Computers, Environment and Urban Systems 129 (2026) 102480

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

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

# A computational framework for measuring dynamic vehicular exposure and equity in the 15-min city

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ARTICLE INFO

*Keywords:*
15-min city
walkability
vehicular exposure
environmental justice
urban accessibility

ABSTRACT

The 15-min city concept promises equitable access to essential services through walkable neighborhoods, yet traditional accessibility assessments fail to capture the dynamic impact of vehicular exposure on pedestrian experiences. This study introduces a novel computational framework that measures near-real-time, path-specific vehicular exposure during individual walking journeys by integrating large-scale mobility datasets including mobile phone trajectories (approximately 50% population coverage), GPS data from heavy trucks (75% coverage), and comprehensive public transit schedules in Beijing, China. We develop multi-scale exposure indices that distinguish between cars, trucks, and buses at road, location, and individual trip levels, revealing systematic inequities across socioeconomic groups: higher-income groups face intense car risks in amenity-rich urban areas, while lower-income groups are disproportionately burdened by truck traffic. Critically, we model an access gap that quantifies how traffic avoidance behavior constrains walkable access, revealing that vehicular exposure creates invisible barriers that systematically reduce the practical reach of the 15-min city. These findings compel a reinterpretation of walkability—from mere proximity to an experiential quality—and provide essential insights to identify and mitigate the environmental injustices that undermine equitable urban design.

## 1. Introduction

The 15-min city has emerged as a transformative vision for sustainable urban development, proposing that residents should be able to access essential services within a short walk from their homes (Moreno, Allam, Chabaud, Gall, & Pratlong, 2021). This human-centered planning paradigm represents a fundamental shift from automobile-centric design toward accessibility and quality of life as primary planning objectives. Cities worldwide have embraced this framework as a pathway to address pressing urban challenges including climate change, social inequity, and declining livability (Murgante, Patimisco, & Annunziata, 2024; Song et al., 2022).

The successful implementation of the 15-min city depends critically on walkability (Rhoads, Solé-Ribalta, & Borge-Holthoefer, 2023; Roper, Ng, Huck, & Pettit, 2024)—a complex concept that extends far beyond the simple proximity of amenities. Current walkability assessments have relied primarily on static measures of the built environment, examining infrastructure provision, land use characteristics, and spatial accessibility through established frameworks such as the “3Ds” of density, diversity, and design (Deng et al., 2020; Gao et al., 2022; Kang, Kim, Park, & Lee, 2023; Ki, Lee, Park, Ha, & Lee, 2025; Lu & Chen, 2024; Pang et al., 2025; Rahman, 2022). While these conventional approaches provide valuable insights into the structural conditions that support pedestrian mobility, they create a significant disconnect between theoretical accessibility and the lived experience of urban walking. Without incorporating dynamic exposure metrics, planners risk systematic misjudgments: neighborhoods may be classified as highly walkable based on proximity alone, yet residents may avoid walking due to hazardous traffic conditions; infrastructure investments may target areas already well-served while neglecting communities where traffic exposure (not distance) constitutes the primary barrier to walking; and equity assessments may overlook how traffic creates invisible boundaries that

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https://doi.org/10.1016/j.compenvurbsys.2026.102480
Received 17 July 2025; Received in revised form 10 April 2026; Accepted 8 June 2026
Available online 11 June 2026

disproportionately constrain access for vulnerable populations (Xu et al., 2024).

Cities function as inherently dynamic systems where conditions affecting pedestrian mobility fluctuate continuously throughout the day (Bongiorno, Santucci, Kon, Santi, & Ratti, 2019). Among these dynamic factors, vehicular exposure—the degree to which pedestrians encounter traffic during their journeys—represents a critical yet systematically underexplored barrier to realizing walkable access (Tran et al., 2025). Unlike static infrastructure, traffic is inherently dynamic, and its volume and composition fluctuate continuously. These spatiotemporal variations generate immediate, variable burdens for the pedestrian, including air and noise pollution, safety hazards, and psychological stress (Bhowmick, Winter, Stevenson, & Vortisch, 2021; Yu et al., 2022). These factors directly and profoundly undermine the appeal of walking, turning a theoretically walkable route into an undesirable one. For example, high concentrations of trucks and buses can severely degrade the pedestrian experience even when sidewalks and crossings are adequate. Research demonstrates that these heavy vehicles generate disproportionate noise (Peng, Liu, Parnell, & Kessissoglou, 2019), emit higher pollutant levels (Breuer, Samsun, Stolten, & Peters, 2021), and pose greater safety risks (Mooren, Grzebieta, Williamson, Olivier, & Friswell, 2014) due to their size and limited maneuverability, altering a street's walkable character regardless of its physical infrastructure quality.

Dynamic vehicular exposure also carries profound implications for social equity and environmental justice (Hwang, Joh, & Woo, 2017). Social equity (Pönkänen, Tenkanen, & Mladenovic, 2025) in urban contexts refers to the fair distribution of resources, opportunities, and burdens across all population groups, while environmental justice (Xu et al., 2019) specifically addresses whether communities face disproportionate exposure to environmental hazards based on socioeconomic status or race. In practice, residential segregation and differential transportation access create systematic disparities in vehicular exposure across socioeconomic groups (Stroope & Garn, 2024; Yuan & Wang, 2021). Studies have documented that lower-income communities, often confined near industrial zones and freight corridors, face disproportionate truck traffic and its pollution and safety hazards (Patwary, Haque, Mahdinia, & Khattak, 2024; Yuan & Wang, 2021). Conversely, affluent populations experience intense car congestion in amenity-rich centers (Chang, Lee, & Choi, 2017; Li, Xiong, & Wang, 2019). These differentiated patterns sort populations into distinct risk profiles, each facing unique barriers to walkable access. Communities enduring the most challenging walking conditions are excluded from pedestrian-oriented planning benefits, threatening the 15-min city's foundational promise of equitable access (Moreno et al., 2021).

Existing research on vehicular exposure has predominantly relied on static methodologies including aggregated traffic counts, land use regression models, and fixed monitoring stations (Obelheiro, da Silva, Nodari, Cybis, & Lindau, 2020; Ren, Li, Yuan, & Shao, 2023; Song, Meng, Kang, Yang, & Li, 2024). These approaches provide averaged estimates across broad geographic areas and extended time periods, failing to capture the dynamic, path-specific nature of individual pedestrian journeys. This disconnect between averaged estimates and actual individual exposure represents a significant methodological constraint in urban environmental health research (Wang et al., 2021). The core challenge lies in measuring exposure as it actually unfolds: traffic volume and composition (cars, buses or trucks) fluctuate continuously throughout the day in response to commuting peaks and delivery schedules, yet static methods cannot track these temporal variations at fine spatiotemporal resolution. Compounding this, walking behaviors introduce path-specific variability—pedestrians traveling at different times encounter entirely different exposure conditions on the same street, a dynamism that aggregate measures inherently miss. Without methods capable of capturing this individualized exposure, the extent to which the 15-min city promise is being fulfilled remains largely unknown. Urban planners lack tools to measure whether walkable access quality is equitably distributed, limiting their ability to identify and address the accessibility disparities that undermine equitable urban design.

In this paper, we use Beijing, China, as our case study. As China's capital with a population exceeding 21 million, Beijing has increasingly adopted elements of the 15-min city paradigm through policies like the "Beijing Urban Master Plan (2016-2035)," which emphasizes compact, mixed-use neighborhoods to enhance accessibility and reduce car dependency. Empirical studies (Ma, Wang, Li, & Sun, 2023; Wang, Kwan, Liu, Liu, & Wang, 2025) show that central urban districts, characterized by high density, mixed land use, and decades of compact development, generally exhibit strong service proximity. Many neighborhoods in core areas feature concentrated amenity provision that aligns well with the 15-min standard, and some areas even meet more ambitious 10-min accessibility goals. Conversely, outer suburban districts and newly developed residential zones face considerable challenges. Rapid spatial expansion at the urban fringe has outpaced infrastructure development, leaving many peripheral communities with dispersed services that require longer walking distances. Additionally, older industrial neighborhoods, though closer to the urban core, often suffer from inadequate service provision despite their central location. These patterns make Beijing an instructive case study for examining the 15-min city framework: the city exhibits both successes in areas where proximity-based planning goals are achieved, and persistent challenges in delivering equitable access across diverse neighborhoods and socioeconomic groups.

To address the critical gaps identified above, this study introduces a novel computational framework that measures near-real-time, path-specific vehicular exposure during individual pedestrian journeys. We integrate multiple large-scale mobility datasets—including mobile phone data covering approximately 50% of the urban population, GPS trajectories from 75% of heavy trucks, and comprehensive public transportation schedules to reconstruct high-resolution, near-real-time encounters between pedestrians and different vehicle types across Beijing metropolitan region. This approach generates multi-scale exposure measures that capture near-real-time variability along individual journeys while distinguishing the unique impacts of cars, trucks, and buses. To evaluate how this exposure affects accessibility, we model an access gap by simulating how the accessible road network functionally shrinks for pedestrians with different tolerances for traffic exposure. This provides a more realistic, human-centered evaluation of equitable access, revealing how traffic conditions functionally redefine the practical reach of the 15-min city.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 details our data and methodology, including the dynamic exposure index and the access gap modeling. Section 4 presents the empirical results of our analysis. Section 5 discusses the findings and policy implications, and Section 6 concludes the paper.

## 2. Literature review

This review critically synthesizes scholarship from three interconnected domains: the conceptualization of the 15-min city and its relationship to walkability; the health and experiential impacts of vehicular exposure; and the principles of social and mobility justice in urban planning. By weaving these threads together, we identify the critical research gaps this study aims to address.

### 2.1. The 15-min city and walkability

The 15-min city has emerged as a transformative framework for sustainable urban development, reimagining how cities can be organized to enhance residents' quality of life while reducing environmental impacts. Originally conceptualized by urbanist Carlos Moreno (Moreno et al., 2021) and subsequently adopted by cities worldwide (Murgante et al., 2024; Song et al., 2022), this model envisions neighborhoods where residents can access essential services and amenities within a 15-min walk from their homes. Its theoretical foundation rests on key principles of proximity, diversity, density, and digitalization, which collectively aim to create more livable and sustainable urban environments.

