ARTICLE IN PRESS

Journal of Safety Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

The interactions between accessibility and crash risk from a social equity perspective: A case study at the Rotterdam-The Hague metropolitan region

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ARTICLE INFO

Article history:
Received 30 January 2023
Received in revised form 26 July 2023
Accepted 19 September 2023
Available online xxxx

Keywords:
Job accessibility
Cycling safety
Safety-accessibility interactions
Social equity
Disadvantaged populations

ABSTRACT

Problem: Transport policies generally prioritize improving safety and accessibility levels, as they are regarded as the most important indicators of the quality of the transport system serving the public. However, inequalities associated with safety and accessibility issues are generally overlooked in these policies. Despite the importance and necessity of transport policies to address equity issues, there is still scarce knowledge on the interactions between equity, safety, and accessibility. This research aims to address this gap in the literature by creating a better understanding of the relationships between accessibility levels and traffic safety with a focus on social equity perspectives. *Method:* A crash risk evaluation method and a Gravity model are utilized to analyze cycling safety and accessibility to jobs by bicycle. Two linear regression models (LM) were conducted to investigate the statistical correlations between cycling crash risk and accessibility. Moreover, the Bivariate local Moran's I method was employed to assess the spatial inequalities of distribution of crash risk and job accessibility over different income-level populations. *Results:* The analyses showed that low-income people are not only disadvantaged in terms of job accessibility by bicycle but are also exposed to higher cycling crash risks, compared to high-income groups. Furthermore, most disadvantaged zones that have the highest need for road safety and accessibility improvements are identified as areas where low-income populations are exposed to higher crash risk and/or have lower access to jobs by bicycle. *Summary:* This study contributes to the transport literature by investigating the interactions between safety and accessibility and the impacts on transport equity. The findings of the statistical and spatial analysis are beneficial for the decision-makers, considering the probable mutual implications of land-use and transport developments and projects aiming to improve safety, accessibility, or both for different population groups.

1. Introduction

Traffic crashes lead to very high societal costs and severe health risks for urban and rural road users. These costs reach 17 billion euros per year in the Netherlands, while over 600 people were killed in traffic, of whom 229 were cyclists and 195 were car users (CBS, 2021a; SWOV, 2020). Traffic safety has been one of the main pillars of transport policymaking in the Netherlands (SWOV, 2018), with transport policies generally prioritizing improvement of safety and accessibility levels. However, the inequalities associated with safety and accessibility issues are generally overlooked in these policies.

Safety and accessibility levels are regarded as the most important the indicators of the quality of the transport system serving the public; however, these levels are generally measured without regarding the disproportionate effects of safety and accessibility problems on different population groups. The concept of equity in transport planning, on the other hand, constitutes providing equal access to economic and social opportunities; thus, distributing the impacts (benefits and costs) of policies fairly and appropriately (Litman, 2015) between individuals and groups with different income levels, social classes, mobility needs, and abilities (Najaf et al., 2017). Examples of equal distribution of safety metrics, given by Najaf et al. (2017), are access to safe vehicles for all income levels, equal provision of safe roadways, and providing access to transport information to all users.

Despite the importance and necessity of transport policies to address equity issues, there is still scarce knowledge on the inter-

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https://doi.org/10.1016/j.jsr.2023.09.015
0022-4375/

Please cite this article as: Masha J.M. Odijk, M. Asadi, M. Baran Ulak et al., The interactions between accessibility and crash risk from a social equity perspective: A case study at the Rotterdam-The Hague metropolitan region, Journal of Safety Research, https://doi.org/10.1016/j.jsr.2023.09.015

actions between equity, safety, and accessibility. One obvious example of the interactions between safety and accessibility is that crash rates intensify when speed limits are increased in an attempt to improve accessibility by reducing travel times. Additionally, there are mutual factors other than speed and travel time that are associated with both safety and accessibility.

Extensive literature exists on the relationship between traffic crashes and factors associated with traffic, roadway design, built environment, and human factors. Similarly, several studies assessed and evaluated accessibility levels of individuals, communities, and regions by utilizing almost identical factors. These mutual sets of factors associated with safety and accessibility include individual characteristics (indicating the needs and behavior of people), land use characteristics (indicating the location of activities), transport system characteristics (indicating the road network infrastructure and traffic variables), and temporal characteristics (indicating the time of the day, year, etc.; Geurs & Van Wee, 2004; Mafi et al., 2019; Schepers et al., 2014; Uijtdewilligen et al., 2022).

For example, it is revealed that higher age is associated with an increased crash risk (Chen & Shen, 2016; Kocatepe et al., 2017; Ulak et al., 2017; Vanparijs et al., 2015). Also, the literature showed that elderly people or children might have less accessibility to destinations due to various circumstances including their ability or the (perceived) traffic safety (Van Wee, 2011). For instance, Martens (2013) showed that bicycle usage and distance traveled by bike start decreasing at 75 years. In addition, the elderly are less likely to make complex trips and travel long distances; hence, their overall accessibility to opportunities is lower (Somenahalli & Shipton, 2013).

Among the land use characteristics, high population density areas are found to be associated with increased crash occurrence and severity (Lee & Li, 2014; Najaf et al., 2018), and with increased accessibility levels (Jayasinghe et al., 2021). It should be noted that increased bicycle crashes in high-population areas are likely to be related to having more cyclists and therefore do not indicate an increase in individual risk. Regarding the transportation infrastructure, it is found that separate cycling facilities are the safest infrastructure (Winters et al., 2012). On the other hand, crash rates on bicycle lanes and roads with mixed-traffic conditions are not significantly different (van Petegem et al., 2021). The temporal factors represent time constraints for individuals and opportunities (e.g., the working start/end time points and shop opening hours) influence the accessibility levels for individuals (Geurs & Van Wee, 2004). Also, several researchers revealed that the severity and probability of crashes vary in different seasons, weekdays, and hours of the day (Eisenberg & Warner, 2005; Mafi et al., 2019; Ulak et al., 2018; Yannis & Karlaftis, 2010; Yu et al., 2013)).

Even though several studies showed the abovementioned relationships, the interactions between safety and accessibility, and the impacts on equity are still not fully clear. The literature clearly shows that accessibility is associated with economic equity (Geurs et al., 2016). That is, the accessibility of lower-income groups is substantially worse than higher-income groups as lower-income groups generally have less mobility (Bastiaanssen et al., 2022). Previous studies also showed that lower-income groups usually suffer more traffic safety problems than other socio-economic groups (Asadi et al., 2022; Najaf et al., 2018; Osama & Sayed, 2017).

