly installed at the footbridges, underpasses, and metro stations. Therefore, accessibility of low mobility groups can be enhanced (Sze and Christensen, 2017).

Pedestrian activities are frequent in urban areas, especially for transit-oriented development. However, the safety of pedestrians has been of concern since they are vulnerable to serious injuries in road crashes (Chimba et al., 2018; Eluru et al., 2008; Zhu et al., 2022a). A quarter of overall road deaths are pedestrians around the world (World Health Organization, 2018). In Hong Kong, pedestrians even constitute more than half of overall road deaths (Zhu et al., 2023a). Studies indicated pedestrian crash frequencies were higher in the areas around metro stations and on the streets with more public transit stops (Lee et al., 2015; Pulugurtha and Penkey, 2010; Osama and Sayed, 2017). This could be because of the unsafe crossing behaviour of pedestrians (Raveesh et al., 2020; Sung et al., 2022). However, the relationship between pedestrian safety and walking accessibility is less studied.

In conventional crash studies, built environment, road network, socio-demographics, traffic, and safety data are often aggregated at different spatial scales. For example, built environment and socio-demographics data are available at the census tract, area or district level. In contrast, road design, transport facility and traffic flow data are broken down into smaller units like street, intersection or grid. To this end, it is necessary to model the multilevel data using the hierarchical approach, accounting for the possible effect of between-individual heterogeneity (Hill and Goldstein, 1998; Huang and Abdel-Aty, 2010; Silvia, 2007). Furthermore, an individual does not belong to one and only one group. Individuals can be nested within multiple groups. Hence, multiple membership multilevel model should be adopted, accounting for the problems of data dependency (Durrant et al., 2018). Last but not least, multiple membership weights should be assigned to an individual for different groups respectively, accounting for the variation in influential power among groups.

On the other hand, crash data are often aggregated over time periods like months or years to provide an adequate sample of observations for crash frequency models. This implies the assumption that the effects of influencing factors on crash frequency are constant over time. However, studies indicate that temporal instabilities may exist when crash data from multiple time periods are used for the estimation (Behnood and Mannering, 2019; Islam et al., 2020). Therefore, it is necessary to address the problem of temporal instability in this study, avoiding the possible bias in parameter estimation (Alnawmasi and Mannering, 2023; Mannering, 2018).

The modifiable areal unit problem is prevalent when data that are aggregated at different spatial scales are modeled using the single level approach (Manley, 2021). Additionally, it is necessary to consider the effects of unobserved heterogeneity when data from a sample of smaller units are aggregated to the larger geographical areas. For example, road segments or intersections in the same districts may exhibit different road design, traffic control and traffic flow characteristics. These unobserved characteristics can also affect the crash frequency of an area (Dupont et al., 2013). To this end, the multilevel modeling approach has been proposed to address the modifiable areal unit problem, for the unevenness and clustering characteristics of data structure (Jones et al., 2018).

On the other hand, an individual road entity or small geographical unit can be nested with two or more larger areas. This is known as a multiple membership problem. If the multiple membership structure of hierarchical data was not accounted for, the importance of group-level factors would be underestimated, and therefore, the parameter estimation would be biased (Hill and Goldstein, 1998). To this end, multiple membership multilevel modeling approach can be adopted to address the clustering problem of individual road entities and the underestimation of the significance of group-level clusters (Yang et al., 2022). Furthermore, multiple membership approach assumed that individual geographical units located within the same catchment area shared all the area-level characteristics. Hence, spatial dependency between units in the same catchment area can be captured.

In this study, a multiple membership multilevel model will be developed to examine the relationship between possible factors, walking accessibility and pedestrian crash frequency in the areas around metro stations. For instance, data on land use, demographics, socio-economic are averaged by the catchment areas of metro stations. On the other hand, street network, walking accessibility and exposure for the smaller zones are estimated. Additionally, both barrier-free and general walking accessibility are considered. Furthermore, multiple membership weights would be assigned to a zone for different metro stations respectively, considering the walking distances between zones and metro stations. Last but not least, temporal stability of parameter estimation would be explored. Contribution of this study is two-fold. First, between-individual heterogeneity in the hierarchical data structure can be accounted using multilevel modeling approach. Second, dependency between zones that are located in the same catchment area would be captured. Results of this study can shed light on effective urban and transport planning policy that can improve the walkability and pedestrian safety.

The remainder of this chapter is structured as follows. Illustration of study design and statistical model are described in Section 7.2 and Section 7.3, respectively. Section 7.4 summarizes the estimation results and discusses the policy implications. Finally, concluding remarks are given in Section 7.5.

7.2 Study design

7.2.1. Study area

In this study, the relationship between built environment, footpath network, socio-demographics, walking accessibility and pedestrian crash frequency in the areas around metro stations will be examined. Figure 7.1 shows the metro network in Hong Kong. For instance, areas within a 500-metre radius of 93 metro stations[1] are considered (Xu et al.,

[1] 5 metro stations are excluded in this study as they are built after 2020 and there are not adequate crash data.

2022).

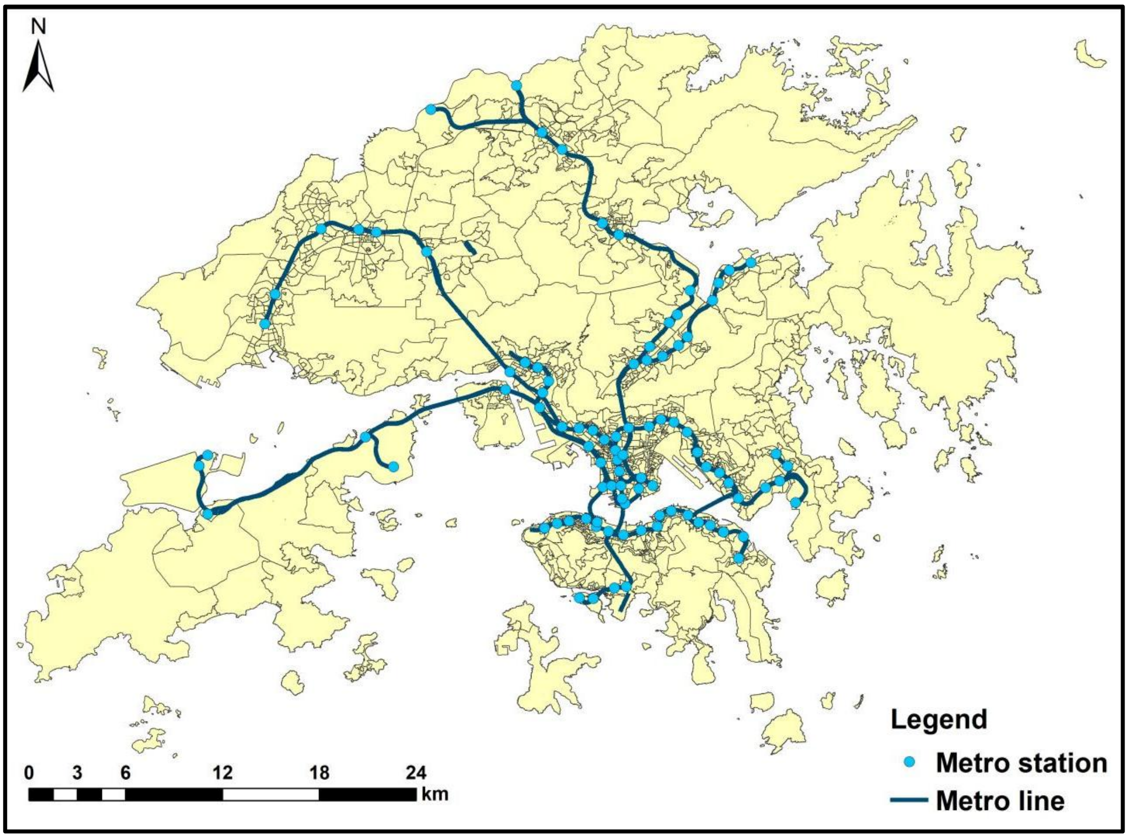


Figure 7.1 Metro network in Hong Kong in 2019

As aforementioned, attributes like crash incidence, traffic flow and network characteristics are usually available at the street level. Hence, each 500-metre radius catchment area for the metro is further stratified into several 150-metre radius hexagonal zones. To this end, the sample consists of 1,156 zones and 93 catchment areas. Figure 7.2 illustrates the configuration of hexagonal zones and catchment areas of some metro stations. As shown in Figure 7.2, some hexagonal zones are nested within the catchment areas of two or three metro stations.