The success of the 15-min city model is intrinsically linked to walkability (Rhoads et al., 2023; Roper et al., 2024)—a multidimensional concept extensively researched across urban planning and public health. Traditional frameworks have focused on objective measures of the built environment, including population density, land use diversity, street connectivity, and infrastructure quality (Aghaabbasi, Moeinaddini, Shah, Asadi-Shekari, & Kermani, 2018; Deng et al., 2020; Gao et al., 2022; Jardim, Neto, & Barriguinha, 2023; Kang et al., 2023; Ki et al., 2025; Lu & Chen, 2024; Rahman, 2022; Tiitu et al., 2024; Wang & Yang, 2019; Yameqani & Alesheikh, 2019; Zhi et al., 2024; Zhi et al., 2024). The widely adopted "3Ds" framework—density, diversity, and design—and its expansions have been instrumental in shaping our understanding of the structural conditions that support pedestrian mobility.

However, contemporary research has increasingly recognized the limitations of these static assessments (Cambra & Moura, 2020; Hassan & Elkhateeb, 2021). While infrastructure provides the stage for walking, the actual pedestrian experience is profoundly influenced by dynamic factors like traffic patterns, noise levels, air quality, and perceived safety, all of which fluctuate throughout the day (Bongiorno et al., 2019; Yang et al., 2024). This has led to calls for more comprehensive approaches that acknowledge infrastructure alone does not guarantee a positive pedestrian experience.

Furthermore, recent studies demonstrate that walkability outcomes are not uniformly distributed, with significant variations across neighborhoods and demographic groups (Fraser et al., 2024; Pereira, Vale, & Santana, 2023; Yu et al., 2022). These disparities reveal that implementing 15-min city principles may not automatically result in equitable access. The chasm between theoretical accessibility on a map and the lived experience on the street remains a critical concern for planners seeking to build genuinely equitable cities.

### 2.2. Vehicular exposure and environmental health

A primary driver of this disconnect between static design and lived experience is vehicular exposure, a critical dimension of urban environmental health (Guo, Ni, Shyu, Ji, & Huang, 2023; Sider, Hatzopoulou, Eluru, Goulet-Langlois, & Manaugh, 2015; Yang et al., 2023; Zou et al., 2025; Yu & Woo, 2022). This exposure is not a single stressor but a multifaceted burden encompassing air and noise pollution, safety risks from traffic collisions, and the psychological strain of navigating high-traffic environments (Jia, 2021; Song et al., 2025; Song et al., 2023; Song, Yang, Yang, Cui, & Zhu, 2023; Su, Zhi, Song, Tian, & Yang, 2023; Tirico, Le Bescond, Sengelin, Gastineau, & Can, 2025; Wang et al., 2024; Wu et al., 2023). While each vehicle type contributes to this multifaceted burden, research indicates differentiated impact profiles: private cars are the dominant source of urban congestion and associated stress (Conceiçao et al., 2023; Gossling, 2020); heavy-duty trucks, though fewer in number, contribute disproportionately to noise pollution (Han, Samarneh, Stock, & Symanski, 2018), particulate matter emissions (Wang et al., 2021), and pedestrian fatality risk due to their mass and limited visibility (Ma et al., 2019); and buses create localized disruption through frequent stops and acceleration patterns (Iliopoulou, Milioti, Vlahogianni, & Kepaptsoglou, 2020). We acknowledge that these categories are not mutually exclusive (trucks also contribute to congestion and cars generate pollution) but this differentiation enables targeted policy interventions addressing the primary concerns associated with each vehicle type.

The health implications of vehicular exposure are extensively documented in epidemiological research (Ho, Wong, & Guo, 2021; Liao, Du, & Chen, 2023; Marek, Campbell, Epton, Kingham, & Storer, 2018). Studies consistently link traffic-related air pollution to a range of maladies, including respiratory diseases, cardiovascular conditions, and neurological disorders, with vulnerable populations facing particularly elevated risks.

Current methods for measuring this exposure—static traffic counts (Braun, Le, Voulgaris, & Nethery, 2021; Hankey et al., 2012), land use regression models (Han, Zhao, Gao, & Gu, 2022; Zhang, Chiu, & Ho, 2019), and fixed monitoring stations (Lu, Chen, & Cai, 2023)—have been valuable but are fundamentally limited. By providing aggregated estimates over broad areas, they fail to capture the temporal variability and spatial heterogeneity of real-world exposure scenarios. This disconnect between averaged estimates and actual individual exposure represents a significant methodological constraint.

Recent technological advances, particularly the emergence of big data, offer unprecedented opportunities to overcome these limitations. Mobility data from mobile phones, GPS tracking, and other sensors enable researchers to analyze pedestrian and vehicular movements at scales and resolutions previously impossible, making it feasible to study the complex, dynamic interactions that define personal exposure (Nilforoshan et al., 2023).

### 2.3. Social equity and environmental justice in urban mobility

The burdens of vehicular exposure are not distributed equally, placing social equity and environmental justice at the heart of walkability assessment (Hwang et al., 2017; Stroope & Garn, 2024; Yuan & Wang, 2021). Social equity in urban mobility demands fair distribution of transportation resources and environmental burdens across population groups, while environmental justice examines whether communities face disproportionate traffic-related hazards based on socioeconomic status or race. Research (Pönkänen et al., 2025; Xu, Jiang, et al., 2019)demonstrates that disadvantaged communities systematically bear heavier traffic pollution and safety collision risks—an inequity rooted in historical planning that routed highways through low-income neighborhoods and co-located industrial zones with affordable housing.

These patterns reflect broader mobility justice principles, which demand consideration of not only transportation access but also the quality of mobility experiences and differential policy impacts on communities (Verlinghieri & Schwanen, 2020). In the 15-min city context, this concern becomes particularly salient. While the model promises universal walkable access, research reveals a paradox: affluent neighborhoods enjoy both quality amenities and pleasant walking environments, while low-income areas may have proximate services but suffer degraded conditions due to high traffic volumes (Luo et al., 2022; Moreno, Gall, Woo, Lee, & Bencekri, 2025; Xu et al., 2024; Zhang et al., 2023). This demonstrates that spatial proximity alone does not guarantee equitable access if pedestrian journeys are compromised by hazardous traffic conditions. The resulting differentiated exposure profiles—lower-income populations facing disproportionate truck traffic near industrial corridors while affluent populations encounter intense car congestion in amenity-rich centers—reveal how urban structure actively sorts populations into distinct risk categories.

The temporal dimension of exposure inequity has received limited attention despite its importance. Different populations experience varying exposure patterns based on daily schedules, commuting behaviors, and constrained mobility choices. Workers with inflexible schedules may travel during peak traffic regardless of risks, while those with limited alternatives cannot avoid high-traffic routes. Understanding these temporal disparities is crucial for evaluating whether the 15-min city delivers on its promise of equitable access.

### 2.4. Analysis of research gaps

While extensive literature validates the 15-min city, walkability, and the need for environmental equity, critical gaps remain at their intersection.

First, walkability research typically relies on static, area-based exposure metrics like average traffic counts. Such methods fail to capture the dynamic, path-specific nature of individual exposure, overlooking the near-real-time encounters with vehicles that shape a pedestrian's journey. This creates a disconnect between theoretical accessibility and the lived experience of mobility.

Second, the 15-min city is promoted as equitable, yet there is little empirical research validating if the quality of access is genuinely equitable. Current assessments have not integrated dynamic vehicular exposure to examine how the journeys of different socioeconomic groups are disproportionately degraded by traffic-related risks. This oversight is critical for evaluating the equity implications of the 15-min city model.

Third, research often treats traffic as a monolithic entity, failing to differentiate the distinct impacts of cars, trucks, and buses. This is a significant omission, as heavy-duty trucks, for instance, contribute disproportionately to pollution and collision risks (Patwary et al., 2024; Yuan & Wang, 2021). A more granular, vehicle-specific analysis is crucial for developing targeted policies that address the most harmful sources of pedestrian exposure.

This study addresses these gaps with a novel computational framework that quantifies dynamic, path-specific vehicular exposure. By integrating large-scale mobility data from mobile phone users, trucks, and transit, we reconstruct high-resolution encounters between pedestrians and distinct vehicle types. This approach moves beyond static averages to empirically assess the equitable distribution of walkable access quality, providing a more realistic and nuanced evaluation of the 15-min city.

## 3. Data and methodology

Our methodology follows a multi-stage approach to quantify the impact of dynamic vehicular exposure on walkability and social equity. First, we integrate large-scale mobility datasets—including mobile phone trajectories, truck GPS data, and public transport schedules—to reconstruct high-resolution, time-stamped travel routes for pedestrians and vehicles (Section 3.1) and infer socioeconomic characteristics of residents (Section 3.2). Building on this foundation, we develop a multi-scale dynamic vehicular exposure index for different vehicle types at the road, location, and individual trip levels (Section 3.3). We then link these exposure metrics with inferred socioeconomic characteristics to analyze equity implications. Finally, we model an access gap, quantifying how pedestrian aversion to high-traffic environments constrains their real-world access to essential services within the 15-min city (Section 3.4). The conceptual framework is shown in Fig. 1.

### 3.1. Data

#### 3.1.1. Mobile phone data

Our primary data source is a large-scale, anonymized mobile phone dataset from a major telecommunications provider in Beijing, covering a one-month period in June 2023. The raw dataset contains 8.38 billion pings from 11 million unique users, representing approximately 50% of the city's population. Each record includes a de-identified user ID, geographic coordinates, and a timestamp. The data covers the entire Beijing metropolitan area, with spatial coverage varying by time of day: ping density is highest in central urban districts during daytime hours and shifts toward residential areas in suburban districts during evening and nighttime hours. To ensure data quality and capture typical mobility patterns, we applied two filtering criteria: (1) users must have at least 300 total pings for meaningful trajectory reconstruction, and (2) users