This research aims to address the abovementioned gap in the literature by creating a better understanding of the relationships between cycling safety and accessibility levels with a focus on social equity perspectives. For this purpose, a risk exposure evaluation and a Gravity model are utilized to analyze traffic safety and accessibility to jobs by bicycle via extending the traditional definition of accessibility based on travel time or proximity to a location. The remainder of this paper is organized as follows. In Sections 2 and 3, the methodology is discussed. This section also describes the case study area and the data used in this research. Then, in Section 4, discussions of the analysis results are elaborated upon. Finally, the paper is concluded in Section 5 and recommendations are provided.

2. Study area and data

2.1. Study area

This study focuses on the relationship between job accessibility, crash risk, and socioeconomic variables, using a case study on work travels by bikes in the Rotterdam – The Hague metropolitan region (MRDH). This region is a metropolitan area surrounding the major cities of Rotterdam and The Hague, as well as 19 other midsize and small size municipalities. The area has a population of about 2.4 million people and approximately 1.3 million jobs. Around 13.5% of the population in the Netherlands is employed in this area, which serves as a significant hub for both domestic and international companies (MRDH, 2023). Additionally, there are several transportation and land use plans in this region for enhancing accessibility, sustainability, and road safety (MRDH, 2023) that encouraged us to focus on this region as a case study.

The study area is divided based on existing Postal Code-4 zones (Fig. 1). In this study, the cycling network consists of road sections on which cycling is allowed, including residential roads where there is mixed traffic of bicycles and motor vehicles, (suggested) bicycle paths, bicycle lanes, and bicycle streets. The shortest routes between origins and destinations (ODs) were created on this network to estimate the crash risk and job accessibility.

2.2. Data

All data sources and their applications are summarized in Table 1. The Fietsersbond network, filtered for facilities that allow cycling, is used as the cycling infrastructure. Five-year police-registered crash data were retrieved from the Database of Registered Crashes in the Netherlands (BRON, 2015-2019). Crashes that happened during weekdays that involve a minimum of one cyclist, varying in severity from Property Damage Only (PDO) to light, severe and fatal injuries were included in the risk estimation. As this study focuses on accessibility to jobs, only weekday data were included. Underreporting of crashes without motor vehicles, single bicycle crashes, and less severe crashes are common in police-registered datasets (SWOV, 2016), and may lead to under- or overestimation of traffic safety consequences (Doggett et al., 2018). Despite this underreporting, the BRON dataset is the highest-quality crash dataset available in the Netherlands.

Cyclist volumes are derived from Bicycle Count Week (*Fietstelweek*) (BCW) data. The unit area characteristics were retrieved from the Central Bureau of Statistics (CBS) and LISA. Fig. 2 gives an overview of the average income level and population density, which are important in transport equity analysis. Fig. 2 shows that the lower income areas are found mainly in the large cities, Rotterdam, and The Hague, where the population densities are high. The unclassified income level areas in Fig. 2 are the areas of the Rotterdam Harbor where very few people live.

3. Methodology

This research adopted a multi-step approach that included a job accessibility analysis, a crash risk estimation, and a statistical and spatial analysis for equity assessment. The job accessibility and crash risk estimations were based on the shortest path routes for cycling trips to jobs. The costs of travel time from an origin (i.e.,

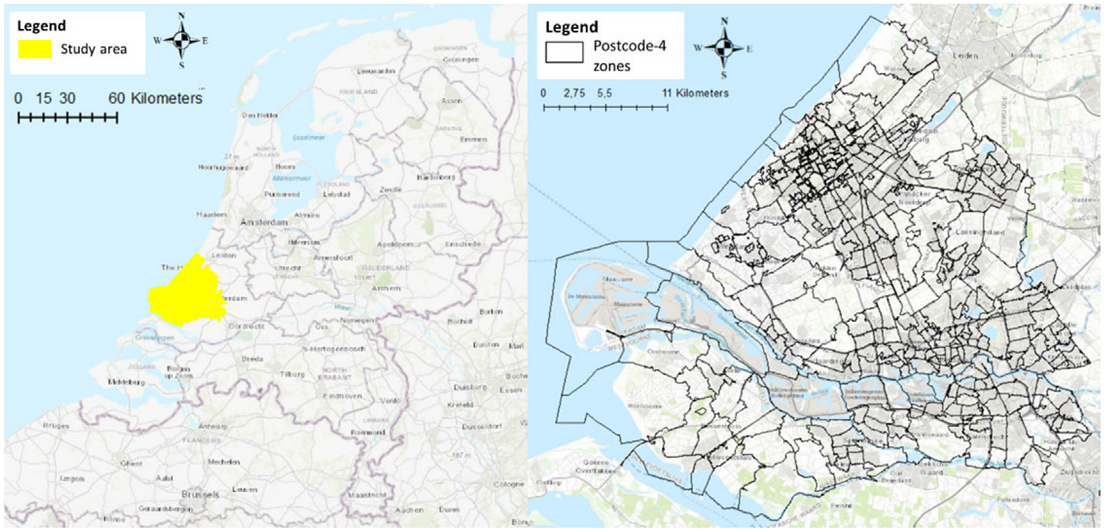

Fig. 1. Study area; Rotterdam – The Hague Metropolitan region (left) in Postal Code-4 zones (right).

Table 1
Data.

Source	Application
Fietsersbond (2016)	Bicycle Network for shortest route calculation
LISA (2014)	Number of jobs D_j per unit area in 2014
BRON (2015-2019)	Crash data (including location, severity, and involved transport modes) in the years 2015–2019 for crash risk calculation.
Fietstelweek (2016)	Bicycle counts in 2016 for exposure in crash risk calculation.
CBS (van Leeuwen & Venema, 2021)	Analysis variables, unit area characteristics: Population density, income level, age of inhabitants.
Planbureau voor de Leefomgeving ("Ruimtelijke dichtheden en functiemenging in Nederland (RUDIFUN)," 2019)	Analysis variables, unit area characteristics: MXI and land use features.

residence) to a destination (i.e., job location) were used in the Gravity model to calculate the potential accessibility levels of a zone. Then, safety risk per route for the identified shortest paths was calculated by weighting the crashes based on the costs associated with their severity levels and the exposure of cyclists through the routes (i.e., € per bicycle-kilometer-traveled). Next, total safety risks for the analysis units in the study region were calculated using aggregated risks per route.