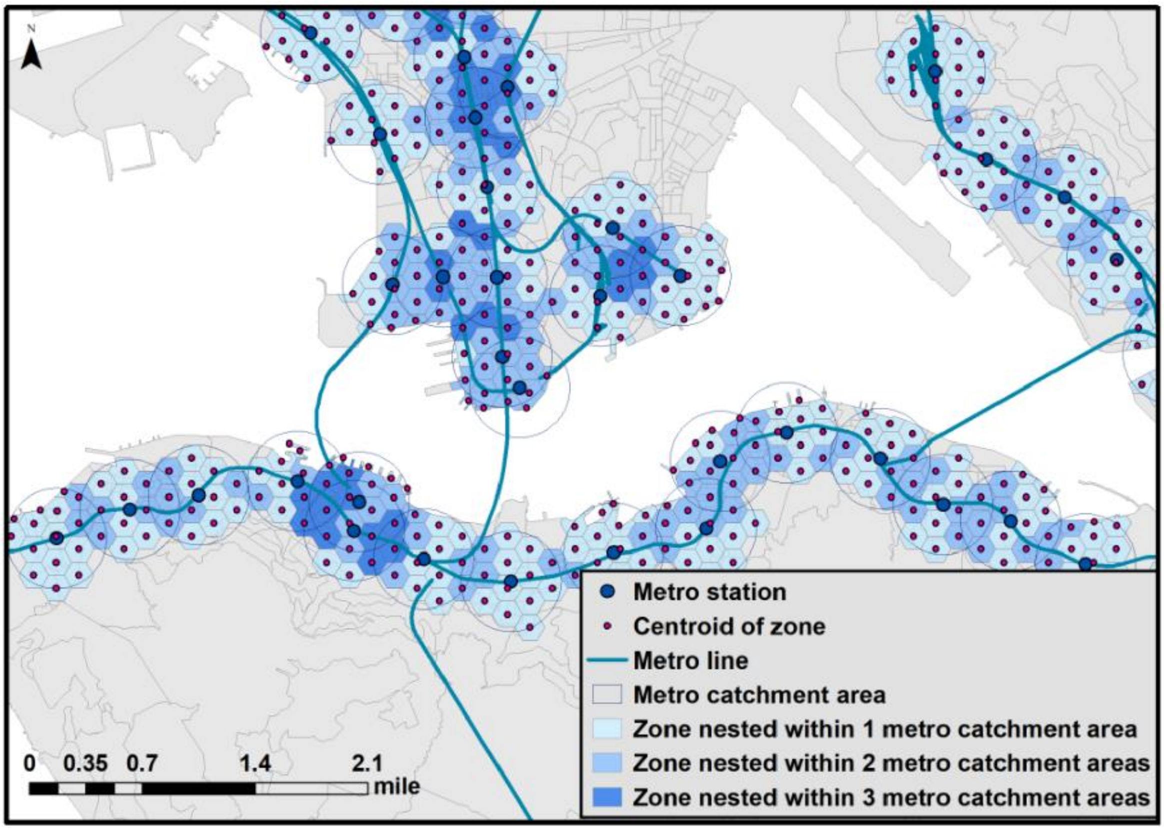


Figure 7.2 Illustration of some hexagonal zones and metro catchment areas

7.2.2. Walking accessibility

(1) General walking accessibility

In this study, walking accessibility refers to the ease of reaching the closest metro station from a zone, considering the topology and geometry of the footpath network.

First, the impedance function between *i* and *j* is given by,

$$T(d_{ij}, d_0) = e^{-\frac{1}{2}\times\left(\frac{d_{ij}}{d_0}\right)^2} \tag{1}$$

where d_{ij} refers to the Euclidean distance between the centroid of zone *i* and catchment area *j* and d_o is set at 500 metres.

Then, the demand potential of *j* from *i* is given by,

$$D_{ij} = P_i \times T(d_{ij}, d_0) \tag{2}$$

where P_i is the population of *i*.

There are often many exits for each metro station. To this end, an impedance function that indicates the generalized travel cost between exit *k* of catchment area *j* and zone *i* is given by,

$$E_{ij}^{k} = e^{-\frac{m_{ijk} \times cross}{2c_{facilities}}} \tag{3}$$

where $m_{ijk} = \frac{d_{ijk}}{d_1}$ when $d_{ijk} \leq d_1$, $m_{ijk} = 1$ when $d_{ijk} > d_1$, d_{ijk} is the shortest walking distance between *k* and centroid of zone *i*, d_1 is the acceptable walking distance (set at 800 metres in this study) (Gori et al., 2014), *cross* is the number of crossings, and $c_{facilities}$ is number of at-grade crossings avoided when footbridges and underpasses are used respectively.

Hence, general walking accessibility can be estimated by,

$$A_{ij} = \frac{s_{ij} E_{ij}^{k}}{D_{ij}} \tag{4}$$

where s_{ij} is attractiveness of *j* for zone *i*.

For instance, attractiveness is correlated to overall trips and the proportion of metro trips for a zone. Walking accessibility is non-negative. If the pedestrian network is better integrated and there are more grade-separated crossing facilities, walking accessibility would increase. Zero walking accessibility implies no metro station can be reached within 800-metre walking distance. In this study, information on the configuration and topology of pedestrian network and characteristics (i.e., gradient, accessible design, crosswalk) of every walking link can be obtained from the digital map of a three-dimensional pedestrian network. The interested reader is referred to our recent paper for the detailed descriptions of digital map (Zhu et al., 2023a).

(2) Barrier-free walking accessibility

In the past decades, many barrier-free facilities like elevators, escalators, lifts, ramps, and wheelchair access were installed, enhancing the accessibility of individuals with physical impairment. Figure 7.3 illustrates a sample of normal (brown colour) and barrier-free (green colour) shortest walking paths from an origin to the nearest metro exit. Criteria of the barrier-free link are: (1) there is no segment with slope exceeding 5%; (2) there is no crosswalk or crossing facility with slope exceeding 2%, and (3) there are escalators, lifts, ramps, or wheelchair access when (1) and (2) are not satisfied.

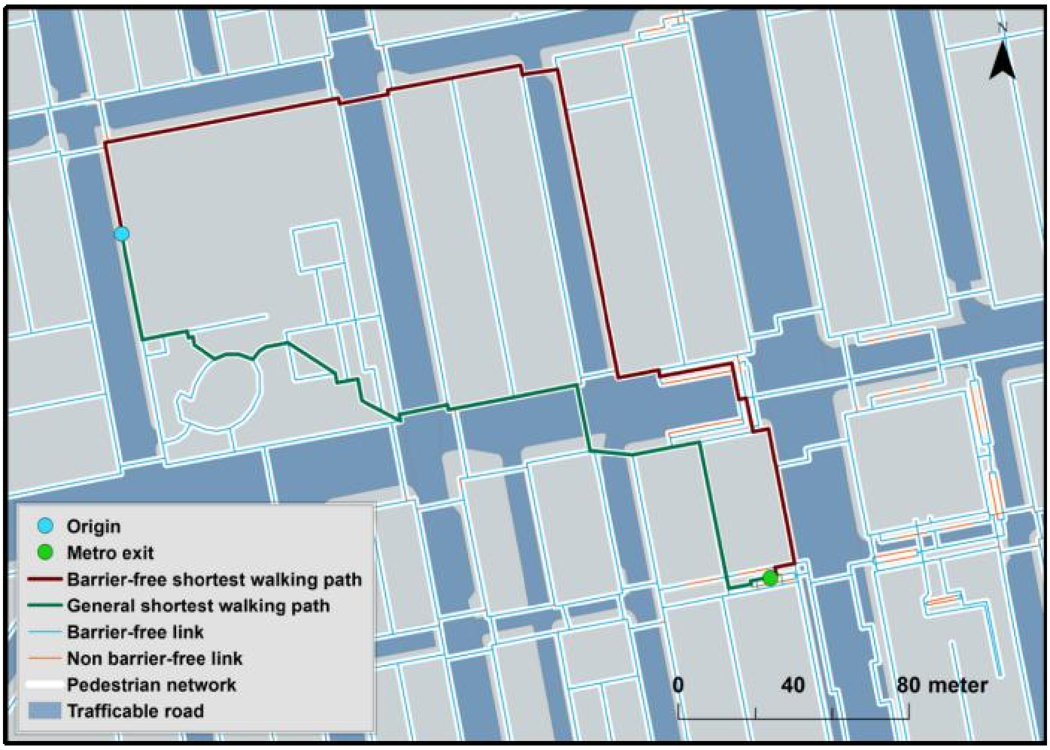


Figure 7.3 Sample of shortest walking paths

For barrier-free walking path, the impedance function that indicates the generalized travel cost between exit k of catchment area j and the centroid of zone i is given by,

$$W_{ij}^{k} = e^{-\frac{m'_{ijk} \times cross}{2c'_{facilities}}} \qquad (5)$$

where $m'_{ijk} = \frac{d'_{ijk}}{d_1}$ when $d'_{ijk} \leq d_1$, $m'_{ijk} = 1$ when $d'_{ijk} > d_1$, d'_{ijk} is the barrier-free shortest walking distance from k to i, d_1 is an acceptable walking distance (set at 800 metres in this study) (Gori et al., 2014), and $c'_{facilities}$ is the number of at-grade crossings avoided when footbridges and underpasses are used respectively.