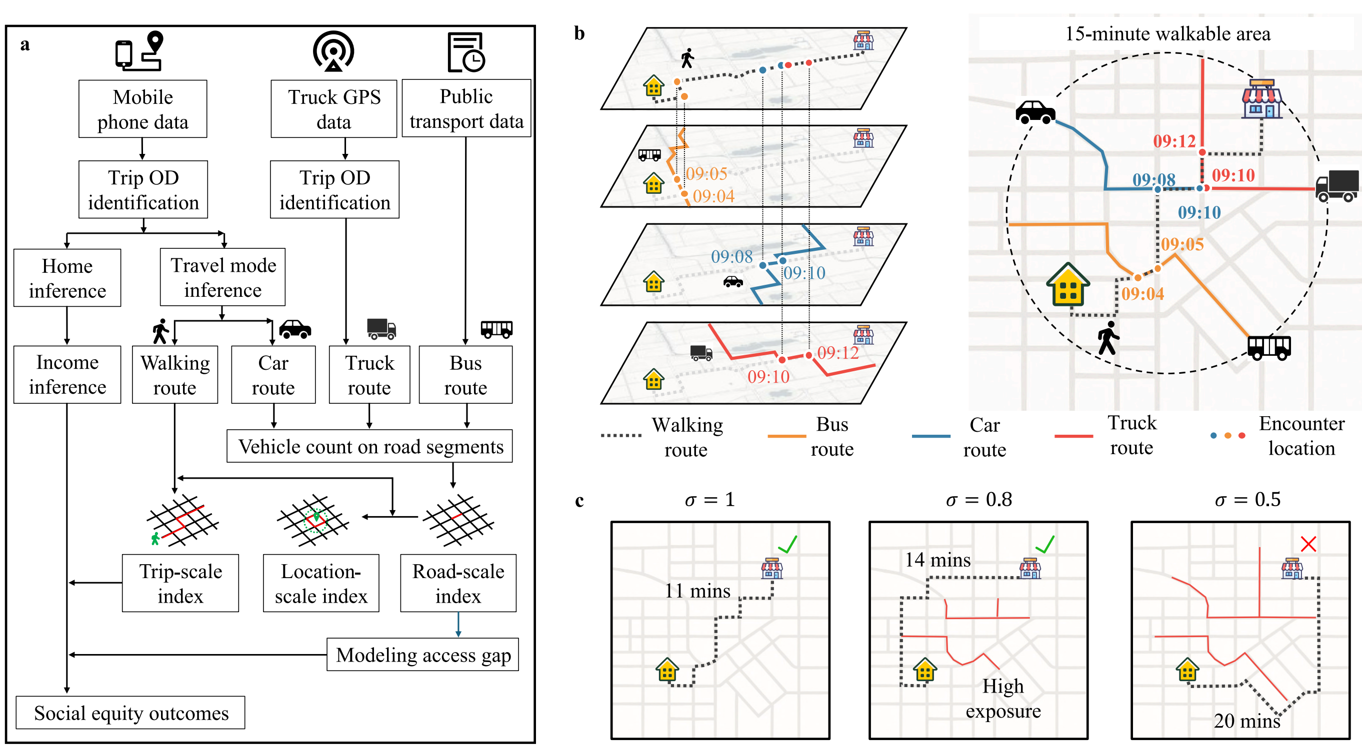


**Fig. 1.** Computational framework. **a** Technical workflow of data integration and indicator calculation. **b** Dynamic vehicular exposure on a walking trip. An individual encounters different types of vehicles (cars, trucks, and buses) at different moments on the roads. **c** Modeling the access gap in the 15-min city. This panel demonstrates how pedestrian aversion to traffic can shrink their accessible area. We simulate this by removing roads (red lines) from the network that exceed a specific exposure tolerance threshold ($\sigma$). For example, with a high tolerance ($\sigma = 1.0$ or 0.8), the pedestrian can still reach the destination within 15 min. When tolerance is lower ($\sigma = 0.5$), the destination becomes unreachable within the 15-min time budget. This creates an access gap. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

must be active for at least consecutive 7 days during the observation period to reflect habitual rather than sporadic behavior. These filters resulted in an analytical dataset of 8.3 million users with 7.9 billion pings (94% of original volume), ensuring adequate coverage. All data processing adhered to strict privacy standards: all identifiers were anonymized by the data provider before transfer, and our research team had no access to any personally identifiable information. The research protocol was reviewed and approved by the institutional ethics board, and the data use agreement prohibits any attempt to re-identify individuals. These privacy protections align with established practices in mobility research using telecommunications data (Nilforoshan et al., 2023).

To transform these raw location pings into meaningful travel data, we first identified individual trips from GPS trajectories. By sorting a user's pings chronologically, we applied the DBSCAN clustering algorithm (Ester, Kriegel, Sander, & Xu, 1996) to group pings that were close in both space (within a 50-m radius) and time (a minimum stay of 5 min). We selected DBSCAN for stay point detection due to its ability to identify clusters of arbitrary shape without requiring a predefined number of clusters, its robustness to noise points common in GPS data, and its established effectiveness in mobility research (Xu, Cui, Zhong, & Wang, 2019). The algorithm's density-based approach naturally accommodates the irregular spatial patterns of human activity locations. A trip was then defined as the movement between two consecutive stay points, yielding an origin-destination (OD) pair for each journey. To justify these parameters and assess robustness, we conducted a sensitivity analysis (see Appendix Table A1) by varying the spatial radius (30 m, 50 m, 100 m) and minimum dwell time (3, 5, 10 min). We evaluated two indicators: (1) Trips detected (M) [Δ% vs. baseline], and (2) Stay–POI alignment (%), defined as the share of detected stay points within 100 m of plausible POIs (residential, office, retail, transit; see Section 3.1.4). Results demonstrate high robustness: alternative parameter configurations yield minimal variation in trip detection (within ±2.8%) and consistently high POI alignment rates (85.7–86.8%), confirming that our trip detection method captures meaningful travel behavior regardless of reasonable parameter choices.

Next, we inferred the travel mode for each trip, distinguishing between walking, private vehicles (e.g., cars, taxis), and public transport. The mobile data lacks explicit mode labels. Therefore, we trained a random forest classifier on the open-source Geolife dataset (Zheng, Zhang, Xie, & Ma, 2009), which contains GPS trajectories with verified travel modes in Beijing. We selected random forest for travel mode classification due to its strong performance on imbalanced datasets, resistance to overfitting, ability to handle nonlinear relationships among features, and established track record in transportation mode inference (Cheng, Chen, De Vos, Lai, & Witlox, 2019). The model was trained on 70% of the Geolife data and validated on 15%, with the remaining 15% held out for testing. The model was trained using a standard set of spatiotemporal features (e.g., trip duration, average and maximum speed, and proximity of the trip's start/end points to transit stations). The reported accuracies, i.e., 96% for walking and cycling (active transport), 93% for private transport, and 91% for public transport, represent performance on the held-out test set (Yang et al., 2025). The trained classifier was subsequently applied to our full mobile phone dataset to assign a probable travel mode—walking, private vehicle, or public transport—to every identified trip.

The classifier predicts three classes: active (walking/cycling), private motorized, and public transport. Because our exposure analysis focuses on pedestrian experiences, we restrict the analysis to active trips and treat them as walking, noting that walking constitutes the majority (approximately 85%) of active trips in our dataset. The transferability of the Geolife-trained model to our mobile phone data is supported by three factors: (1) both datasets were collected in the same city (Beijing), ensuring similar road network topology and urban form; (2) the Geolife dataset spans multiple years (2007–2012) and includes diverse participants, capturing a range of travel behaviors; and (3) the validation against independent data showed consistent mode share distributions (Yang, Liu, Jia, & Manley, 2025).

To enable the analysis of dynamic vehicular exposure, we generated detailed, plausible travel routes for trips identified as walking or driving. For each of these trips, we used the Amap navigation API (https://lbs.amap.com/), a leading mapping service in China. By inputting the trip's origin and destination coordinates, we generated the most time-efficient route. To significantly improve the accuracy of these reconstructed paths, we incorporated all available intermediate GPS pings from the original trajectory as waypoints in the API query. This ensures the generated route closely mirrors the user's actual path, accounting for real-world detours and individual choices. The validation can be found in the previous work (Yang, Liu, Chen, et al., 2025).

After the data processing, we obtained the time-stamped walking routes for all pedestrians and the driving routes for cars. Each route is structured as a continuous sequence of traversed road segments defined by unique identifiers and geographic coordinates, with the time of entry and the duration of travel on that segment. This representation provides the spatial-temporal precision necessary for measuring vehicular exposure at the path level, as shown in Fig. 1b. All final analyses reported in this paper are based on the filtered dataset of 7.9 million users with identified home locations (see Section 3.2), ensuring consistency throughout the manuscript.

### 3.1.2. *Truck GPS data*

To specifically account for exposure from heavy-duty vehicles—a primary source of traffic-related noise and air pollution—we collected GPS trajectory data for trucks operating in Beijing. Our dataset, covering the same one-month period of June 2023 to ensure temporal alignment with the mobile phone data, includes over 64,000 trucks with a load capacity exceeding 12 tons. This cohort represents approximately 75% of all such heavy-duty trucks registered in the city, providing comprehensive coverage of freight movement. Sourced from the China Road Freight Supervision and Service Platform (https://www.gghypt.net/), the data offers high temporal resolution, with location pings recorded at 30-s intervals. This resulted in a total of more than 24 million GPS records for the study period.

After data preprocessing, we applied a recent origin-destination identification method (Yang et al., 2022) to extract individual trips from the raw trajectories. This method employs speed thresholds to determine stops and utilizes multilevel time thresholds to distinguish between temporary stops and actual trip origins and destinations, adapting to the complexities of truck routes and freight delivery patterns (Yang et al., 2022). Following trip identification, we generated detailed travel routes for each truck journey using the Hidden Markov Model (HMM) map-matching algorithm (Newson & Krumm, 2009). To enhance route accuracy, we incorporated all available intermediate GPS pings from the original trajectories, ensuring that the generated routes closely reflected the actual paths traveled by freight vehicles.

Each truck trip is thus converted from a series of raw coordinates into a time-stamped sequence of traversed road segments. This allows for the exact reconstruction of heavy-duty vehicle presence and volume on any given road at any moment.

### 3.1.3. *Public transportation timetables*

To account for public transport vehicles as another key source of traffic exposure, we obtained bus schedule and route data from the Amap API, ensuring it covered the same one-month period in June 2023. This dataset provided detailed information for each bus line operating within Beijing, including the route name, full timetable information, and route geometry. The timetables specified the operational hours and service frequencies, often differentiating between peak and off-peak periods with stated headways, such as every 7 min during peak hours and every 10 min during off-peak. Each route was described by a detailed polyline, a sequence of geographic coordinates that precisely outlines its path through the city's road network.

By parsing the timetable and frequency information, we calculated the number of buses expected to be traversing any given road segment at any time of day. Using the polyline data, we mapped these bus journeys onto the same road networks established for cars and trucks. This procedure allowed us to accurately integrate bus volumes into our overall vehicular exposure measurement, capturing another component of urban traffic environment that pedestrians experience.

#### 3.1.4. Points-of-interest (POIs)

To evaluate access to essential services, we collected a Points-of-Interest (POIs) dataset for Beijing from the Amap API. This dataset provides the precise geographic coordinates for thousands of urban amenities and facilities that are critical to the 15-min city concept. The data is organized under a detailed classification system, encompassing a wide spectrum of destinations necessary for daily life, work, and leisure.