Consequently, linear regression modeling was utilized to model the relationships between accessibility, safety, and socio-economic factors. Similar to the unit area characteristics, the accessibility from the origin zone to the destination zones, and the crash risk on the shortest routes to the destination zones, were modeled as characteristics of the origin zone. To further address any inequities in accessibility and crash risk between the study area units, a spatial correlation test (i.e., Local Bivariate Moran's I) was conducted.

3.1. Job accessibility

For this study job accessibility is defined as the extent to which jobs can be reached by bicycle, depending on the number of jobs accessible and the travel time. Job accessibility is important since jobs are the primary source of income for households (Moya-Gomez & Geurs, 2018), and in the Netherlands in 2019, 36% of the distance traveled and 23% of the trips were work-related (StatLine, 2019). We estimated the potential job accessibility for

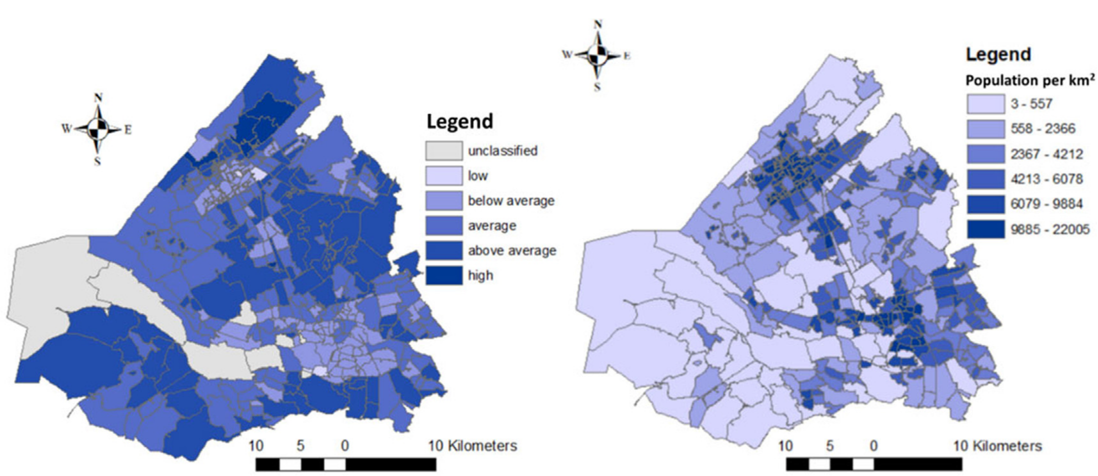

Fig. 2. Average income levels and population per km^2.

each postcode-4 (PC-4) zone using a Gravity model that weights the number of jobs at the destination based on the travel time between the origin–destination pairs (Hansen, 1959) (Fig. 3). The impedance between the origin–destination pairs was weighted using a decay function, such that more distant opportunities are less preferable as a destination. A negative exponential impedance function was used as it is the most common approach in travel behavior theory (Geurs & Van Wee, 2004). The resulting impedance function is shown in Eq. (1).

$$A_i = \sum_{j=1}^{n} D_j e^{-\beta c_{ij}} \tag{1}$$

where the accessibility of zone i A_i to all jobs D_j in the zone, j comprises the weighted impedance $e^{-\beta c_{ij}}$ of route ij, with β as the cost sensitivity parameter and c_{ij} travel costs between zones i and j. In this study, travel costs were expressed in travel time based on network travel distances and the average cycling speed, which was found to be 15 km/h (Fietsersbond, 2019). The cost sensitivity parameter should be carefully chosen as it greatly affects the accessibility outcomes. The value could be any number above zero, where a higher value means a steeper decay. For this study, a cost sensitivity parameter of $\beta = 0.07$ was estimated from fitting existing trip data (CBS, 2021b) to an exponential function (Fig. 4).

3.2. Crash risk

In the traffic safety literature, the safety is quantified and expressed with different metrics, which include or exclude exposure to traffic (e.g., car volume). In this study, the safety of routes is quantified not only based on crash frequencies but also using the number of cyclists and distance traveled to calculate crash rates (Yiannakoulias et al., 2012). A total of 8,160 bicycle-involved crashes were registered by the police on weekdays within the 5 years. As this study focuses on accessibility to jobs, only weekday data are included. For this purpose, the crashes that are located on the shortest path routes between residence and job locations were identified. Then, the crashes were weighted using the Equivalent Property Damage Only (EPDO) values (Eq. (2)) based on the relative severity of a crash.

$$EPDO_x = \frac{C_x}{C_{PDO}} \tag{2}$$

where the Equivalent Property Damage Only $EPDO_x$ is the ratio between the cost C_x for accident type x (PDO, slight injury, severe injury, or fatal crash) and the cost C_{PDO} for a PDO crash. Next, the relative crash risk per route was calculated based on these weighted crash costs (i.e., EPDO) and the bicycle volumes on the routes as shown in Eq. (3).

$$CR_{ij} = \sum\nolimits_{l=1} \frac{\sum_l EPDO}{V_l} \tag{3}$$

where the crash risk CR on route ij between origin i and destination j is the sum of crash risks on all segments l on the route ij, with the crash risk on link l calculated as the sum of EPDO values of all crashes divided by the bicycle volume V_l. The bicycle volume was derived from Bicycle Count Week (*Fietstelweek*) counts that were calibrated by multiplying the collected counts with a factor of 42 as suggested by Uijtdewilligen et al. (2022). Finally, the monetary crash risk per residential zone (i.e., PC4) was calculated following Eq. (4). As such, this crash risk is the risk of traveling from origin i to any destination j, weighted by the number of opportunities at j.