Then, the impedance function that reflects the influence of road gradient is given by,

$$G_{ij}^{k} = e^{-\frac{g_{ijk}}{2}} \tag{6}$$

where g_{ijk} is the average gradient of barrier-free path from k to j.

Hence, overall barrier-free walking accessibility can be estimated by,

$$A_{ij} = \frac{S_{ij} \times W_{ij}^{k} \times G_{ij}^{k}}{D_{ij}} \tag{7}$$

Again, barrier-free walking accessibility is non-negative. If the accessible design is extensively implemented, barrier-free walking accessibility would increase. Zero accessibility implies no metro station can be reached.

7.2.3. Built environment, traffic and safety data

In this study, data on the traffic crashes involving pedestrians in the period between 2017 and 2018 obtained from the Traffic Information System is used. For every crash, information on the location, time, and crash severity is available. Crash severity refers to the injury severity level of the most severely injured pedestrian involved in the crash. For example, there were 3,277 pedestrian-vehicle crashes in the study area. Additionally, crashes are stratified into two classes by severity, namely fatal and severe injury crash (20.9%), and slight injury crash (79.1%). For crash exposure, traffic count data are obtained from the Annual Traffic Census and walking trip data are obtained from the Travel Characteristics Survey respectively. For example, information on the origin, destination, departure time and walking time of the walking trips can be obtained from the latter (Sze et al., 2019). Last but not least, land use data is obtained from the Planning Department's database and population socio-demographics data is obtained from the Census and Statistics Department's database respectively. For example, there are four land use types, namely residential, commercial, government and utility, and green space (Su et al., 2021b).

Table 7.1 summarizes the data adopted in this study. As shown in Table 7.1, pedestrian crash frequency, exposure, pedestrian network characteristics, and general and barrier-free walking accessibility are averaged at zone level, while land use and socio-demographics are aggregated at catchment area level respectively.

Table 7.1 Descriptive statistics of the data

Scope of work	Variable	Mean	SD	Min	Max
Zone level					
Pedestrian crash frequency	Slight injury crash	2.24	4.05	0.00	37.00
	Fatal and severe injury crash	0.59	1.24	0.00	12.00
Exposure	Ln (Annual average daily traffic)	9.66	0.98	6.17	11.84
	Ln (Population density)	9.90	1.80	4.51	12.34
	Ln (Daily walking trip)	3.35	1.46	0.00	6.70
Transport facility	Number of bus stop	1.27	1.62	0.00	10.00
Pedestrian network characteristics	Footpath density (m per 100 m^2)	4.12	2.48	0.00	15.98
	Node density (per 100 m)	4.83	2.34	0.00	20.58
	Barrier-free access density (m per 100 m^2)	3.41	2.29	0.00	15.39
	Average gradient	0.06	0.05	0.00	0.48
Walking accessibility	General walking accessibility	0.52	0.50	0.00	4.68
	Barrier-free walking accessibility	0.25	0.42	0.00	4.13
	Barrier-free accessibility X % of age below 15	3.04	5.90	0.00	70.36
	Barrier-free accessibility X % of age over 64	3.84	6.48	0.00	55.80
Catchment area level					
Land use	% of residential area	22.41	12.64	0.00	45.25
	% of commercial area	6.14	13.95	0.00	97.50
	% of government and utility area	12.95	9.23	0.00	48.96
	% of green area	7.36	9.90	0.00	39.87
Socio-demographics	% of working population	52.37	3.78	40.56	61.99
	% of working population with monthly income below HKD 20,000	31.45	5.27	17.40	41.33
	% of age below 15	11.70	3.41	0.15	24.44
	% of age over 64	15.57	6.09	0.02	54.28

7.3 Method of analysis

7.3.1 Multiple membership multilevel model

As aforementioned, hierarchical data structures are adopted in this study. Additionally, individual hexagonal zones are nested within more than one catchment area of metro station. Hence, a multiple membership multilevel model is adopted for the spatial analysis of pedestrian crashes and walking accessibility.

First, influences of zone level and catchment area level factors on pedestrian crashes are given by Equation (8), Equation (9) and Equation (10) respectively,

$$Y_{ij} \sim Poisson(\lambda_{ij}) \tag{8}$$

$$\log(\lambda_{ij}) = \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} X_{pij} + e_{ij} \tag{9}$$

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} Z_{qj} + \mu_{0j} \text{ with } \mu_{0j} \sim N(0, \sigma_{\mu}^2) \tag{10}$$

where Y_{ij} refers to the number of pedestrian crashes in zone i of catchment area j, λ_{ij} is the expected number of crashes in zone i of catchment area j, X_{pij} is the vector of zone level factors, Z_{qj} is the vector of catchment area level factors, β_{0j}, β_{pj}, γ_{00} and γ_{0q} are the parameters, μ_{0j} is normally distributed between area residuals, and e_{ij} is a gamma-distributed error term with the mean of 1 and variance of $1/\varphi$.

φ is the inverse overdispersion parameter that allows the variance to be different from the mean as,

$$Var(Y_{ij}) = E(Y_{ij}) + \{E(Y_{ij})\}^2/\varphi \tag{11}$$

Then, the multiple membership issue can be accommodated by modifying Equation (10) as,

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} \sum_{j \in area(i)} w_{ij} Z_{qj} + \sum_{j \in area(i)} w_{ij} \mu_{0j} \tag{12}$$

where w_{ij} is the weight that reflects the influential power of j on i, γ_{0q} reflects the fixed effect, and $\sum_{j \in area(i)} w_{ij} \mu_{0j}$ reflects the random effects, $j \in area\ (i)$ represents the set of catchment areas that affect the crash occurrence in zone i, and zone i is nested within N metro stations with $area(i) = \{1, ..., n, ..., N\}$, N is the number of catchment areas to which zone i

belongs, and $\sum_{j\in area(i)} w_{ij} = 1$ respectively.

In this study, two approaches for the weight assignment of multiple membership, (i) equal weight, and (ii) walking distance, are considered (Wang and Huang, 2016; Park et al., 2020). For the latter, multiple membership weight is given by,

$$\psi_{in} = \frac{{d_{in}}^2}{\sum_{j\in area(i)} {d_{ij}}^2} \tag{13}$$

where d_{in} is the shortest walking distance between the centroid of zone i and metro station n.

Poisson family models including Poisson-gamma and negative binomial regression models are commonly adopted to estimate crash frequency since crash incidence can be modeled as count data and over-dispersed (Park et al., 2022).

To assess the appropriateness of multilevel modeling approach, variance partition coefficient, which indicates the correlation in crash counts between individual zones within the same catchment area, is estimated by.

$$VPC = \frac{\overbrace{(\lambda_{ij}^M)^2\{\exp(\sigma_\mu^2)-1\}}^{\text{catchment area level variance}}}{\underbrace{(\lambda_{ij}^M)^2\{\exp(\sigma_\mu^2)-1\}}_{\text{catchment area level variance}} + \underbrace{\lambda_{ij}^M + (\lambda_{ij}^M)^2\exp(\sigma_\mu^2)\phi}_{\text{zone level variance}}} \tag{14}$$

where λ_{ij}^M is the marginal expectation of y_{ij} and is given by

$$\lambda_{ij}^M = E(y_{ij}) = \exp(\beta_{0j} + \sigma_\mu^2/2) \tag{15}$$

If there is weak dependency between individual zones, the value of variance partition coefficient will be close to zero. Then, single level models should be used. Otherwise, multilevel model is appropriate (Leckie et al., 2020; Yoon et al., 2017).

7.3.2 Modeling approach and assessment

In this study, three models would be considered for the spatial analysis of walking accessibility and pedestrian crash risk, namely multilevel model (Model 1), multiple membership multilevel model with equal weight (Model 2), and multiple membership multilevel model with walking distance-based weights (Model 3).

To assess the model fit, Deviance Information Criterion is estimated by,

$$DIC = Dbar + pD \tag{16}$$

where *Dbar* is the posterior mean of deviance and *pD* is the number of parameters.