These categories include, but are not limited to, shopping services (e.g., supermarkets, convenience stores), healthcare services (e.g., hospitals, clinics), educational and cultural institutions (e.g., schools, libraries), dining and leisure venues (e.g., restaurants, parks). By geolocating these essential destinations, the POI data serves as the foundation for our accessibility analysis, allowing us to measure which services are reachable within a 15-min walk from any given origin and thereby assess the practical realization of this urban planning model.

### 3.2. Individual socioeconomic status inference

To analyze the social equity implications of vehicular exposure, we developed a methodology to infer individual socioeconomic characteristics from mobility patterns. Home locations were first determined by analyzing nighttime mobility patterns between 10:00 PM and 6:00 AM, identifying each user's most frequently visited location during these hours as their primary residence. We recognize that this widely used approach, while scalable, has known limitations. As discussed in recent studies (Chen & Poorthuis, 2021), this approach can misclassify individuals with atypical routines, such as night-shift workers (whose workplace may be flagged as their home) or individuals who split time between multiple residences. To mitigate these issues and ensure the robustness of approach, we applied a strict filter, requiring that more than 70% of visits between 10 PM–6 AM occur at the identified primary residence. This filter is designed to exclude users with highly irregular patterns or multiple residences, ensuring our analysis focuses on individuals with a stable, primary home base. Finally, we identified home locations for 7.9 million users out of the 8.3 million (a success rate of approximately 95%), with unidentified users removed from the dataset. All subsequent analyses in this paper are based on this final sample of 7.9 million users.

Next, we inferred a proxy for income level. Lacking direct income data, we used the average housing price of the user's residential community, defined as the xiaoqu, a bounded residential compound typically containing 500–5000 households that represents the basic unit of residential organization in Chinese cities (Wan, 2016), obtained from the Lianjia real estate database (https://bj.lianjia.com/), as an indicator of their neighborhood's socioeconomic status. While this approach provides a relative measure rather than precise individual income data, it enables analysis of broad socioeconomic patterns across different segments of the population, a practice supported by previous work (Yabe, Bueno, Dong, Pentland, & Moro, 2023). We classified users into four income groups based on quartile thresholds of the housing price distribution: low-income (bottom 25%), lower-middle income (25th to 50th percentile), upper-middle income (50th to 75th percentile), and high-income (top 25%). This classification system provides a balanced framework for examining how socioeconomic status influences mobility patterns and vehicular exposure experiences within the urban environment.

### 3.3. Quantifying dynamic vehicular exposure

To capture the fluctuating nature of traffic and its impact on the pedestrian experience, we developed a multi-scale framework to quantify dynamic vehicular exposure. This framework measures exposure at three distinct levels: the road segment, specific locations (POIs), and the individual pedestrian trip. We differentiate the exposure contributions from different vehicle types, including cars, trucks, and buses.

#### 3.3.1. Road-scale vehicular exposure index

The foundation of our exposure measurement framework is the road-scale vehicular exposure index ($VEI^{v}_{Road,r}$), which quantifies the density of different vehicle types $v$ on individual road segment $r$ during specific time periods. We recognize that each vehicle type contributes differently to the pedestrian experience: cars are a primary driver of general congestion and stress; heavy-duty trucks disproportionately generate noise, air pollution, and safety hazards; and buses create distinct patterns of stop-and-go disruption. To capture these distinct impacts without making assumptions about their relative weights, our framework avoids creating a single, aggregated exposure index. Instead, we treat exposure from each vehicle type as a separate environmental dimension and calculate parallel indices $VEI^{v}_{Road,r}$ for each vehicle type $v$. For each road segment $r$ and time interval $t$, the road-scale vehicular exposure index for vehicle type $v \in \{\text{car}, \text{truck}, \text{bus}\}$ is defined as

$$VEI^{v}_{Road,r,t} = \text{Normalize}\left(N_{v,t}/L_r\right) \tag{1}$$

where $N_{v,t}$ is the vehicle count on road segment $r$ during time interval $t$ for vehicle type $v$, using the processed route data described in Section 3.1, $L_r$ is the length of road segment $r$. The same number of vehicles on a shorter road represents a higher concentration and thus a greater potential exposure. Normalize() is a min-max scaling function, which transforms the density values for each vehicle type onto a uniform scale of 0 to 1 across all roads and time intervals. The temporal resolution of our analysis is 1-min time intervals, representing a significant methodological advancement. This granularity allows us to capture the rapid fluctuations in traffic conditions and provides a near-real-time understanding of the pedestrian environment, which is crucial for accurately assessing dynamic exposure.

#### 3.3.2. Location-scale vehicular exposure index

Moving from individual roads to specific places, we introduce the location-scale vehicular exposure index ($VEI^{v}_{Location,p,t}$). This metric is designed to characterize the environmental quality affected by different vehicle types $v$ within the immediate vicinity of urban amenity $p$, such as parks, schools, or residential communities. For each amenity $p$ and vehicle type $v$, the location-scale index is calculated as:

$$VEI^{v}_{Location,p,t} = \frac{\sum_{r \in \Theta(p)} VEI^{v}_{Road,r,t} \cdot L_r}{\sum_{r \in \Theta(p)} L_r} \tag{2}$$

where the summation is over all road segments $\Theta(p)$ within a 200-m buffer zone around amenity $p$, and $L_r$ is the length of each respective road segment. This length-weighted averaging approach ensures that longer road segments, which contribute more substantially to the overall traffic environment, receive proportionally greater influence in the location-scale exposure calculation. The 200-m buffer distance was selected based on pedestrian behavior research (Lee, Lee, Son, & Joo, 2013) indicating that this radius captures the immediate walking environment that influences destination accessibility and comfort. This calculation is performed separately for each of the three vehicle classes (cars, trucks, and buses). Consequently, every amenity is assigned three distinct exposure scores, each representing the specific exposure level attributable to one category of vehicle.

### 3.3.3. Individual trip-scale vehicular exposure index

The most critical component of our framework is the individual trip-scale vehicular exposure index ($VEI^{v}_{Trip,j}$), which quantifies the actual exposure for vehicle type $v$ accumulated by a pedestrian during a specific walking journey $j$. This path-specific metric moves beyond static environmental assessments to capture the lived experience of walkability. For each individual walking trip $j$, which consists of a sequence of traversed road segments $r$, the $VEI^{v}_{Trip,j}$ is calculated as a time-weighted average of the road-level exposure indices $VEI^{v}_{Road,r}$ encountered along the path. The exposure on each segment is weighted by the duration the pedestrian spends on that segment. The formula is:

$$VEI^{v}_{Trip,j} = \frac{\sum_{r\in\Theta(j)} VEI^{v}_{Road,r,t_{j,r}} \cdot D_r}{\sum_{r\in\Theta(j)} D_r} \tag{3}$$

where the summation is over all road segments $\Theta(j)$ that constitute the walking trip $j$. $D_r$ is the duration the pedestrian spends on segment $r$. For each traversed segment $r$, we use $VEI^{v}_{Road,r,t_{j,r}}$, where $t_{j,r}$ denotes the specific one-minute interval when pedestrian $j$ is on segment $r$. Crucially, the $VEI^{v}_{Road,r}$ value used for each segment corresponds to the specific one-minute time interval when the pedestrian was present. Likewise, this process generates three distinct exposure indices for each walking trip, corresponding to cars, trucks, and buses.

To quantify the inequality in exposure experiences across different socioeconomic groups for specific activities, we introduce an exposure inequality index (*EII*). For any given category of destination (e.g., museums, parks), we first calculate the average $VEI_{Trip}$ for each of the four income groups ($E_i$, where $i = 1, 2, 3, 4$). We then determine the proportion of the total exposure burden borne by each group, $p_i = E_i / \sum_{j=1}^{4} E_j$. The *EII* is defined as 1 minus the normalized entropy of this distribution:

$$EII = 1 - \left( -\frac{1}{\log(4)} \sum_{i=1}^{4} p_i \log(p_i) \right) \tag{4}$$

An *EII* value approaching 0 indicates high equity, where all socioeconomic groups experience similar levels of exposure for that activity. Conversely, a value approaching 1 signifies maximum inequality, where the exposure burden is concentrated within a single group.

### 3.4. Modeling the access gap in the 15-min city

To evaluate how dynamic vehicular exposure impacts the goal of the 15-min city, we developed a model to quantify the access gap—the inequality between theoretical accessibility and the perceived accessibility by pedestrians who may avoid high-traffic routes. This model simulates how individual avoidance of unpleasant or hazardous streets can shrink the range of services and amenities they can comfortably reach, as shown in Fig. 1c.

Our methodology is based on a scenario-based simulation. First, we establish a baseline of maximum potential access for each individual. Using the complete, unmodified road network, we calculate the total number of unique POIs that a person can reach within a 15-min walk from their homes, assuming they follow the shortest path. This represents the ideal accessibility envisioned by the 15-min city concept. Next, to simulate pedestrian aversion to traffic, we introduce a vehicular exposure tolerance threshold $\sigma \in [0,1]$. Because $VEI^{v}_{Road,r}$ is min-max normalized to the [0,1] interval for each vehicle type $v$ and road segment $r$ (Section 3.3.1), $\sigma$ can be interpreted as a relative exposure tolerance: a lower $\sigma$ indicates higher sensitivity to traffic (e.g., children, elderly, or risk-averse individuals), while a higher $\sigma$ reflects greater tolerance (e.g., commuters prioritizing speed over comfort). For a given $\sigma$ and vehicle type $v \in \{\text{car}, \text{truck}, \text{bus}\}$, we construct a *perceived road network* by removing all road segments $r$ where the dynamic exposure $VEI^{v}_{Road,r}$ exceeds this threshold. With this modified network, we recalculate the number of POIs accessible to each individual within the same 15-min travel time budget. The difference between the number of POIs reachable on the complete network $N_{\text{complete}}$ and the number reachable on the exposure-constrained network $N_{\text{constrained},\sigma}$ reveals the access gap:

$$AccessGap_{\sigma} = \frac{N_{\text{complete}} - N_{\text{constrained},\sigma}}{N_{\text{complete}}} \tag{5}$$

By applying a range of $\sigma$ from 0 to 1, we model a spectrum of pedestrian sensitivity profiles and quantify how traffic avoidance behavior constrains walkable accessibility. At the lower extreme ($\sigma \to 0$), only road segments with minimal vehicular exposure—such as quiet residential alleys or pedestrian-only lanes—are retained, simulating highly sensitive individuals (e.g., children or elderly) who avoid streets with noticeable traffic. The resulting walkable area becomes severely fragmented, isolating users from nearby amenities despite geographic proximity. The $AccessGap_{\sigma}$ approaches 1. Conversely, at the upper extreme ($\sigma \to 1$), nearly all road segments remain accessible, including high-exposure arterials and freight corridors, representing pedestrians with high traffic tolerance (e.g., time-constrained commuters) who prioritize route efficiency over environmental comfort. In this scenario, the perceived network closely matches the physical one, and the $AccessGap_{\sigma}$ approaches 0.