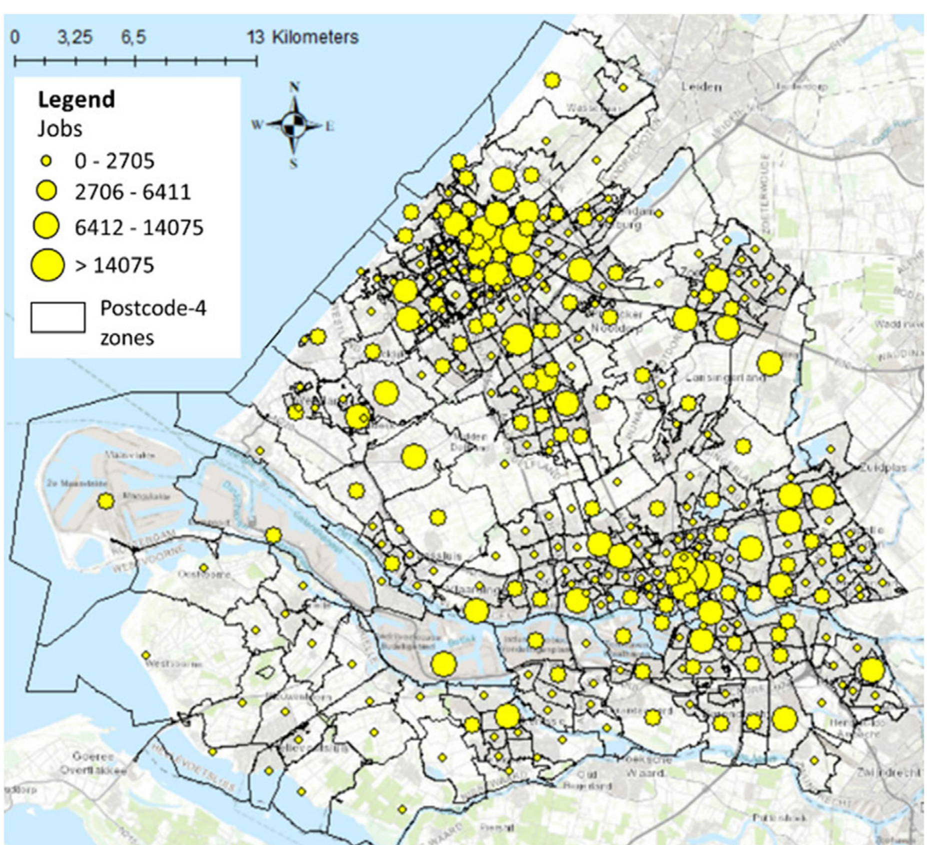

Fig. 3. Job distribution in PC4 zones.

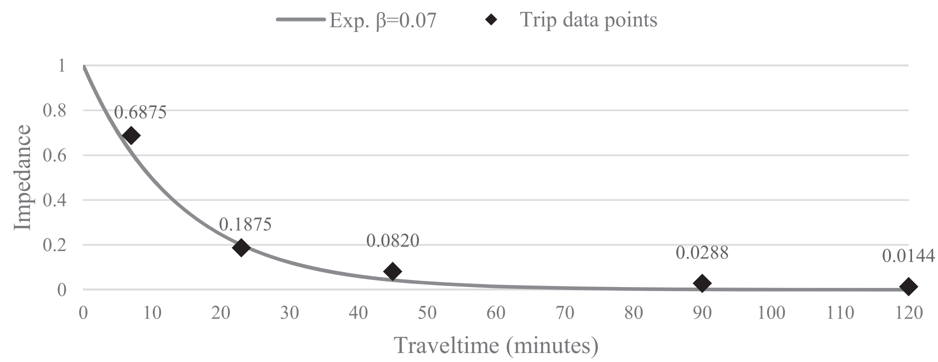

Fig. 4. Distance decay estimation for bicycle trips.

Table 2
Regression analysis variables.

LR	Dependent variable	Independent variables
1	Monetary crash risk MCR_i	Job accessibility A_i
2	Job accessibility A_i	Monetary crash risk MCR_i
Both Models		Population density [Inhabitants per km2]
		Income level (low, below average, average, above average, high)
		Age [ratio < 14, 15–24, 25–44, 45–64, >65 years old]
		Total bicycle infrastructure length [Km/Km^2 area]
		Cycle path, cycle lane, and shared road [ratio of total bike infra]
		Mixed land use index MXI (range 0–1)
		Land use features: living, facilities, and industrial [ratio of total area]

$$MCR_i = \frac{PDO}{n} * \sum_{j=1}^{n} CR_{ij} * \frac{D_j}{\sum_i D} \tag{4}$$

where the MCR_i is the monetary crash risk per origin i, per inhabitant, per year, n is the number of years of crash data and PDO is the cost of each property damage-only crash. The final metric is the summation of crash risks of all routes between origin i and destination j, accounting for the weight of the route depending on the number of jobs at destination j.

3.3. Regression modeling of safety and accessibility

To further analyze the relationships between job accessibility, crash risk, and socio-economic variables two linear regression models (LM) were conducted. These models allow for the assessment of the impacts of the predictor variables on the dependent variable. In this study, the dependent variables in the two aforementioned regression models are job accessibility and crash risk, whereas independent variables are population density, income level, populations of different age groups, the density of different types of bicycle infrastructure, as well as land use features (Table 2). Eq. (5) defines the relationship between the dependent and independent variables as follows:

$$Y_i = \beta_0 + \sum_{i=1}^{n} \beta_i * X_i \tag{5}$$

where the dependent variable Y_i is modeled by a linear function of independent variables, X_i with intercept β_0 and a set of coefficients β_i. Other statistical models such as the negative binomial regression are commonly used for modeling traffic safety (Lord et al., 2005). However, the majority of these models require a count variable (e.g., negative binomial regression) or a binary variable (e.g., logit regression). In this study, a linear regression method was preferred due to two reasons: (1) linear regression results are easier to communicate and more intuitive to interpret compared to other models, and (2) the same model type is deemed more suitable for the analysis and both dependent variables in this study are of continuous nature (i.e., potential accessibility level and monetary crash risk).

To avoid multicollinearity, we conducted a Pearson correlation test on the independent variables (van den Berg, 2020). As Fig. 5 shows, the correlations between the variables were between −0.69 and 0.55, indicating that the correlations between the variables were not high.

3.4. Local Bivariate Moran's I

Bivariate Local Moran's I (BLMI), determining the spatial autocorrelation between two variables, was employed to investigate spatial inequalities (Anselin et al., 2014). The BLMI method was previously used by Chen et al. (2020) to explore the communities that have better accessibility to green areas, and Sharma and Patil (2021) studied equity in access to public healthcare services via accessibility to public transport. Similarly, Hu et al. (2020) analyzed spatial equity in accessibility to urban parks by conducting the BLMI method between accessibility level and population density, whereas Knap et al. (2023) evaluated spatial equity using BLMI within 15 minutes city concept. Eq. (6) shows the statistic of Bivariate Local Moran's I.

$$I_i^B = c x_i \sum_j w_{ij} y_j \tag{6}$$

where x_i shows the static of variable × (e.g., potential job accessibility by bicycle) and y_j shows the static of variable y (e.g., crash risk by bicycle) in the areas of i and j. w_{ij} indicates the spatial weight matrix between area i and j. In this study, this matrix was created based on K-Nearest-Neighbors (K-NN) of each zone i indicated as zones j. GeoDa Software (Anselin & McCann, 2009) facilitates visualization of the maximum of five types of relationships that can be found between the two selected variables.