Models with a smaller deviance information criterion are preferred. Last but not least, the models would be estimated using Markov Chain Monte Carlo simulation method in the Bayesian framework. For instance, the first 10,000 samples are discarded as burn-in, and a further 20,000 iterations would be run for each chain. Model convergence would be assessed by visual inspection of the simulation chains and autocorrelation plots.

7.3.3 Temporal stability

The influences of explanatory factors on crash occurrence may change over time because of the variations in road conditions, vehicle technology, road user perception and behaviour. This is known as temporal instability (Alnawmasi and Mannering, 2023; Mannering, 2018). To this end, the simulated maximum likelihood approach is adopted to assess the temporal stability. Both global and pairwise likelihood ratio tests are conducted. For instance, global test for the stability of crash frequency model across years can be given by,

$$\chi_t^2 =- 2[LL(\beta_t) - LL(\beta_{2017}) - LL(\beta_{2018})] \tag{16}$$

where $LL(\beta_t)$ is the log-likelihood at the convergence of all year model, $LL(\beta_{2017})$ is the log-likelihood at the convergence of 2017 model and $LL(\beta_{2018})$ is the log-likelihood at the convergence of 2018 model respectively.

The null hypothesis is that all year model and 2017 and 2018 models are equal. If the null hypothesis can be rejected, separated models for 2017 and 2018 are warranted.

On the other hand, pairwise test for the transferability of parameters across years can be given by,

$$\chi^2 =- 2\left[LL\left(\beta_{p_1p_2}\right) - LL\left(\beta_{p1}\right)\right] \tag{17}$$

where $LL\left(\beta_{P_1P_2}\right)$ is the log-likelihood at the convergence of a model using converged parameters from p_1 and data from p_2; $LL\left(\beta_{p_1}\right)$ is the log-likelihood at the convergence of a model using data from p_1.

7.4 Results and discussion

7.4.1 Model performance

In this study, three models are estimated for the assessment of model performance. For example, simple multilevel model (Model 1), multiple membership multilevel model with equal weights (Model 2), and multiple membership multilevel model with walking distance-based weights (Model 3) are estimated. Table 7.2 compares the performance among the three candidate models. As also shown in Table 7.2, for slight injury crash, between-group variance of Model 1 (0.231) is remarkably lower than that of Model 2 (0.572) and Model 3 (0.588). The same phenomenon is observed for fatal and severe injury crashes (Model 1: 0.238; Model 2: 0.591; Model 3: 0.598). This implies that between-group variance may be underestimated when multiple membership approach is not adopted. Hence, the multiple membership multilevel model approach is justified.

Table 7.2 Between-group and within-group variances of the models

Variance	Model 1: Multilevel Model		Model 2: Multiple Membership Multilevel Model with Equal Weights		Model 3: Multiple Membership Multilevel Model with Walking Distance-based Weights	
	Slight Injury Crash	Fatal and Severe Injury Crash	Slight Injury Crash	Fatal and Severe Injury Crash	Slight Injury Crash	Fatal and Severe Injury Crash
Between-group variance	0.231	0.238	0.572	0.591	0.588	0.598
Within-group variance	0.785	0.798	0.792	0.804	0.807	0.819
Variance partition coefficient	0.079	0.085	0.356	0.353	0.348	0.347

Prior to the model estimation, multicollinearity of the variances considered should be assessed. In this study, values of variance inflation factor are all less than five. Table 7.3 summarizes the goodness-of-fit assessment results of the models. As shown in Table 7.3, multiple membership multilevel model with walking distance-based weights is preferred since values of the deviance information criterion are the lowest for both slight injury (Model 1: 6092; Model 2: 5571; Model 3: 5459) and fatal and severe injury crashes (Model 1: 5983; Model 2: 5563; Model 3: 5438) (Ding et al., 2023). Hence, the multiple membership multilevel model with walking distance-based weights should be adopted.

Table 7.3 Goodness-of-fit assessment of the models

Crash Severity	Model 1: Multilevel Model	Model 2: Multiple Membership Multilevel Model with Equal Weights	Model 3: Multiple Membership Multilevel Model with Walking Distance-based Weights
Slight injury crash	6092	5571	5459
Fatal and severe injury crash	5983	5563	5438

As the multiple membership multilevel model with walking distance-based weights is adopted, the simulated maximum likelihood approach will be used for temporal instability.

For the global test, chi-square test statistics are 84.6 (with 19 degrees of freedom) for slight injury crash and 79.4 (with 18 degrees of freedom) for fatal and severe crash respectively. This implies that the null hypothesis for temporal stability of the models across years can be rejected at the 1% level of significance. As shown in Table 7.4, chi-square test statistics in pairwise tests are all significant at the 5% level. Hence, separated models for 2017 and 2018 should be estimated.

Table 7.4 Pairwise likelihood ratio tests for 2017 and 2018

	Slight Injury Crash		Fatal and Severe Injury Crash	
Year	2017	2018	2017	2018
2017		64.9[21](0.017)		67.5[21](0.019)
2018	59.4[21](0.034)		54.3[21](0.043)	

Note: Degrees of freedom in the brackets and significant levels in the parentheses.

7.4.2 Parameter estimations and discussion

Table 7.5 presents the results of multiple membership multilevel model, with walking distance-based weights, for slight injury crash and fatal and severe injury crash respectively. In addition, estimates of average marginal effect are summarized in Table 7.6.

Table 7.5 Results of multiple membership multilevel model with walking distance-based weights

Variable	Slight injury crash		Fatal and severe injury crash	
	Coefficient	(95% Bayesian credible interval)	Coefficient	(95% Bayesian credible interval)
2017				
Zone level				
Intercept	-9.017**	(-11.221，-7.893)	-8.881**	(-10.344,-7.417)
Ln (Annual average daily traffic)	0.236*	(0.145，0.401)	0.241*	(0.043,0.502)
Ln (Population density)	0.162**	(0.082,0.257)	0.145*	(0.019,0.306)
Ln (Daily walking trip)	0.643**	(0.451,0.868)	0.601**	(0.293,0.908)
Number of bus stop	0.151**	(0.068,0.223)	0.147**	(0.051,0.234)
Footpath density (m per 100 m^2)	0.300**	(0.157,0.421)	0.297**	(0.193,0.401)
Node density (per 100 m)	0.227**	(0.108,0.334)	0.218**	(0.096,0.331)
Barrier-free access density (m per 100 m^2)	0.231^	(0.019,0.553)	0.243*	(0.004,0.503)
Average gradient	-0.732**	(-1.108,-0.376)	-0.780**	(-1.05.-0.509)
General walking accessibility	-0.207**	(-0.381,-0.052)	-0.237*	(-0.452,-0.008）
Barrier-free walking accessibility	-0.231*	(-0.399,-0.121)	-0.210*	(-0.409,-0.009)
Barrier-free walking accessibility X % of age below 15	-0.021^	(-0.051,-0.008)	-0.028^	(-0.069,-0.003)
Barrier-free accessibility X % of age over 64	-0.026^	(-0.058,-0.007)	-0.023*	(-0.045,-0.002)
Catchment area level				
% of residential area	0.050**	(0.024,0.071)	0.057*	(0.006,0.113)
% of commercial area	0.043*	(0.009,0.084)	0.048*	(0.003,0.098)
% of government and utility area	0.022^	(0.007,0.055)	0.023^	(0.002,0.056)
% of green area	-0.019*	(-0.042,-0.003)	-0.015*	(-0.036,-0.003)
% of working population	0.110**	(0.048,0.177)	0.115**	(0.078,0.156)
% of working population with monthly income below HKD 20,000	0.132**	(0.077,0.185)	0.146*	(0.052,0.265)
% of age below 15	0.004	(0.001,0.039)	0.008	(0.001,0.021)