Additionally, our model calculates the access gap at specific time points rather than aggregating across the day. In practice, a road segment may be accessible during off-peak hours but exceed the tolerance threshold during rush hour. For our primary results, we calculate exposure and accessibility at peak pedestrian travel times (7:00–9:00 AM and 5:00–7:00 PM on weekdays), representing conditions when most walking trips occur. This approach captures the accessibility constraints faced during typical daily routines; however, it means that the reported access gaps reflect worst-case (peak-hour) conditions rather than daily averages. This temporal specificity is a strength for policy targeting (interventions should address the conditions pedestrians actually face during their journeys) but users should recognize that accessibility may improve during off-peak periods.

It is critical to clarify the interpretation of this $AccessGap_{\sigma}$ metric. Our model is not a behavioral simulation predicting if an individual will make a trip, but rather a tool for quantifying environmental barriers. The meaning of the $AccessGap_{\sigma}$ changes based on the nature of the destination. For non-essential amenities (e.g., parks, cafes, cultural venues), a high $AccessGap_{\sigma}$ can be interpreted as a loss of practical walkability or a reduction in the willingness to walk, as individuals may forgo the trip or choose another mode if the journey is too unpleasant. For essential services (e.g., supermarkets, clinics, schools), pedestrians must often complete the journey regardless of exposure. In this context, a high $AccessGap_{\sigma}$ does not represent a lost trip. Instead, it quantifies the degree of forced environmental injustice—that is, the proportion of essential services that cannot be reached without forcing the pedestrian to endure hazardous or unpleasant exposure levels that exceed their comfort or safety threshold ($\sigma$).

## 4. Results

Our analysis, centered on the metropolitan area of Beijing, China, reveals the complex spatiotemporal patterns of vehicular exposure and its inequitable impacts on walkability within the 15-min city framework. By integrating multi-source mobility data, we quantify how dynamic exposure to cars, trucks, and buses varies across urban spaces and populations, ultimately shaping the lived experience of access to essential services.

### 4.1. The spatiotemporal landscape of urban vehicular exposure

Analysis of road-level vehicular exposure in Beijing reveals distinct yet interconnected spatiotemporal patterns across vehicle types. These patterns are closely shaped by Beijing's strongly monocentric, ring-radial urban form, which concentrates employment and commercial functions in a compact central core and distributes residential, freight, and industrial uses outward along a concentric ring-and-radial backbone. Spatially, private car and bus exposures share remarkably similar distributions, both concentrating on arterial roads in the urban core and major commuter corridors, reflecting their shared infrastructure use (see Fig. 2). This overlap is a direct signature of Beijing's monocentric form: daily movement between peripheral residential areas and the central core is funneled onto the same radial and ring-road backbone that carries most scheduled bus services. However, bus exposure demonstrates substantially lower intensity than car exposure, consistent with buses sharing these corridors with a much larger private-vehicle fleet.

In contrast, truck exposure follows a completely different spatial logic, predominantly confined to peripheral ring roads and industrial zones due to freight regulations and land use patterns. This separation is reinforced by a specific municipal regulation that restricts heavy-duty truck access to the central area during daytime hours, mechanically redirecting freight onto peripheral corridors (Lv, Yan, Jia, Yang, & Liu, 2024; Yin et al., 2026; Yang, Chen, Bai, Liu and Cheng, 2025). Persistent high-exposure hotspots for trucks include the freight corridors surrounding major logistics parks, the industrial zones on the urban fringe, and the outer ring roads connecting major distribution centers; these areas exhibit consistently elevated truck exposure throughout daytime hours.

Temporally, the three vehicle classes behave differently (Fig. 3). Car and truck exposures remain persistently high and relatively stable across the diurnal cycle on primary and secondary roads, indicating that they operate as continuous background conditions of the arterial environment rather than as transient peak-hour phenomena. This is consistent with the sustained pressure that Beijing's monocentric form places on central arterials throughout the day. Bus exposure, by contrast, is the only class with pronounced diurnal structure, with sharp declines during non-service hours and a rapid increase as scheduled services resume, opening brief windows of improved walkability on transit corridors. Together, these results show that vehicular exposure in Beijing is shaped not only by road hierarchy but also by how the city's monocentric, ring-radial form organizes employment, residence, transit provision, and freight activity across its metropolitan structure.

Destination-level exposure analysis ($VEI_{Location}$) demonstrates clear alignment with Beijing's economic geography (see Fig. 4). A strong positive correlation exists between car and bus exposure within the immediate vicinity of urban amenities, which contrasts sharply with the patterns of truck traffic (Yang, Liu, Chen, et al., 2025). Commercial and cultural destinations (like theaters, museums, shopping malls) exhibit high private car and bus exposure with minimal truck presence, while industrial facilities (such as factories, agricultural bases and logistics points) demonstrate elevated truck exposure with reduced car and bus traffic. This functional differentiation reflects the spatial organization of economic activities and creates different environmental conditions based on amenity category. These results indicate that pedestrian environmental quality is determined by both geographic location and the economic function of destinations, creating systematic disparities based on trip purpose.

### 4.2. Inequality in vehicular exposure across socio-economic groups

To understand the social dimensions of this exposure landscape, we analyze the trip-level vehicular exposure ($VEI_{Trip}$) experienced by individuals across distinct income groups. It is important to clarify that our analysis is based on individual trajectories. The exposure values reflect

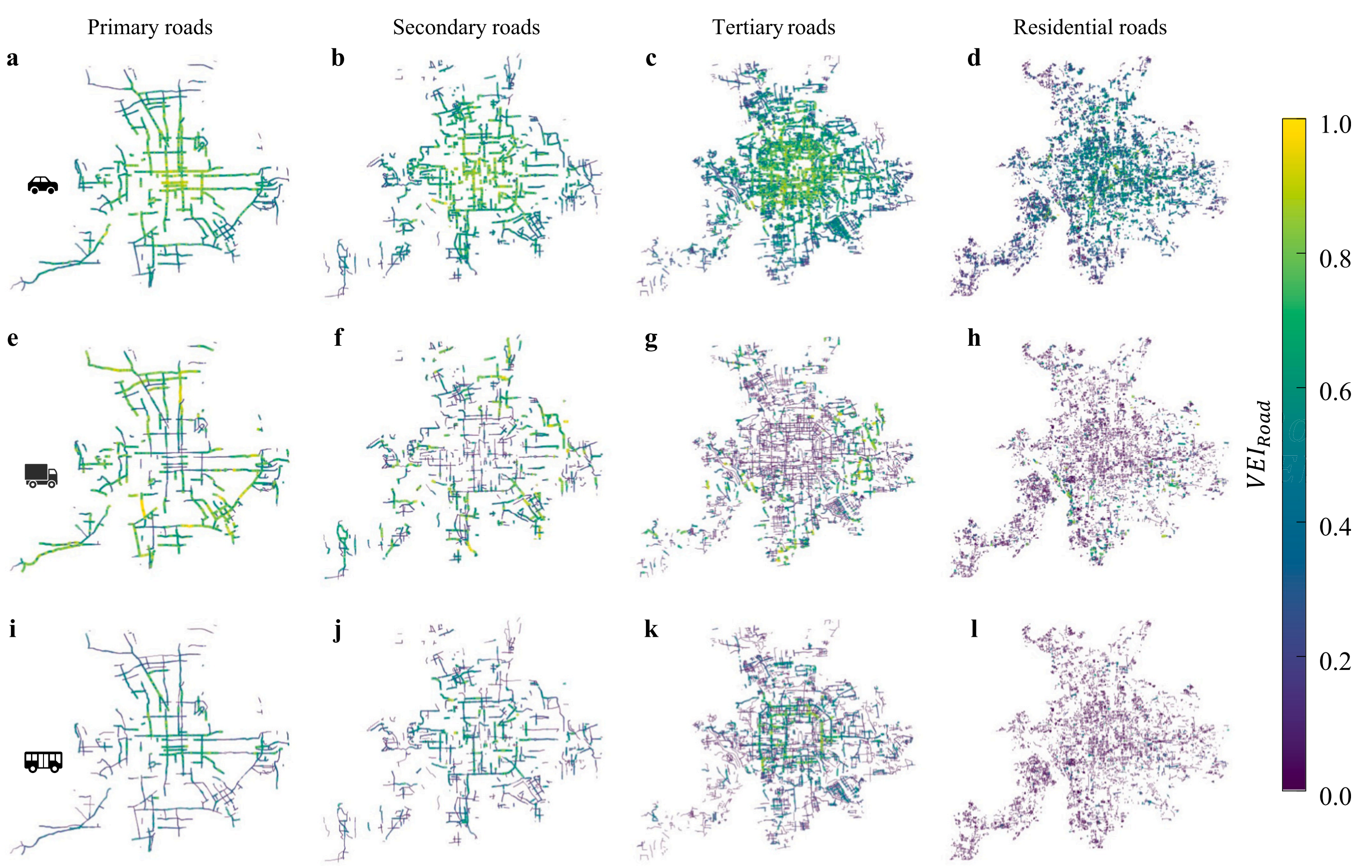


**Fig. 2.** Spatial patterns of road-scale vehicular exposure index $VEI_{Road}$ in Beijing metropolitan area. Distribution of $VEI_{Road}$ for cars (**a-d**), trucks (**e-h**), and buses (**i-l**) across road hierarchies, including primary (**aei**), secondary (**bfj**), tertiary (**cgk**), and residential (**dhl**).

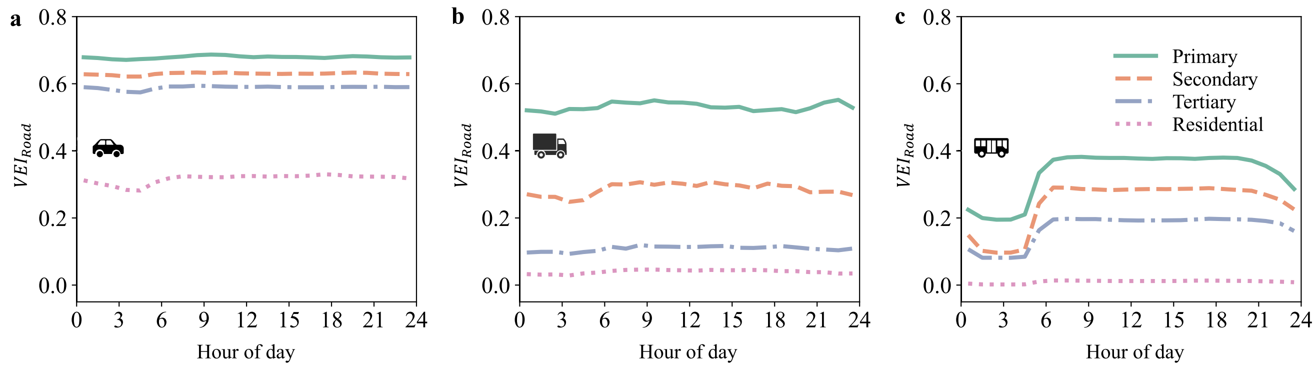


**Fig. 3.** Temporal variation in $\boldsymbol{VEI_{Road}}$ across road hierarchies in Beijing metropolitan area. a Car. **b**. Truck. **c**. Bus.