The relationships include High-High (HH), Low-Low (LL), High-Low (HL), Low-High (LH), and non-significant. HH indicates groups with high levels of both variables, whereas LL represents groups with low levels of them. HL highlights areas with a high value in the first variable and LH indicates clusters with a low value in the first variable and a high value in the second one.

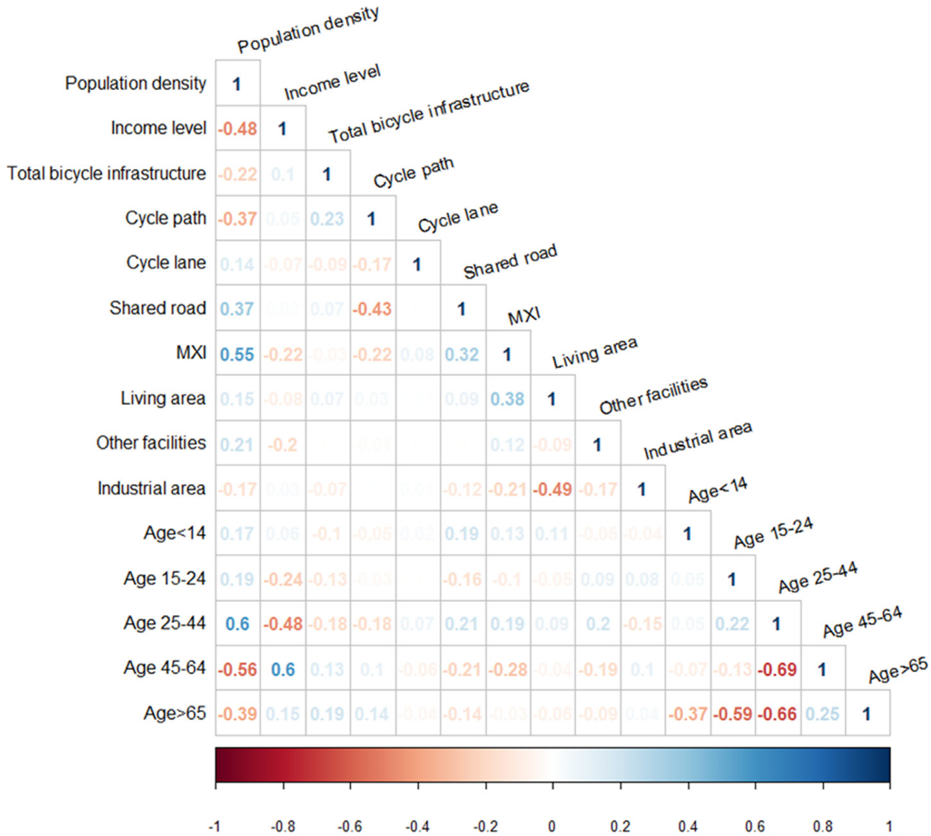

Fig. 5. Correlation coefficient matrix with low-medium correlations between −0.69 and 0.55.

However, the non-significant type shows there are no significant spatial relationships between the variables (in the specified confidence interval). In this study, to explore the potential inequalities in the areas we focused on the LH and LL clusters in analyzing the low-income areas with high crash risk and low job accessibility.

4. Results and discussion

4.1. Potential accessibility and crash risk by bicycle

Fig. 6 shows potential job accessibility in each PC-4 area within the study region. The potential accessibility level indicates the

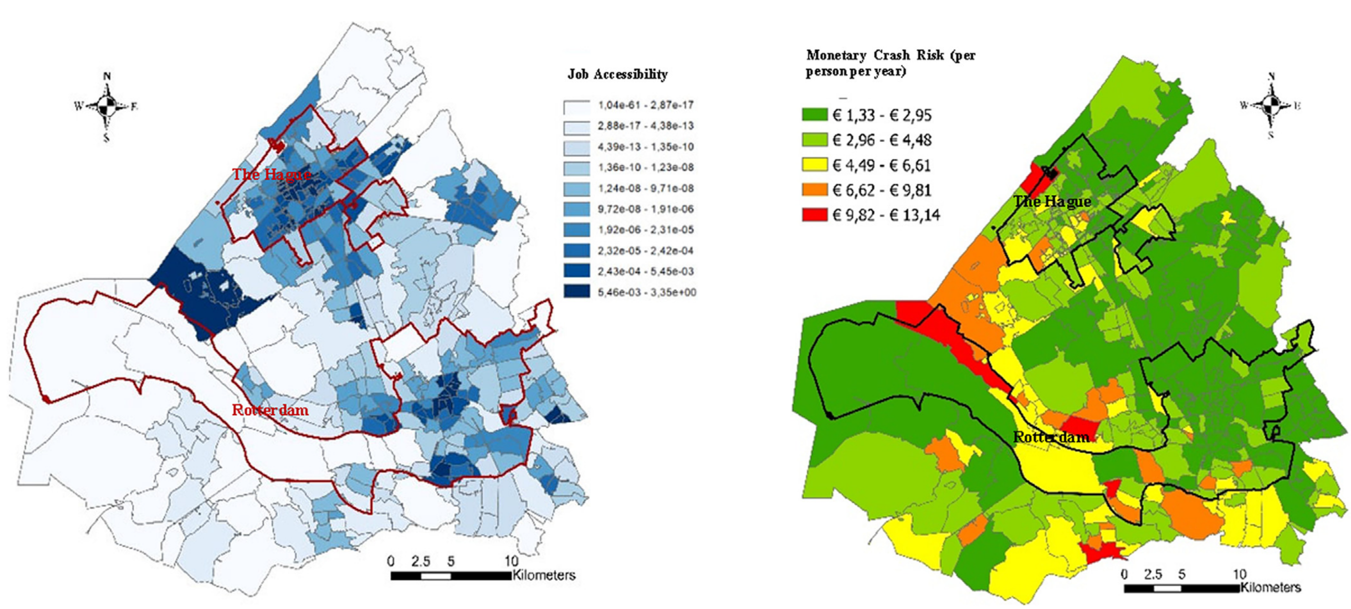

Fig. 6. Potential job accessibility level (left) and monetary crash risk per inhabitant (right) per PC4.

level of opportunities (i.e., the total number of jobs) that can be reached from a PC-4 area, which decreases as the distance between the areas increases. As expected, the highest job accessibility levels are mainly observed in urban areas, including the cities of Rotterdam and The Hague. The lowest accessibility levels can be found in the southwest part of the study area where the job density is smaller compared to other areas (Fig. 3). Fig. 6 also shows the estimated average value of yearly crash risk cost per traveler for each origin (PC-4). This figure differs from the potential job accessibility levels by revealing that there is no clear pattern in the monetary value of crash risk on cyclists in the PC-4 zones. For example, the figure shows that the crash cost in zones located in the west of Rotterdam (city center) is low, whilst it is medium in the (city) center of The Hague.