% of age over 64	0.006	(0.002,0.038)	0.007	(0.001,0.025)
Catchment area level variance	0.281**	(0.103,0.439)	0.247**	(0.139,0.345)
Zone level variance	0.536**	(0.293,0.789)	0.549**	(0.318,0.712)
2018				
Zone level				
Intercept	-8.985**	(-11.048,-5.922)	-8.739**	(-10.688,-6.789)
Ln (Annual average daily traffic)	0.281*	(0.008,0.493)	0.249*	(0.044,0.501)
Ln (Population density)	0.147*	(0.055,0.319)	0.144**	(0.038,0.227)
Ln (Daily walking trip)	0.684**	(0.543,0.825)	0.630**	(0.268,0.952)
Number of bus stop	0.145**	(0.049,0.241)	0.149**	(0.068,0.234)
Footpath density (m per 100 m^2)	0.304**	(0.177,0.431)	0.301**	(0.160,0.442）
Node density (per 100 m)	0.234**	(0.098,0.367)	0.224**	(0.124,0.345)
Barrier-free access density (m per 100 m^2)	0.242*	(0.027,0.411)	0.249*	(0.027,0.426)
Average gradient	-0.771**	(-1.002,-0.256)	-0.785**	(-1.168,-0.381)
General walking accessibility	-0.223**	(-0.387,-0.059)	-0.242**	(-0.385,-0.100)
Barrier-free walking accessibility	-0.201*	(-0.405,-0.013)	-0.209*	(-0.326,-0.085)
Barrier-free walking accessibility X % of age below 15	-0.023^	(-0.052,-0.002)	-0.027*	(-0.052,-0.002)
Barrier-free accessibility X % of age over 64	-0.025^	(-0.060,-0.001)	-0.026*	(-0.055,-0.001)
Catchment area level				
% of residential area	0.052*	(0.009,0.113)	0.059**	(0.018,0.101)
% of commercial area	0.046*	(0.003,0.088)	0.045*	(0.005,0.096)
% of government and utility area	0.020^	(0.002,0.050)	0.025*	(0.002,0.052)
% of green area	-0.017^	(-0.039,-0.001)	-0.013**	(-0.021,-0.005)
% of working population	0.111**	(0.051,0.162)	0.116**	(0.071,0.160)
% of working population with monthly income below HKD 20,000	0.143*	(0.026,0.302)	0.147**	(0.074,0.236)
% of age below 15	0.006	(0.002,0.036)	0.008	(0.001,0.033)

% of age over 64	0.009	(0.004,0.040)	0.009	(0.002,0.038)
Catchment area level variance	0.218**	(0.047,0.369)	0.241**	(0.096,0.394)
Zone level variance	0.521**	(0.296,0.744)	0.553**	(0.253,0.828)

^ *Significant at the 10% level*

* *Significant at the 5% level*

***Significant at the 1% level*

Note: Separated models for 2017 and 2018 using Model 1, Model 2 and Model 3 were considered. For 2017, loglikelihood values are the lowest when multiple membership multilevel model with walking distance-based weights (Model 3) is used (Slight injury crash: Model 1- 6189, Model 2- 5707, Model 3- 5576; Fatal and severe injury crash: Model 1- 6024, Model 2- 5683, Model 3- 5521). The same also applies for 2018 (Slight injury crash: Model 1- 6163, Model 2- 5688, Model 3- 5542; Fatal and severe injury crashes: Model 1- 6107, Model 2- 5675, Model 3- 5524). Hence, subsequent description will focus on multiple membership multilevel model with walking distance-based weights.

Table 7.6 Average marginal effects

Variable	Slight injury crash		Fatal and severe injury crash	
	2017	2018	2017	2018
Zone level				
Ln (Annual average daily traffic)	0.591	0.589	0.559	0.510
Ln (Population density)	0.406	0.308	0.336	0.295
Ln (Daily walking trip)	1.611	1.435	1.394	1.290
Number of bus stop	0.378	0.304	0.342	0.305
Footpath density (m per 100 m^2)	0.752	0.638	0.689	0.616
Node density (per 100 m)	0.569	0.491	0.505	0.458
Barrier-free access density (m per 100 m^2)	0.579	0.508	0.564	0.510
Average gradient	-1.835	-1.618	-1.809	-1.607
General walking accessibility	-0.519	-0.468	-0.550	-0.495
Barrier-free walking accessibility	-0.579	-0.422	-0.487	-0.428
Barrier-free walking accessibility X % of age below 15	-0.053	-0.049	-0.065	-0.056
Barrier-free accessibility X % of age over 64	-0.065	-0.052	-0.054	-0.053
Catchment area level				
% of residential area	0.125	0.109	0.133	0.121
% of commercial area	0.108	0.096	0.111	0.092
% of government and utility area	0.055	0.042	0.054	0.051
% of green area	-0.048	-0.035	-0.034	-0.026
% of working population	0.276	0.232	0.267	0.237
% of working population with monthly income below HKD 20,000	0.331	0.300	0.338	0.301

(1) Zone level factors

For the crash exposure, pedestrian crash frequency remarkably increases with annual average daily traffic (Slight injury crash: Coefficient is 0.236 for year 2017 and 0.281 for year 2018; Fatal and severe injury crash: Coefficient is 0.241 for year 2017 and 0.249 for year 2018), population density (Slight injury crash: 0.162 for year 2017 and 0.147 for year 2018; Fatal and severe injury crash: 0.145 for year 2017 and 0.144 for year 2018), and daily walking trips (Slight injury crash: 0.643 for year 2017 and 0.684 for year 2018; Fatal and severe injury crash: 0.601 for year 2017 and 0.630 for year 2018), at the 5% level. For the marginal effect, a 1% increase in log transformed traffic flow would result in 0.51 – 0.59% increases in pedestrian crashes. Such findings are consistent with previous studies. For instance, pedestrian-vehicle crash exposure increased with traffic volume and pedestrian activities. Just, increase in pedestrian crash was less than proportionate with exposure (Su et al., 2021b; Sze et al., 2019). This justifies the safety-in-numbers effect and driver awareness when there are more pedestrians (Elvik and Bjørnskau, 2017).

For the transport facility, pedestrian crash frequency significantly increases with number of bus stops (Slight injury crash: 0.151 for year 2017 and 0.145 for year 2018; Fatal and severe injury crash: 0.147 for year 2017 and 0.149 for year 2018) at the 1% level. For the marginal effect, a 1% increase in the number of bus stops would result in 0.30 – 0.38% increases in pedestrian crashes. This could be attributed to the frequent roadside pick-up and drop-off activities and reckless crossing behaviour near the bus stops (Su et al., 2021b; Zhu et al., 2022a). Such findings are indicative to the street design and traffic control that can mitigate the road hazards attributed to the unsafe crossing behaviour of pedestrians.

For the configuration of pedestrian network, pedestrian crash frequency remarkably increases with footpath density (Slight injury crash: 0.300 for year 2017 and 0.304 for year 2018; Fatal and severe injury crash: 0.297 for year 2017 and 0.301 for year 2018), node density (Slight injury crash: 0.227 for year 2017 and 0.234 for year 2018; Fatal and severe injury crash: 0.218 for year 2017 and 0.224 for year 2018) and barrier-free access density (Slight injury crash: 0.242 for year 2018; Fatal and severe injury crash: 0.243 for year 2017 and 0.249 for year 2018). For the marginal effect, 1% increases in footpath density and node density would result in 0.62 – 0.75% and 0.46 – 0.57% increases in pedestrian crashes respectively. Figure 7.4 illustrates a sample of pedestrian network. The positive association between footpath, node and pedestrian crash frequency implies that pedestrian safety would be worsened when the pedestrian network is more complicated. This is consistent with a previous study (Zhu et al., 2023b). Pedestrian crash hotspots are concentrated in areas with more building access and roadside drop-off, pick-up and loading activities (Guo et al., 2017; Osama and Sayed, 2017) for all population groups

(Wennberg et al., 2010). Such findings are indicative to the design and planning of traffic calming measures, especially for individuals with physical disabilities. In contrast, pedestrian crash frequency remarkably decreases with average gradient (Slight injury crash: 0.732 for year 2017 and 0.771 for year 2018; Fatal and severe injury crash: 0.780 for year 2017 and 0.785 for year 2018) at the 1% level. For the marginal effect, a 1% increase in average gradient would result in 1.61 – 1.84% reduction of pedestrian crashes. This could be attributed to the increase in driver awareness and speed reduction at the inclined road segments (Chen and Zhou, 2016).