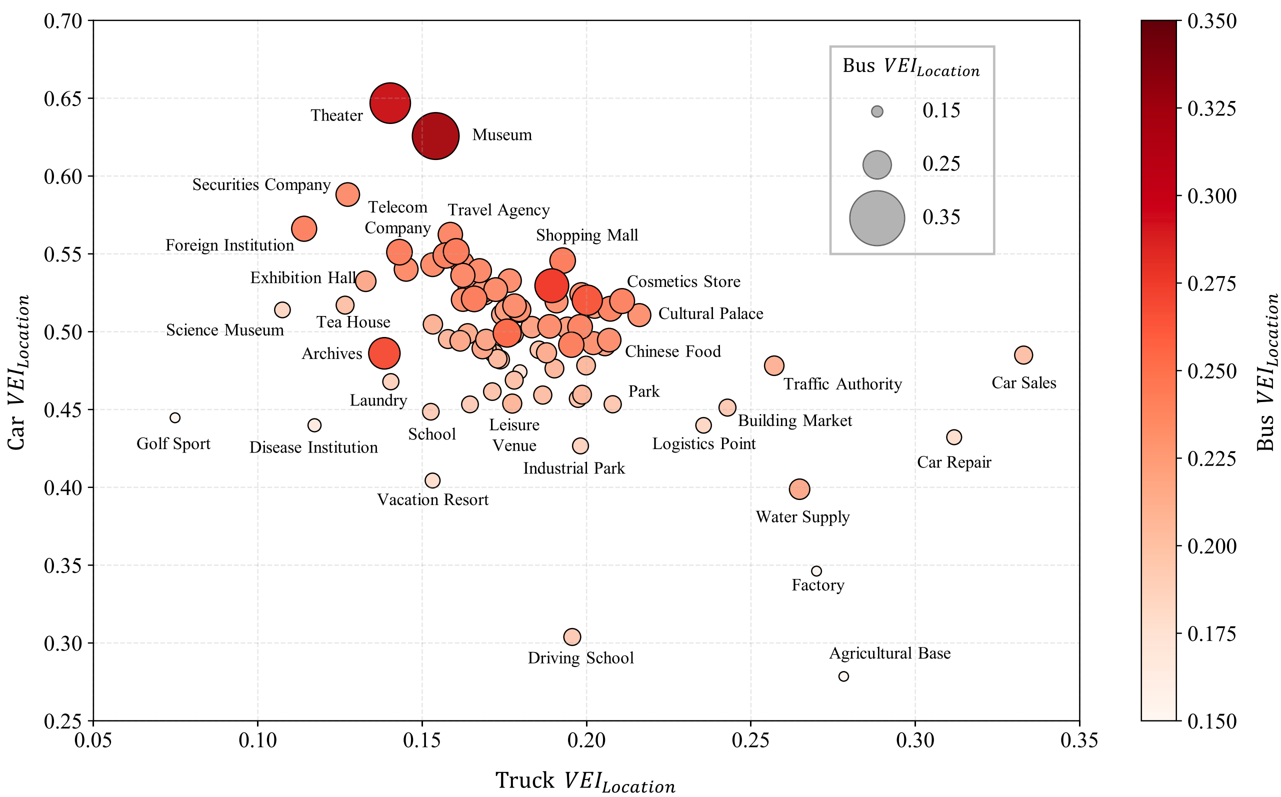


**Fig. 4. Vehicular exposure profiles by amenity category.** This scatter plot illustrates the location-scale vehicular exposure index ($VEI_{Location}$) for different types of urban amenities. The x-axis represents exposure to trucks within the immediate vicinity of urban amenities, and the y-axis represents exposure to cars. The color and size of each point correspond to the level of bus exposure, with warmer colors and larger sizes indicating higher exposure.

what pedestrians encounter during their actual walking journeys, which may traverse neighborhoods of varying income levels. When we discuss "higher/lower-income groups", we refer to individuals classified by their residential neighborhood's housing prices, not the neighborhoods through which they travel. The patterns we observe emerge from the interaction between where people live (which shapes their origin points and available routes) and where they travel (which determines their path-specific exposure). Our findings reveal systematic inequities in the environmental burden of daily mobility, which vary significantly by vehicle type and time of day (see Fig. 5a-c). Higher-income groups experience peak exposure to cars during morning commutes (6:00–9:00 AM), aligning with professional work schedules in central business districts (Helminen, Rita, Ristimäki, & Kontio, 2012). Conversely, lower-income groups face substantially higher truck exposure throughout the daytime, reflecting residential location patterns where lower-income communities are situated near industrial zones and logistics corridors while wealthier residents occupy areas spatially removed from freight traffic (Yang et al., 2024; Yang et al., 2024). Bus exposure patterns further highlight these disparities. Lower-income groups encounter higher exposure during operational hours, indicating greater reliance on transit-adjacent routes, while higher-income groups show elevated exposure during off-peak times, likely reflecting leisure trips in central areas.

Next, we analyze the statistical relationship between the ambient exposure at a destination ($VEI_{Location}$) and the exposure accumulated during the journey ($VEI_{Trip}$), which reveals the inequality in how different groups experience the city when accessing amenities (see Fig. 5d-f). Higher-income groups maintain low truck exposure even when traveling to moderately exposed destinations, with exposure rising sharply only when destinations are located in highly congested industrial zones (see Fig. 5e). This pattern demonstrates their capacity to select alternative, low-impact routes that bypass traffic for most

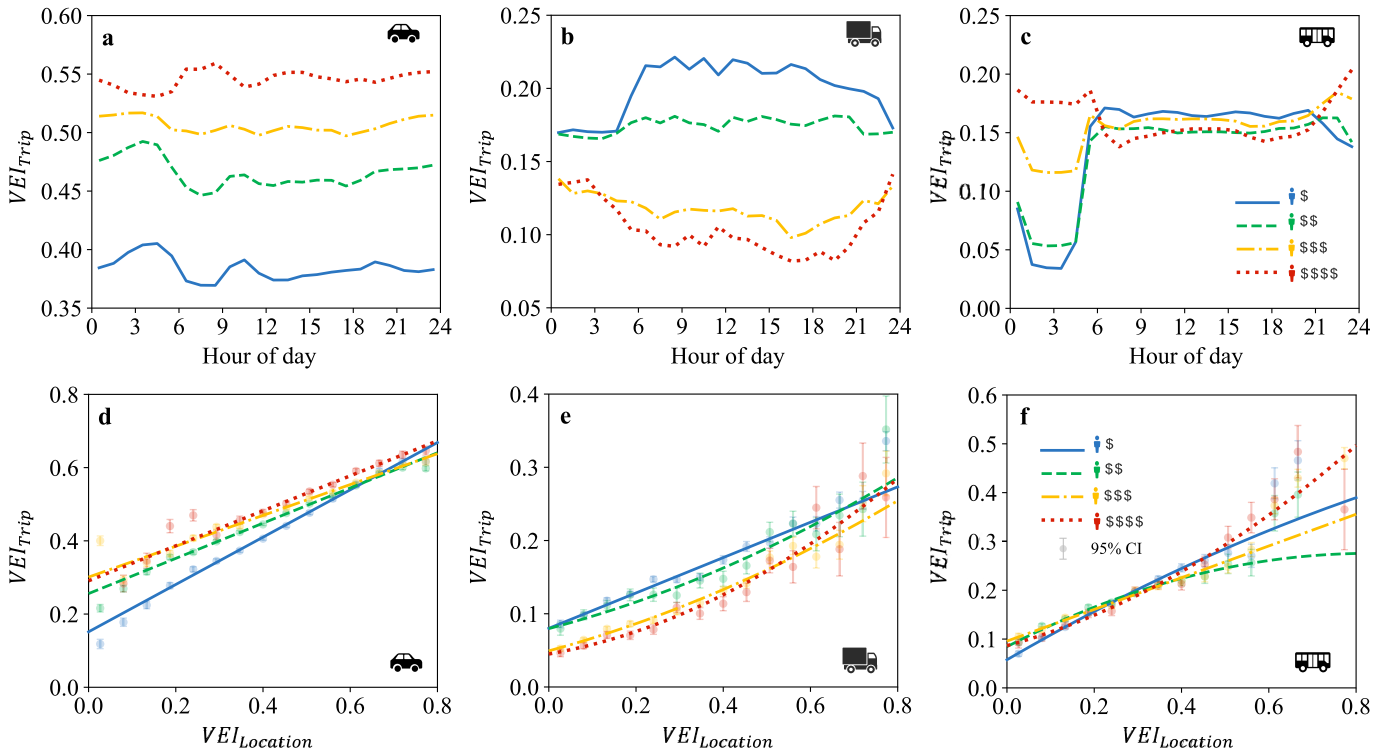


**Fig. 5.** Socio-economic inequities in vehicular exposure. **a-c** Diurnal patterns of trip-level exposure ($VEI_{Trip}$) to (**a**) cars, (**b**) trucks, and (**c**) buses for four income groups. **d-f** Statistical relationship between destination-level exposure ($VEI_{Location}$, x-axis) and trip-level exposure ($VEI_{Trip}$, y-axis) for cars (**d**), trucks (**e**), and buses (**f**) across income groups.

journeys. In contrast, lower-income groups exhibit a tight coupling between trip and destination exposure to cars; their $VEI_{Trip}$ rises steeply and consistently with $VEI_{Location}$ (see Fig. 5d), indicating a lack of viable low-traffic alternatives. For these populations, accessing a high-traffic destination commonly means a high-exposure journey.