4.2. Regression models of crash risk and potential job accessibility

The results of regression models are shown in Table 3 and Fig. 7. To compare the impacts of the independent variables on both crash risk and job accessibility, we compared the magnitude of the coefficients of a similar set of land use and socioeconomic variables in both models. To make the coefficients comparable they are transformed into standardized coefficients (Fig. 7; Asadi et al., 2022).

4.2.1. Cycling infrastructure

The results show that the kilometers of cycling infrastructure in an area is correlated with a minimal increase in crash risk. Job accessibility is negatively correlated with the length of bicycle facilities, whilst one would expect that more bicycle facilities increase the accessibility of an area. The reason for this finding could be that the bicycle network used in the analysis was very extensive as it included all residential roads (i.e., Mixed-traffic roads), and slight increases or decreases do not directly influence the accessibility.

Results also show that areas with a higher ratio of cycling paths are correlated with increased crash risk and job accessibility, which contradicts the general perception of the safety of bicycle paths. Two Scandinavian studies have shown that introducing new bicycle paths often increases crash occurrences, however, they did not comment on changes in bicycle volumes (Agerholm et al., 2008; Jensen, 2008). Generally, the segregation of cyclists from motor vehicles is associated with improved bicycle safety (Schepers et al., 2013). Furthermore, comparing the mixed traffic and bicycle lane ratio coefficients of the crash risk model, it is found that mixed-traffic roads are significantly associated with increased crash risk. This contradicts the findings of van Petegem et al. (2021), who concluded that cycle lanes do not provide safety benefits in terms of reducing crash rates over mixed-traffic roads.

4.2.2. Land use characteristics

From the land use design characteristics perspective, we found that higher ratios of housing, facilities, and industrial land uses are correlated with increased crash risk and reduced job accessibility in the analysis units. Additionally, it was found that developing high mixed land use areas helps to enhance cyclists' safety. This result is in line with the findings of Asadi et al. (2022) representing that low-income level areas are associated with higher crash frequencies implying diminishing traffic safety in these areas. However, for these areas, our results show decreased job accessibility. This result is contrary to the findings of Jayasinghe (2021) who found that in high-density zones, high levels of accessibility are linked with high land use mixture.

4.2.3. Socioeconomic characteristics

For each age group, the direction of the impact of crash risk and job accessibility is the same. The only exception to the relationship is the population group aged between 45 and 65 years old. More specifically, the crash risk model shows that a higher population aged between 44 and 65 years old is associated with higher crash risk in the PC-4 areas. The negative relationship between crash risk and the ratio of elderly (65 + years old) is surprising as the elderly make up the majority of bicycle road fatalities and serious injuries ("Fietsers, SWOV Factsheet," 2023).

Furthermore, it stands out that for the income level variable, the direction of the estimated coefficients in the crash risk model is negative, whilst they are positive in the job accessibility model. This means that greater population density and income levels in the areas are associated with lower crash risk and higher job accessibility. Additionally, the crash risk model showed that cyclists are at more crash risk in areas with lower income levels. This result is in line with the findings of Asadi et al. (2022) and Najaf et al. (2018) representing that there are higher crash frequencies in low-income areas. These findings show inequalities between different income level areas regarding crash risk and job accessibility and suggest the decision-makers for further investigations on trade-offs between improving safety and enhancing accessibility.

4.3. Spatial correlations between job accessibility and crash risk by bicycle

Both accessibility and crash risk are spatially dependent variables, and their relationship may expand beyond similarities and

Table 3
Regression model results.

	Crash risk model		Job accessibility model	
	β	*SE*	*β*	*SE*
Intercept	8.771	2.88	−0.391	0.31
Length of Cycling infra. ($x10^{-5}$)	2.885	48.50	−3.858	5.11
Ratio of Separated cycle path	0.544	1.11	0.068	0.12
Ratio of Cycling lane	−0.060	1.35	−0.013	0.14
Ratio of Mixed traffic	0.322	0.65	0.037	0.07
MXI	−1.474	0.92	−0.164	0.10
Ratio of Housing Land use	0.545	0.50	−0.035	0.05
Ratio of Facility land use	1.104	1.16	−0.022	0.12
Ratio of Industrial land use	0.303	0.84	−0.070	0.09
Total population ($x10^{-6}$)	−4.320	37.85	8.859	3.96
Age 15–24	−9.769	4.12	0.540	0.44
Age 25–44	−7.588	3.35	0.598	0.36
Age 45–64	3.342	4.08	0.344	0.43
Age 65+	−3.893	2.94	0.418	0.31
Income Level	−0.612	0.18	0.021	0.02