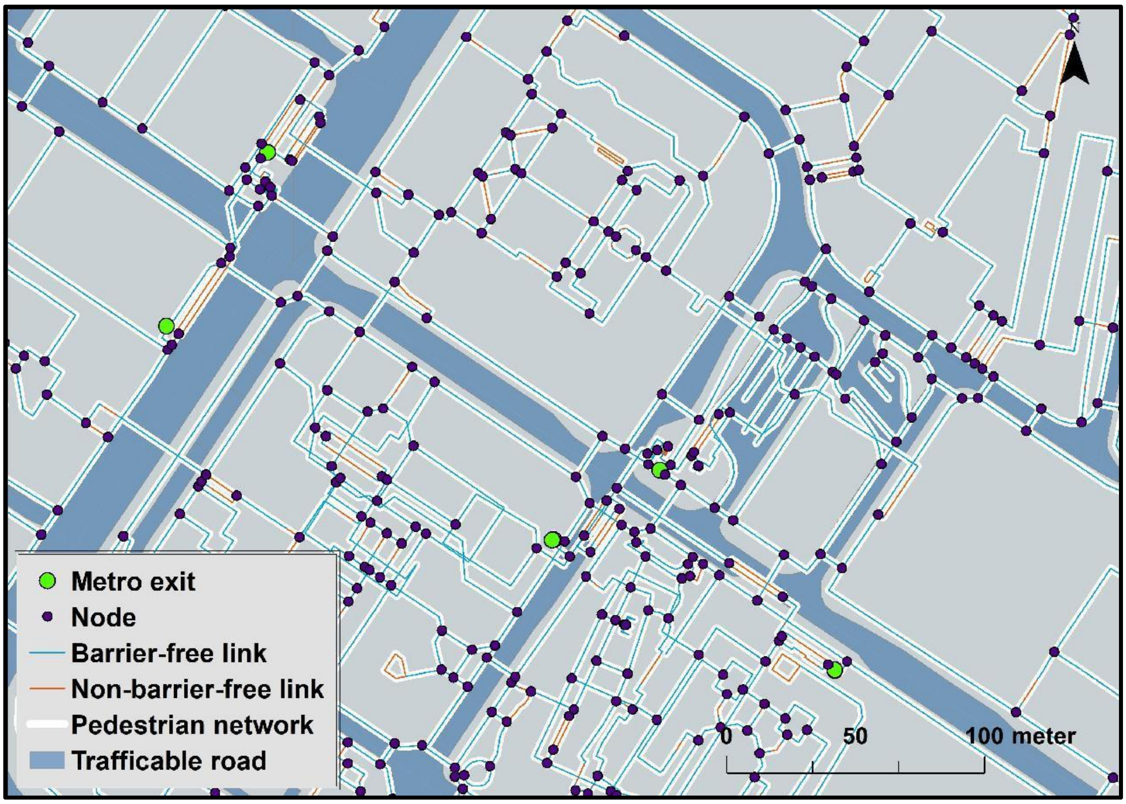


Figure 7.4 Illustration of a sample of pedestrian network

(2) Catchment area level factors

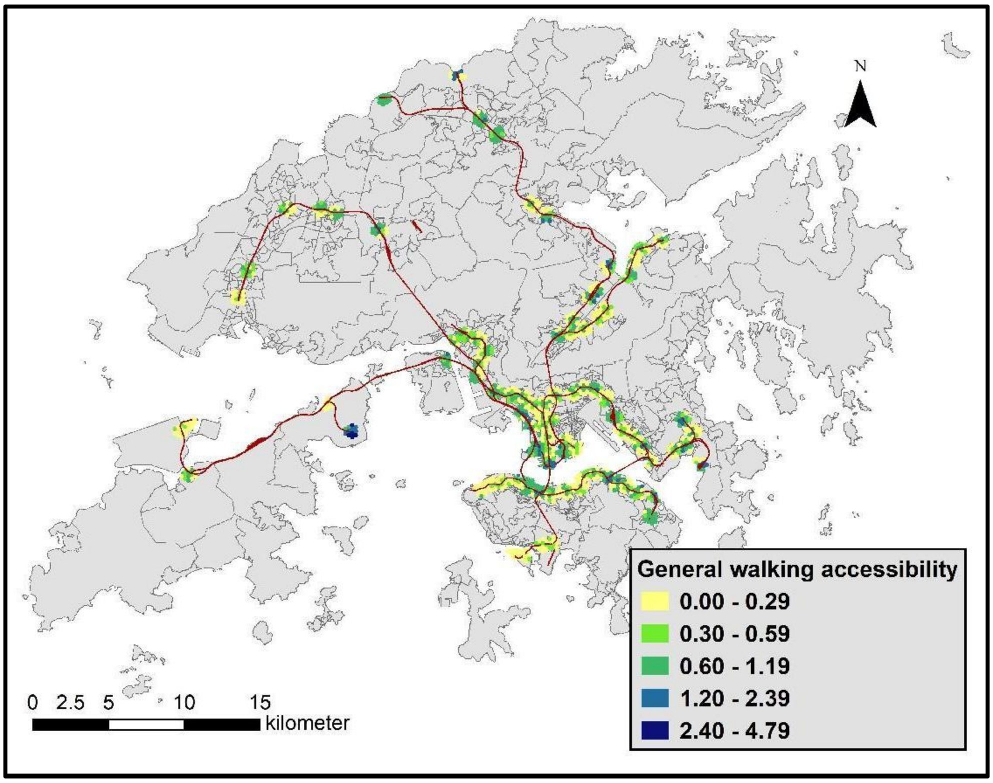
For the effects of land use, pedestrian crash frequency increases with residential area (Slight injury crash: Coefficient is 0.050 for year 2017 and 0.052 for year 2018; Fatal and severe injury crash: Coefficient is 0.057 for year 2017 and 0.059 for year 2018), commercial area (Slight injury crash: 0.043 for year 2017 and 0.046 for year 2018; Fatal and severe injury crash: 0.048 for year 2017 and 0.045 for year 2018), government and utility area (fatal and severe injury crash: 0.025 for year 2018), at the 5% level. Hence, 1% increases in the areas for residential, commercial, and government and utility land use would result in 0.11 – 0.13%, 0.09 – 0.11% and 0.04 – 0.06% increases in pedestrian crashes respectively. Such findings are consistent with previous studies (Effati and Saheli, 2022; Jermprapai and Srinivasan, 2014). Just, pedestrian crash frequency remarkably decreases with green area (Slight injury crash: -0.019 for year 2017; Fatal and severe injury crash: -0.015 for year 2017 and -0.013 for year 2018), at the 5% level. A 1% increase in the green area would result in 0.03 – 0.05% reduction in pedestrian crashes. This justifies the favorable effect of green space on the quality of living and well-being of the commuters (Abd Kadir et al., 2012; Hong et al., 2018; Zhu et al., 2022a). More importantly, vegetation can improve the visual perception, awareness and driving behaviour of drivers (Naderi et al., 2008).

For population socio-demographics, pedestrian crash frequency remarkably increases with the proportions of working population (Slight injury crash: 0.110 for year 2017 and 0.111 for year 2018; Fatal and severe injury crash: 0.115 for year 2017 and 0.116 for year 2018) and that with monthly income below HKD 20,000 (Slight injury crash: 0.132 for year 2017 and 0.143 for year 2018; Fatal and severe injury crash: 0.146 for year 2017 and 0.147 for year 2018) at the 5% level. For the marginal effect, a 1% increase in the working population with lower monthly income would result in 0.30 – 0.34% increases in pedestrian crashes. Such findings are consistent with the previous studies for the relationship between poverty, travel behaviour and pedestrian safety (Dong et al., 2020; Giuliano, 2005; Rhee et al., 2016).