These disparities manifest clearly when examining specific daily activities (see Fig. 6). While journeys to industrial or commercial hubs (e.g., machinery companies, convention centers) involve universally high car exposure, the greatest income-based inequities (high *EII*) emerge in access to cultural (museums) and recreational (golf sport) facilities. Critically, high inequality is also observed for essential services, such as disease institutes. This indicates that the most vulnerable populations often face the most hazardous conditions when seeking care, challenging the 15-min city's promise of equitable access based solely on proximity.

### 4.3. *Vehicular exposure as accessibility barrier and forced environmental injustice*

To quantify how vehicular exposure compromises the promise of the 15-min city, we modeled an access gap—the inequality between theoretically available amenities and what is reachable when pedestrians avoid high-traffic routes. As a first step, we establish each resident's maximum potential access by modeling an ideal, best-case scenario. Using the complete urban road network, we calculate the total number of unique urban amenities reachable within a 15-min walk from an individual's home, assuming they follow the shortest path. The results reveal a stark inequality before considering traffic's impact (see Fig. 7a). Individuals in the higher income quartiles can access a significantly greater number of services and facilities than those in the lower quartile, highlighting a pre-existing locational privilege (Tozer, Hörschelmann, Anguelovski, Bulkeley, & Lazova, 2020).

Building on this baseline, we then simulate traffic avoidance behavior to reveal how this inequality is compounded under real-world conditions. For this simulation, we generate a series of perceived road networks. In each scenario, we set a tolerance threshold ($\sigma$) and temporarily removed all road segments where the dynamic vehicular exposure to a specific vehicle type (e.g., cars, trucks) exceeded that threshold. By recalculating the 15-min accessibility on these newly constrained networks, we could measure the resulting access gap for each individual. This simulation reveals complex dynamics that vary by the type of vehicle being avoided (see Fig. 7b-d). Notably, higher-income groups experience a larger access gap when avoiding cars (see Fig. 7b). This suggests that while they reside in amenity-rich areas, these neighborhoods are also the most saturated with car traffic; thus, any attempt to find low-traffic routes drastically shrinks their otherwise high potential access (Yang, Liu, Jia, & Manley, 2025). Conversely, the access gap from avoiding trucks disproportionately penalizes lower-income groups (see Fig. 7c). This reflects their spatial entrapment: residing near freight corridors means that avoiding these high-exposure arteries often severs their primary connections to nearby amenities, as few alternative paths exist (Jia, Liu, Yang, & Yan, 2023; Lin, Liu, Yang, Jia, & Yan, 2023). The impact of bus exposure is more nuanced, shifting between groups based on their sensitivity to traffic (see Fig. 7d).

These findings demonstrate that vehicular exposure creates significant barriers to walkable access that go beyond simple spatial proximity. The quality and safety of the journey—which is directly shaped by traffic—is just as important in determining what is truly reachable on foot.

To illustrate how the interpretation of $AccessGap_{\sigma}$ varies by service type, we calculated access gaps at a moderate tolerance threshold ($\sigma = 0.5$) for specific POI categories (see Table 1). For car exposure, access gaps are universally high (0.78–0.97) across all groups and service types, reflecting Beijing's pervasive automobile saturation. The interpretation differs by destination: for non-essential amenities (e.g., cafés, museums, theaters), these high values suggest potential walkability loss as individuals may forgo discretionary trips when routes involve intense traffic; for essential services (e.g., clinics, schools, supermarkets), they

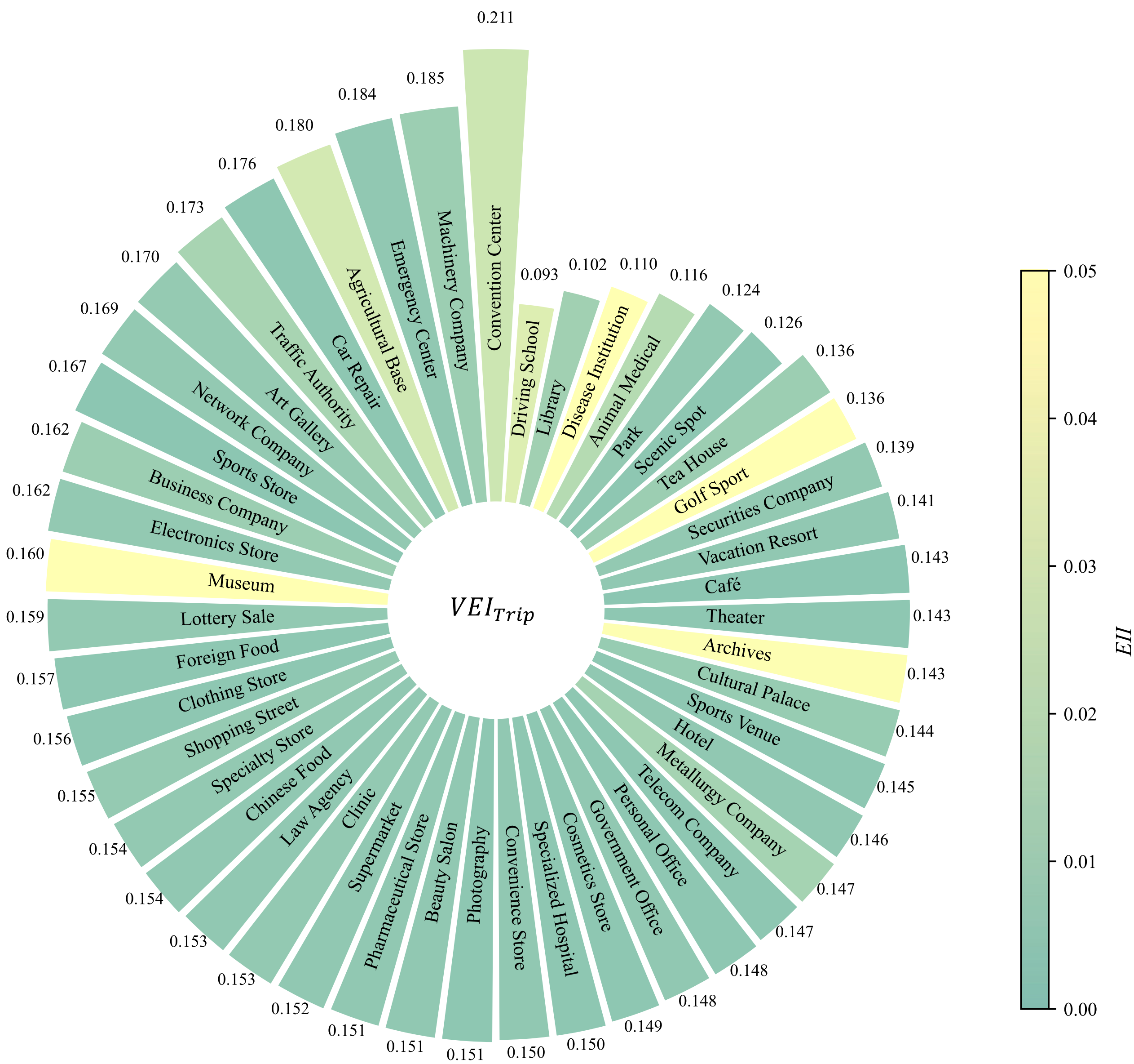


**Fig. 6.** Activity-specific car exposure and associated inequality. This radial bar chart displays two key metrics for walking trips to different categories of urban amenities. The length of each bar indicates the average trip-level vehicular exposure ($VEI_{Trip}$) encountered when traveling to that destination type, indicated by the number above the bar. The color of each bar represents the exposure inequality index (*EII*) across the four socioeconomic groups. Warmer colors signify higher inequality, indicating a greater variance in exposure experiences among the groups.

quantify that residents must tolerate uncomfortable exposure to access necessities, though higher-income groups can mitigate this through private vehicle ownership. Truck exposure reveals stark environmental injustice: lower-income groups (Q1) face access gaps of 0.26–0.29 for essential services, meaning roughly one-quarter to one-third of critical facilities lie beyond routes with acceptable truck exposure. As emphasized in Section 3.4, this quantifies forced environmental injustice (Vaz, Anthony, & McHenry, 2017)—lower-income residents are systematically compelled to traverse hazardous freight corridors to meet basic needs, while higher-income groups (Q4) enjoy dramatically lower gaps (0.08–0.12), accessing the same services via safer routes. This difference reflects the structural legacy of planning that co-located affordable housing with industrial zones, making environmental hazard an inescapable condition for accessing fundamental services among disadvantaged populations. Bus exposure shows intermediate patterns: lower-income groups face moderately higher access gaps (0.18–0.22 for essential services) compared to higher-income groups (0.12–0.15), reflecting their greater dependence on transit corridors where bus frequencies are highest. Unlike the stark disparities in truck exposure, bus-related access gaps are more evenly distributed, though they compound the cumulative exposure burden for transit-dependent populations.

## 5. Discussion

This study introduced a high-resolution, dynamic framework to measure vehicular exposure and its impact on walkability and social equity in the 15-min city. Our findings, which reveal systemic inequities embedded in Beijing's urban fabric, have significant implications for urban planning, transportation policy, and environmental justice.

### 5.1. Methodological innovation in urban computing

This research introduces a significant methodological innovation designed to overcome the critical limitations of static models in urban environmental analysis (Kang et al., 2023; Lu & Chen, 2024; Rahman,