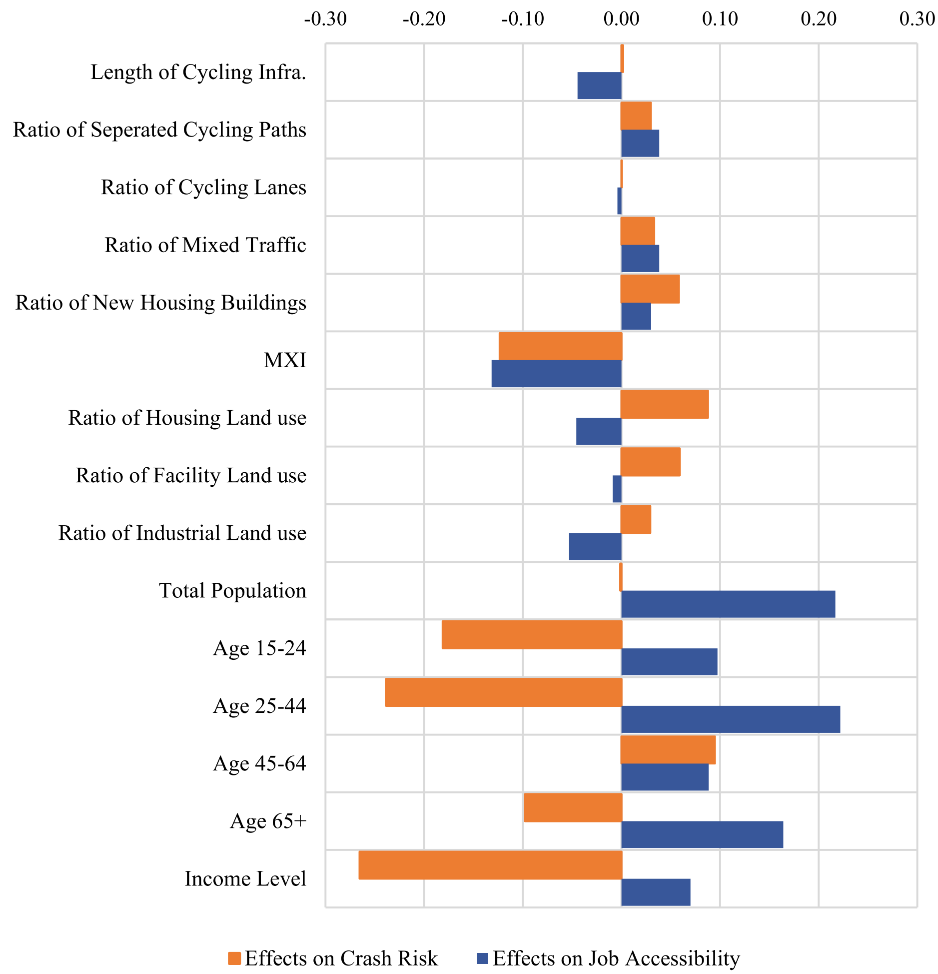

Fig. 7. Standardized regression coefficients for two models.

differences within a unit area. In addition, closely located neighborhoods with differing high crash risk and/or low accessibility values can reveal inequality issues in these areas. This study used a Bivariate Local Moran's I method to examine the spatial correlations between potential job accessibility by bicycle in PC-4 zones and crash risk associated with bicycle trips originating from each zone with the population income levels in the zones. To do this analysis the spatial weight matrix was created based on the K-NN method in which we accounted for 30 PC-4 neighbor zones. The results of this analysis show five different types of clusters of not-significant, High-High (HH), Low-Low (LL), Low-High (LH), and High-Low (HL) (Fig. 8).

The bivariate spatial autocorrelations between income levels with crash risk and job accessibility values are shown in Fig. 8a and b, respectively. In the crash risk map, the LH zones, represent the cluster of zones with low-income populations who are more exposed to crash risks. These zones are mainly located in the west and south parts of the study area. Whilst, in the accessibility and crash risk maps (Fig. 6), the white colored zones represent the low job accessibility level zones, and the green zones are the low crash risk zones (i.e., LL cluster). Therefore, both the LH and LL clustered zones, shown in red color, respectively, in the left and right sides map in Fig. 8, represent the most disadvantaged areas where low-income populations are exposed to high crash risk, have low access to jobs by bicycle, or both. These 26 zones are illustrated by dark red colors on the map in Fig. 9. Additionally, Fig. 9 shows, there are only 7 (out of 314) PC-4 zones in the study where people are the most advantaged in terms of income level, higher road safety level, as well as higher accessibility level to jobs by bicycle. These zones are located in the center of the city of Rotterdam. Moreover, the orange zones in Fig. 9 represent equality where the clusters of areas with high-income populations are not advantaged from the cycling safety and job accessibility levels.

5. Limitations and future directions

The approach taken in this paper has several limitations. Firstly, a limitation of this study is the use of the shortest route for both the crash risk and job accessibility calculation. The literature revealed, however, that cyclists do not necessarily take the shortest route so they consider factors such as the number of crossings, the type of road infrastructure, or other environmental factors such as the greenness of the area in their route choice (Chen et al., 2018; McArthur & Hong, 2019; Prato et al., 2018; Ton et al., 2018). Thus, future studies may elaborate on the estimation of crash risks associated with individuals' trips by accounting for alternative routes between ODs.

A second limitation is that we were unable to account for job matching and competition, which is relevant to examine inequalities in job accessibility. Competition for jobs is determined by differences in the spatial distribution of workers and jobs, but also workers' skills and job requirements such as the required education level for a job (Geurs & Van Wee, 2004) (Geurs & van Eck, 2003; Geurs & Van Wee, 2004). Bastiaansse (2021) examined the relationships between job accessibility and individual employment

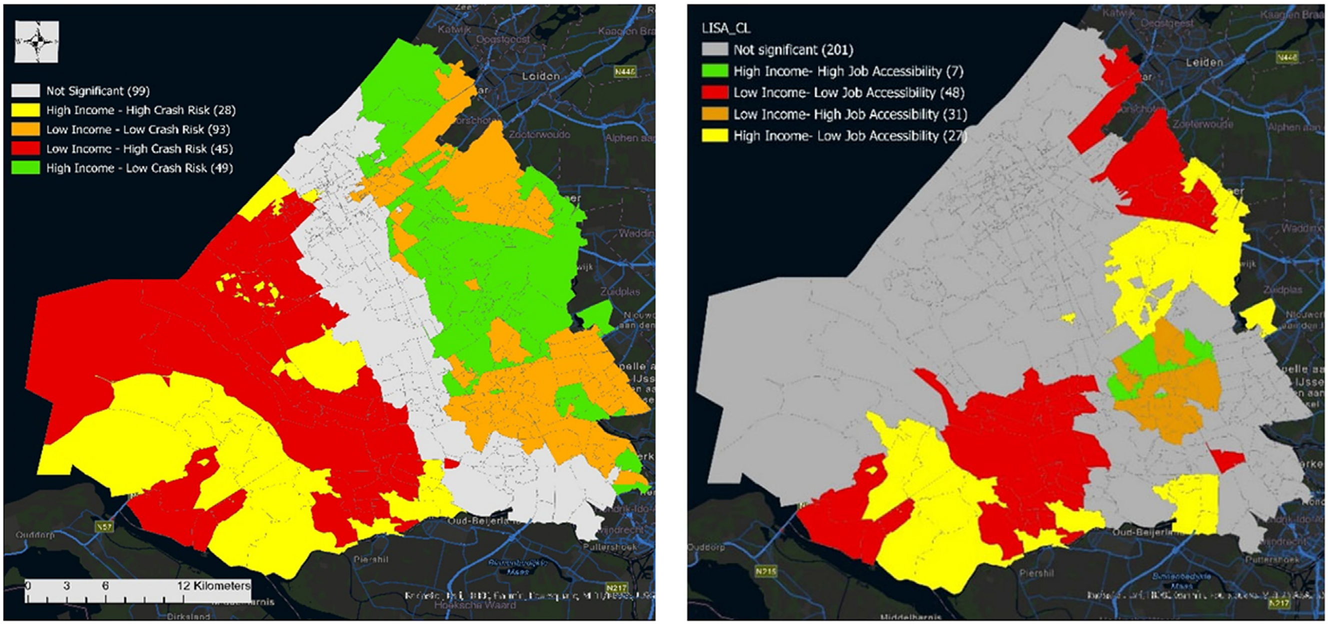

Fig. 8. Spatial correlations: a) between Income level and Crash Risk; b) between Income level and Job accessibility.