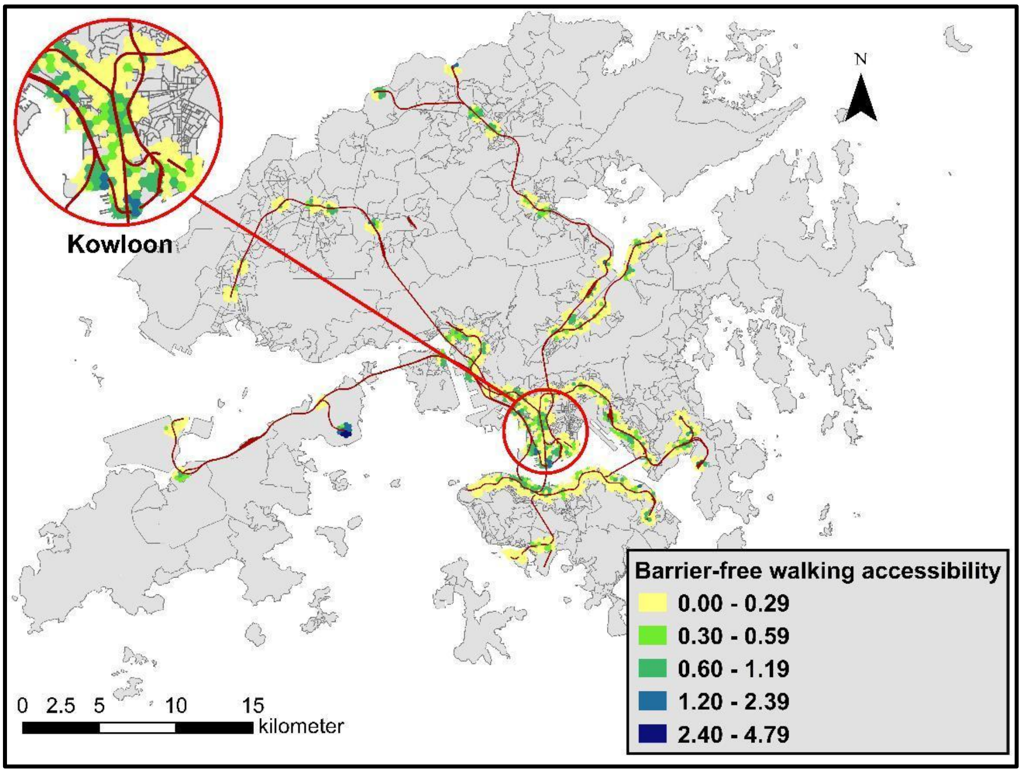
(3) Effects of walking accessibility

Favorably, pedestrian crash frequency remarkably decreases with general walking accessibility (Slight injury crash: Coefficient is -0.207 for year 2017 and -0.223 for year 2018; Fatal and severe injury crash: Coefficient is -0.237 for year 2017 and -0.242 for year 2018) and barrier-free walking accessibility (Slight injury crash: -0.231 for year 2017 and -0.201 for year 2018; Fatal and severe injury crash: -0.210 for year 2017 and

-0.209 for year 2018). A 1% increase in walking accessibility would result in 0.47 – 0.55% reduction in pedestrian crashes. Figure 7.5 illustrates the spatial distribution of walking accessibility. As aforementioned, transit-oriented development was extensively implemented in the city. Therefore, walking accessibility in the areas around metro stations is generally high. However, as shown in Figure 7.5(b), barrier-free walking accessibility tends to be lower, except central business districts. This could be attributed to the planning and development strategy of transport authority and transport operator for escalators, lifts, and wheelchair access (Mass Transit Railway Corporation, 2023). Moreover, facilities like barriers, warning signs, footbridges and underpasses significantly reduce pedestrian-vehicle conflicts and crashes (Cui et al., 2013; Oviedo-Trespalacios and Scott-Parker, 2017; Zhu et al., 2023a). Last but not least, improved barrier-free walking accessibility also has favorable effect on transport equity (Yairi and Igi, 2006).



(a) General walking accessibility



(b)Barrier-free walking accessibility

Figure 7.5 Walking accessibility in the areas around metro stations

Even though there is no significant association between pedestrian crash frequency and population age, the negative association between pedestrian fatal crash frequency and barrier-free walking accessibility is more obvious when proportion of children (Age below 15: -0.027 for year 2018) and the older adults (Age over 64: -0.023 for year 2017 and -0.026 for year 2018) increase. This could be because children and the older adults are prone to unsafe crossing behaviour and more severe road crashes (Salehian et al., 2023; Tournier et al., 2016). Hence, the safety risk of vulnerable pedestrian groups would be reduced when accessibility is improved (Sun et al., 2019). Table 7.7 summarizes the implications of the empirical analysis.

Table 7.7 Implications of influencing factors

<table>
<tr><th>Factor</th><th>Effect</th><th>Implication</th><th>Reference</th></tr>
<tr><td colspan="4">Zone level</td></tr>
<tr><td>Annual average daily traffic</td><td>↑</td><td rowspan="3">Pedestrian crash increases with population, traffic volume and walking activity. Pedestrian crashes increase less than proportionate with the exposure. This implies possible “safety-in-numbers” effect.</td><td rowspan="3">Elvik and Bjørnskau, 2017</td></tr>
<tr><td>Population density</td><td>↑</td></tr>
<tr><td>Daily walking trip</td><td>↑</td></tr>
<tr><td>Number of bus stop</td><td>↑</td><td>Pedestrian crash increases with number of bus stop. Street design and traffic control should be improved.</td><td>Su et al., 2021b; Zhu et al., 2022a</td></tr>
<tr><td>Footpath density</td><td>↑</td><td rowspan="3">Building access, roadside drop-off and pick-up, and loading area are prone to pedestrian crash. Effective traffic calming measures should be implemented.</td><td rowspan="3">Wennberg et al., 2010; Guo et al., 2017; Osama and Sayed, 2017</td></tr>
<tr><td>Node density</td><td>↑</td></tr>
<tr><td>Barrier-free access density</td><td>↑</td></tr>
<tr><td>Average gradient</td><td>↓</td><td>Traffic speed decreases with the inclination angle. Hence, pedestrian crash frequency reduces.</td><td>Chen and Zhou, 2016</td></tr>
<tr><td>General walking accessibility</td><td>↓</td><td rowspan="2">Walking accessibility, especially for the elderly and individuals with disabilities, has a favorable effect on pedestrian safety. Accessible design should be adopted for transport facilities.</td><td rowspan="2">Mass Transit Railway Corporation, 2023; Cui et al., 2013; Zhu et al., 2023a</td></tr>
<tr><td>Barrier-free walking accessibility</td><td>↓</td></tr>
<tr><td>Barrier-free accessibility X % of age below 15</td><td>↓</td><td rowspan="2">The favorable effect of accessible design on pedestrian safety is more significant for children and older adults because unsafe crossing behaviour is more prevalent for these population groups.</td><td rowspan="2">Salehian et al., 2023; Tournier et al., 2016</td></tr>
<tr><td>Barrier-free accessibility X % of age over 64</td><td>↓</td></tr>
<tr><td colspan="4">Catchment area level</td></tr>
<tr><td>% of residential area</td><td>↑</td><td rowspan="4">Negative association between green area and pedestrian crash frequency indicates the favorable effect of green areas on pedestrian safety. This may be because of the enhanced visual perception and awareness of drivers.</td><td rowspan="4">Hong et al., 2018; Naderi et al., 2008; Zhu et al., 2022a</td></tr>
<tr><td>% of commercial area</td><td>↑</td></tr>
<tr><td>% of government and utility area</td><td>↑</td></tr>
<tr><td>% of green area</td><td>↓</td></tr>
<tr><td>% of working population</td><td>↑</td><td rowspan="2">Positive association between working population and pedestrian crash is more significant for lower income group. This implies the vulnerability of disadvantaged social group.</td><td rowspan="2">Giuliano, 2005; Rhee et al., 2016; Dong et al., 2020</td></tr>
<tr><td>% of working population with monthly income below HKD 20,000</td><td>↑</td></tr>
</table>

Notes: “ ↑ ” indicates the positive association between factor and pedestrian crash frequency; “ ↓ ” indicates the negative association between factor and pedestrian crash frequency

7.4.3 Multiple membership multilevel model

In this study, multilevel models are estimated, accounting for the hierarchical structure of data including built environment, population socio-demographics, road network configuration, transport facilities and traffic flow characteristics, and the clustering problem of individual zones. Additionally, multiple membership model outperforms the conventional multilevel model. This implies that the spatial dependence among zones within the same catchment area of metro station can be accommodated. Furthermore, two weighting strategies including equal weighting and walking distance-based weighting for the multiple membership model are explored. Results indicate that the model with walking distance-based weights has the best fit. This justifies that the strength of relationship between individual zones and catchment areas is sensitive to walking distance (Sze et al., 2019; Su et al., 2021b).

7.4.4 Temporal stability

It is necessary to explore the temporal stability of parameter estimation when data over multiple time periods (i.e., years) are used. Results of global and pairwise likelihood ratio tests indicate significant temporal instability of the models between years. Therefore, separated multiple membership multilevel models for 2017 and 2018 are estimated in this study. For example, there are remarkable temporal shifts for the influences of traffic flow, population density, walking accessibility on pedestrian crash frequency. This could be attributed to the unobserved changes in the road environment and road user behaviour over time (Mannering, 2018).

7.5 Concluding remarks

Previous studies have evaluated the effects of built environment, traffic characteristics and population socio-demographics on pedestrian safety. However, the relationship between walking accessibility and pedestrian crash frequency is less studied. On the other hand, disturbances by spatial dependency, boundary crash and modifiable areal unit problems on the association measure should be accounted for. In this study, a multiple membership multilevel model is adopted to estimate the influences of both zone level (exposure, transport facility, pedestrian network, and walking accessibility) and catchment area level (land use and socio-demographics) factors on pedestrian crash frequencies in the areas around metro stations. For instance, walking accessibility of individuals with physical impairment is also considered. Furthermore, multiple membership weights are estimated using the shortest walking distances to metro stations. Both the within-group and between-group variances attributed to hierarchical data structure are considered for the estimation.

Results indicate that pedestrian crashes increase with exposure, footpath and node density, bus stops, residential area, commercial area, utility area and working population. In contrast, there are favorable effects for general and barrier-free walking accessibility on pedestrian safety. Such findings should shed light on the effective urban design and planning strategy that could enhance the safety of all pedestrian groups. For example, traffic calming, and lower speed limit zones could be implemented to improve the pedestrian environment and promote walking.

Nevertheless, there are some limitations to this study. For example, underreporting of pedestrian related crashes is well recognized. Crashes involving non-motorized transport mode and minor injuries only are often resolved privately by the parties involved (Ahmed, et al., 2019). It is worthwhile to explore the advanced statistical methods that can mitigate the imbalanced crash data problem (Ding et al., 2022). Additionally, near misses or precursor events should be considered (Lanzaro et al., 2022). High incidence of precursor events like vehicle-pedestrian conflicts should indicate underlying safety issues. Furthermore, temporally partially constrained model can be considered to test for temporal instability of parameters (Alnawmasi and Mannering, 2023).

Chapter 8 Conclusions and recommendations

8.1 Conclusion

In this study, pedestrian behaviour and safety in urban environments will be evaluated at different levels. Firstly, at the individual level, this study explores the relationship between environmental factors, traffic conditions, safety perceptions, and pedestrian walking behaviour through pedestrian crossing simulation experiments and stated preference surveys. Secondly, at the microscopic level, the impact of street design, urban street trees, and traffic characteristics on pedestrian crash risk is assessed, utilizing pedestrian counts as exposure data. Thirdly, at the macroscopic level, this study examines the associations between the built environment, street network configuration, transportation facilities, walkability, and socio-demographic characteristics with pedestrian crash risk.

As presented in Chapter 3, effects of walking environment on pedestrian path choice are revealed by using a stated preference approach. An integrated choice and latent variable model, based on a random utility framework, examines the direct and indirect effects of socio-demographics, stated choice attributes, and latent variables on decision-making. The findings reveal that route attributes, such as walking time, indoor link proportion, vertical access, and sky and green views, significantly influence path choices for work, leisure, and return trips from metro stations. Pedestrians generally prefer shorter routes with more indoor links, better vertical access, and enhanced sky views. However, perceived safety, comfort, socio-demographics, and weather conditions can also affect the relationship between route attributes and path choices.

As presented in Chapter 4, influences of weather and traffic conditions on pedestrian risk perception are proposed by conducting an immersive Cave Automatic Virtual Environment (CAVE) experiment. The propensity score method was employed to estimate the causal effects of weather conditions on pedestrian safety perception.

Additionally, the effects of multilevel data for multiple treatments were accounted for using inverse probability of treatment weighting. The results indicate that pedestrian risk perception significantly increases under adverse weather conditions, such as rain and fog. This increase is even more pronounced in poor visibility conditions, such as during dusk and heavy fog. Furthermore, there are notable associations between pedestrian risk perception and factors such as age, safety attitude, vehicle speed, and waiting time.

Chapter 5 proposes risk factors to pedestrian safety at microscopic level. The effects of road geometric design, transport facilities, and urban street trees on pedestrian crash risk at the street level are evaluated using data on tree density and canopy cover, alongside comprehensive pedestrian count data to estimate pedestrian crash exposure. A multivariate Bayesian spatial approach is applied to account for spatial dependency and multivariate correlation. The results reveal that factors such as road width, the presence of bus stops and tram stations, on-street parking, and the 85th percentile speed are positively associated with pedestrian casualties. Conversely, the presence of pedestrian crosswalks is associated with a reduction in casualties, while increased tree density and canopy are linked to higher casualty rates. Additionally, temporal variations in pedestrian injury risk are significant.

Chapter 6 reveals the safety effect of pedestrian network and facility at macroscopic level. A multivariate Poisson lognormal approach is employed to estimate the association between pedestrian crashes, pedestrian network characteristics, and other potential influencing factors at the zonal level. The roles of footbridges and underpasses in pedestrian safety are explored. A three-dimensional digital map is utilized to assess the topology, connectivity, and accessibility of the pedestrian network. The results indicate that pedestrian crashes increase with factors such as population density, traffic flow, walking trips, footpath density, node density, the number of vertices, and the presence of residential, commercial, government, and utility areas, as well as bus stops and metro exits. Conversely, pedestrian crashes decrease with a higher average gradient and improved accessibility of footbridges, underpasses, and at-grade crossings.

As presented in Chapter 7, hierarchical data structure issue of pedestrian safety analysis at macroscopic level is addressed. The influences of both zone-level factors (such as exposure, transport facilities, pedestrian network, and walking accessibility) and catchment area-level factors (including land use and socio-demographics) on pedestrian crash frequencies in areas surrounding metro stations is revealed by adopting the multiple membership multilevel modeling approach. The model also considers walking accessibility for individuals with physical impairments. Multiple membership weights are calculated based on the shortest walking distances to metro stations. The model accounts for both within-group and between-group variances due to the hierarchical data structure and identifies additional significant risk factors for individuals with and without physical disabilities.

Based on the conclusion from the proposed research questions, this thesis can make contributions to traffic management, control, design and planning of pedestrian networks, urban design and planning strategies that could enhance perceived walkability, promote active transportation and urban transit use and improve pedestrian safety in compact cities. Here suggest some potential implications derived from the above findings. For instance, (i) pedestrians' walking preferences in various physical environments can be significantly influenced by perceived walkability. This perception can be enhanced through environmentally friendly designs, such as covered walkways, and accessible features, including ramps, elevators, and moving walkways. Additionally, the provision of open spaces and expansive sky views further contributes to an improved walking experience. (ii) Pedestrian risk perception significantly increases under adverse weather conditions such as rain and fog. Therefore, implementing traffic management and adaptive traffic control measures is essential to mitigate pedestrian crash risks at accident-prone locations during such conditions. (iii) At the microscopic level, enhancing pedestrian safety can be achieved through optimal street design and traffic calming measures. Strategies such as reducing crossing distances, lowering speed limits, removing on-street parking, and introducing pedestrian-priority zones can significantly improve safety at road segments.

These measures help create a safer and more pedestrian-friendly environment by minimizing potential conflicts between vehicles and pedestrians and encouraging more cautious driving behaviour. (iv) Pedestrian safety can be enhanced by improving the accessibility of footbridges, underpasses, and crosswalks. This can be achieved by strategically installing footbridges and underpasses in locations with high pedestrian and traffic volumes. (v) Walking accessibility in areas surrounding metro stations is generally high. Facilities such as barriers, warning signs, footbridges, and underpasses significantly reduce pedestrian-vehicle conflicts and crashes. Enhanced barrier-free walking accessibility also positively impacts transport equity, ensuring that all individuals, regardless of physical ability, have equitable access to transportation options. These improvements contribute to safer and more inclusive urban environments.

8.2 Study limitations and future research

Firstly, future studies should address current limitations and explore new directions to enhance the understanding of pedestrian behaviour and safety. The influence of factors such as the built environment and road geometric design on observed associations requires further investigation, particularly as the number of study sites increases. This can be achieved through comprehensive surveys and experiments on human factor metrics, along with larger sample sizes for improved generalization and representation. Future research could combine a CAVE environment with electroencephalography (EEG) and eye-tracking to effectively capture human factors and physiological indicators, offering deeper insights into pedestrian behaviour.

Secondly, it would be valuable to conduct studies on a greater variety of street segments. This thesis focuses solely on segments within the Central Business District (CBD) area. Additionally, the study is limited to examining the yearly trend of tree canopy cover. Some trees are deciduous, tree canopy cover may change more significantly due to seasonal effects. Furthermore, when comprehensive empirical data on tree canopy and pedestrian behaviour becomes available, it would be worthwhile to explore how factors such as climate, socio-cultural mechanisms, and walking behaviour moderate the relationship between tree canopy and pedestrian safety.

Thirdly, the issue of imbalanced crash data arises when the number of crash events is significantly smaller than the number of non-crash events in a dataset. Addressing this imbalance is crucial for accurate analysis and modelling. Exploring the use of deep learning and data generation methods to tackle the problem of imbalanced crash data is a promising avenue for future research. These approaches can enhance the ability to detect and predict crash events by effectively managing the class imbalance inherent in such datasets.

Fourthly, in the analysis of pedestrian crashes, current methodological issues remain due to limitations in computational power and model formulation. For instance, a temporally partially constrained model could be considered to test the temporal instability of parameters. Future research should also explore the effects of correlation between random effects on parameter estimation using advanced statistical and machine learning modelling frameworks. A hybrid model of econometric and machine learning approaches can be adopted to address challenges such as imbalanced crash data, underreporting, and latent structures.

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