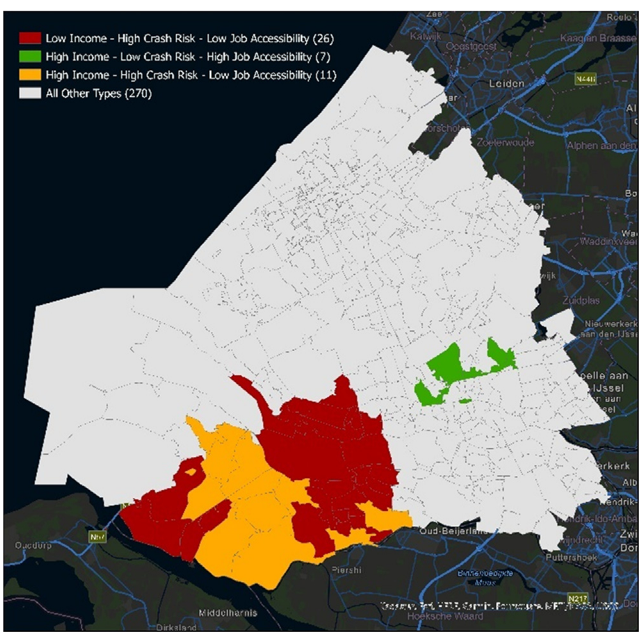

Fig. 9. Summary of spatial correlations between the levels of average income, imposed crash risk, and job accessibility by bicycle.

probabilities in the Rotterdam-The Hague metropolitan region and concludes that better job accessibility and vehicle access increase individual employment probabilities, especially for low-income workers in dense urban areas. To conduct this analysis, the author used micro data sets including employment status and detailed individual characteristics of all individuals living in the study area, available only with special permission from Statistics Netherlands (CBS).

Thirdly, although the crash data used in this study is an extensive dataset, slight injury crashes and crashes without motor vehicles are likely to be underrepresented in this dataset similar to other police-recorded datasets (Doggett et al., 2018). There are efforts to involve other datasets such as ambulance records to alleviate this underreporting issue. However, there are currently no other available data to investigate traffic crashes. Furthermore, this study sheds light on the estimation of the crash risk costs associated with commute trips by bicycle by accounting for average and generalized commute trip patterns made on weekdays and during the daytime. However, such a pattern may not be equal for low- versus medium/high-income jobs, or females versus males. For example, literature shows that low-income residents commute mostly between 5–7 AM and 4–6 PM, while middle/high-income residents commute between 7–9 AM and 5–7 PM (Pieroni et al., 2021). In addition, as females are more responsible for household duties and child care, they are more likely to perform trip chaining than men, even when both work full-time (Nobis & Barbara, 2004). Thus, consideration of variations in travel patterns to compare the associations between safety and accessibility for different population groups would be an interesting direction for future transport equity studies.

Fourthly, the built environment variables showed useful results for transport equity, where increasing land use mixture may benefit both traffic safety and job accessibility in low-income areas. Based on this, examining the impacts of interactive variables, such as the percentage of residential land use * MXI, on safety and accessibility may result in more beneficial outcomes. Finally, a sensitivity analysis will provide more insight into the impacts of different built environment factors on improvements in safety and accessibility.

6. Conclusions

This paper creates a better understanding of the relationships between safety and accessibility levels with a focus on social equity perspectives. To do this, job accessibility levels per zone were calculated using a Gravity model. The crash risk in the zones is estimated based on the sum of risks on all shortest routes between ODs. Then, two linear regression models were conducted on crash risk and job accessibility with various socio-economic variables as predictor variables.

The study was conducted in the Rotterdam-The Hague Metropolitan region, which currently hosts a considerable number of inhabitants and jobs in the Netherlands. In the next few decades, approximately 400,000 new individuals will settle in this region, necessitating the creation of more job opportunities, additional commercial areas, and about 240,000 new houses in the urban area (MRDH, 2023). However, the growing urbanization also leads to increased mobility, which requires additional steps to avoid a surge in car travel, resulting in undesirable traffic congestion. Hence, encouraging the use of bicycle mode as a sustainable and accessible mode of transport for almost all people with different socio-economic backgrounds should be advantageous. In this regard, plans for improving road safety as well as accessibility are devised (MRDH, 2023), which necessitates being fairly distributed over population groups.

The main finding of the regression models is that low-income people are not only less advantaged in terms of job accessibility by bicycle, but also are exposed to relatively higher levels of cycling crash risk. In addition, compared to other age groups, the population group aged between 45 and 64 is exposed to higher cycling crash risks, and also their accessibility to jobs is lower than other age groups. The bivariate spatial analysis between income levels with crash risk and job accessibility identified 26 disadvantaged zones where low-income populations are exposed to high crash risk and/or have low access to jobs by bicycle. The most advantaged seven zones in terms of income level, high levels of cycling safety, and high job accessibility by bicycle are all located in the city center of Rotterdam.

From an equity perspective, clusters of such disadvantaged zones are most in need of road safety and accessibility improvements. The findings of the statistical and spatial analysis are beneficial for the decision-makers, considering the probable mutual impacts of land-use and transport developments and projects (i.e., improved accessibility) on the safety of different population groups. For example, the models showed that high MXI levels are associated with both increased safety and accessibility, while zones with high residential land use are associated with reduced safety and accessibility. Therefore, raising MXI levels in residential areas by building more diverse land use classes can be advantageous in terms of improving both accessibility and traffic safety in low-income areas. To conclude, this study contributes to the transport literature by investigating the interactions between safety and accessibility, and the impacts on equity.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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