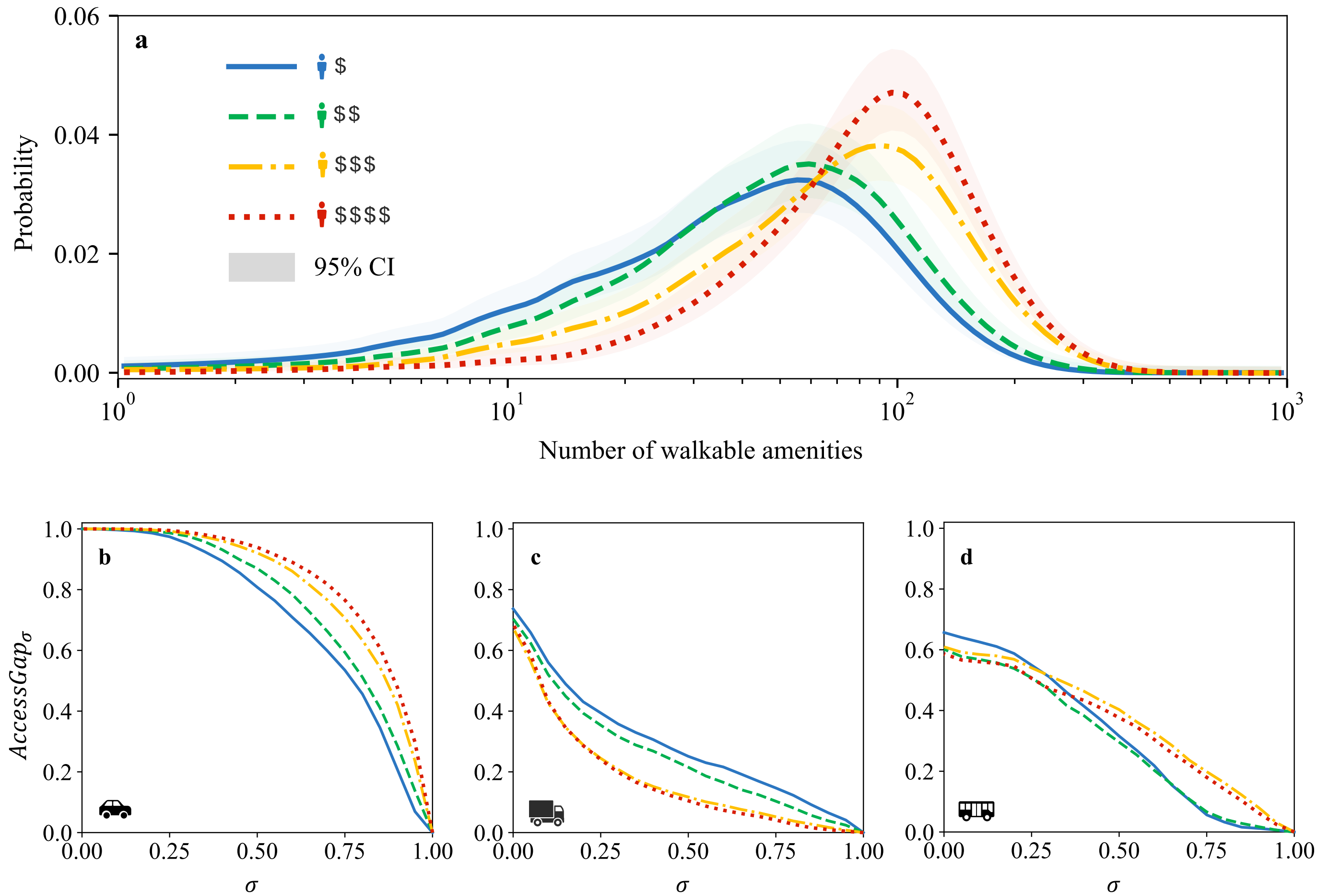


**Fig. 7.** Inequities in theoretical accessibility and the traffic-induced access gap. **a** Distribution of theoretically accessible amenities within a 15-min walk from homes across four income groups under ideal conditions (shortest path). **b-d** The modeled access gap as a function of pedestrian sensitivity to traffic (tolerance threshold $\sigma$, from highly sensitive at 0 to insensitive at 1). The analysis is simulated separately for aversion to cars **(b)**, trucks **(c)**, and buses **(d)**.

**Table 1**
Access gap by vehicle type and POI category ($\sigma = 0.5$).

| Vehicle Type | POI Type | POI Category | Q1 (Lowest) | Q2 | Q3 | Q4 (Highest) |
|---|---|---|---|---|---|---|
| Car | Essential | Clinic | 0.78 | 0.85 | 0.9 | 0.92 |
| | | School | 0.79 | 0.86 | 0.91 | 0.93 |
| | | Supermarket | 0.81 | 0.87 | 0.92 | 0.94 |
| | | Banks | 0.82 | 0.88 | 0.93 | 0.95 |
| | Non-essential | Café | 0.83 | 0.89 | 0.94 | 0.96 |
| | | Museum | 0.84 | 0.9 | 0.95 | 0.97 |
| | | Theater | 0.85 | 0.91 | 0.96 | 0.97 |
| | | Parks | 0.8 | 0.86 | 0.91 | 0.93 |
| Truck | Essential | Clinic | 0.28 | 0.24 | 0.13 | 0.12 |
| | | School | 0.26 | 0.22 | 0.12 | 0.11 |
| | | Supermarket | 0.29 | 0.25 | 0.14 | 0.12 |
| | | Banks | 0.27 | 0.23 | 0.13 | 0.11 |
| | Non-essential | Café | 0.24 | 0.2 | 0.1 | 0.09 |
| | | Museum | 0.23 | 0.19 | 0.09 | 0.08 |
| | | Theater | 0.22 | 0.18 | 0.09 | 0.08 |
| | | Parks | 0.25 | 0.21 | 0.11 | 0.10 |
| Bus | Essential | Clinic | 0.22 | 0.19 | 0.15 | 0.14 |
| | | School | 0.20 | 0.17 | 0.13 | 0.12 |
| | | Supermarket | 0.21 | 0.18 | 0.14 | 0.13 |
| | | Banks | 0.18 | 0.16 | 0.12 | 0.12 |
| | Non-essential | Café | 0.17 | 0.15 | 0.11 | 0.10 |
| | | Museum | 0.16 | 0.14 | 0.10 | 0.09 |
| | | Theater | 0.15 | 0.13 | 0.09 | 0.08 |
| | | Parks | 0.19 | 0.16 | 0.12 | 0.11 |

2022). Conventional approaches, which rely on fixed monitors or aggregated traffic data for broad areas, fail to capture the dynamic, path-specific nature of how individuals experience traffic exposure during their daily travels. Our study addresses this challenge by integrating multiple large-scale mobility datasets. By leveraging mobile phone trajectories capturing approximately 50% of the population, GPS data from 75% of heavy-duty trucks, and comprehensive public transit schedules, we reconstruct a high-resolution digital representation of movement for pedestrians, cars, buses, and freight trucks across the entire metropolitan region. This enables us to precisely quantify the encounters between people on foot and the vehicles sharing their immediate environment.

The framework's core innovation lies in its capacity to quantify vehicular exposure as pedestrians actually experience it: continuously throughout their journey and along the exact sequence of streets they traverse. This represents a critical shift in analytical perspective—from an abstract, bird's-eye view of the city to a dynamic, human-centric one focused on the lived experience. Consequently, our approach reveals the hidden environmental injustices that remain invisible to conventional methods.

Beyond introducing a new metric, this framework addresses a fundamental limitation in how walkability has been conceptualized and measured. Traditional 15-min city assessments answer the question "What is nearby?" Our approach answers a different but equally important question: "What can residents actually reach safely and comfortably?" This distinction matters because it shifts the evaluative focus from infrastructure provision to experiential quality—a dimension that determines whether proximity translates into actual walking behavior. The framework thus provides planners with a diagnostic tool that can identify where the 15-min city is succeeding (proximity plus quality access), where it is partially failing (proximity without quality access), and where targeted interventions are most needed. This fills a critical gap between the aspirational goals of pedestrian-oriented planning and the empirical assessment of whether those goals are being achieved in practice.

### 5.2. Reinterpreting walkability: from proximity to lived experience

Our results compel a reinterpretation of walkability. The 15-min city model, in its common application, equates accessibility with spatial proximity, assuming that if amenities are geographically close, they are equally accessible to all residents (Moreno et al., 2021). Our analysis of the access gap (see Fig. 7) decisively challenges this assumption. We demonstrate that high volumes of vehicular traffic function as an invisible barrier, effectively shrinking the walkable world for residents. The finding that higher-income groups, despite living in amenity-rich areas, face the largest potential loss of access when avoiding car traffic highlights a paradox: the very density that creates vibrant, amenity-rich neighborhoods also generates intense traffic that degrades the pedestrian experience.

Conversely, the disproportionate impact of truck traffic on lower-income groups reveals a different kind of barrier—one of spatial entrapment. For these communities, the most efficient routes to essential services are often the most polluted and dangerous, leaving them with a stark choice between exposure and isolation. This confirms that walkability is not a static property of the built environment but a dynamic, experiential quality. Genuine accessibility is determined not only by the distance to a destination but by the safety, comfort, and healthfulness of the journey itself. Without accounting for the lived experience of exposure, the 15-min city risks becoming a model that delivers proximity in theory but fails to provide genuine, equitable access in practice.

These inequalities are not random but reflect systematic structural forces documented in urban planning literature (Wu & Liu, 2022). The concentration of truck exposure in lower-income areas directly results from historical planning practices that co-located affordable housing with industrial zones and freight corridors (Yang et al., 2023). Conversely, the intense car exposure in affluent central areas reflects residential sorting patterns where higher-income groups cluster in amenity-rich cores, accepting vehicular congestion as a tradeoff for proximity to cultural and economic opportunities (Lyons & Chatterjee, 2008). This stratification creates differentiated risk profiles rather than a simple gradient of environmental burden, necessitating targeted rather than uniform policy responses.

### 5.3. Policy implications

The findings of this study suggest a reframing of how the 15-min city is evaluated and implemented. Our analysis reveals that current assessments (Bruno, Monteiro Melo, Campanelli, & Loreto, 2024) relying on static, proximity-based metrics are insufficient, as they fail to capture the experiential quality of access. Vehicular exposure functions as an invisible barrier, encouraging planners to evolve from asking “Are services nearby?” to posing a more critical question: “What is the quality, safety, and healthfulness of the journey required to reach them?” Integrating this dynamic, human-centered perspective requires incorporating a new evaluative framework directly into urban planning practice.

Specifically, planners could benefit from moving beyond proximity-only assessments to formally integrate metrics that capture the pedestrian experience—particularly the dynamic, path-specific vehicular exposure we quantified. A neighborhood where the only walkable route to a clinic or supermarket traverses a high-traffic arterial may not fully realize the 15-min city vision, regardless of distance. This approach would enable planners to identify and address the forced environmental injustice we revealed: situations where reaching essential services requires enduring hazardous exposure. The evaluative focus could shift from mere amenity provision to ensuring dignified, safe, and healthy access for all residents. Operationally, this means calculating exposure-adjusted accessibility—measuring what remains reachable when pedestrians avoid high-traffic routes—and disaggregating results by vehicle type, service category, and socioeconomic group to pinpoint where environmental barriers undermine walkability.

This refined evaluative framework enables more targeted and equitable policy interventions. For lower-income communities experiencing compromised access quality due to disproportionate freight traffic, policy could prioritize freight management and temporal restrictions (Holman, Harrison, & Querol, 2015; Yang et al., 2026) that limit heavy vehicle movement during peak pedestrian hours. In Beijing's context, this aligns with existing policies such as the Heavy Vehicle Restriction Zones that already prohibit trucks from entering the Fifth Ring Road during daytime hours; our findings suggest extending similar protections to industrial-residential interfaces in peripheral districts where lower-income communities are concentrated. However, such restrictions involve trade-offs: limiting truck access during peak hours may increase delivery costs, shift freight to nighttime (creating noise concerns), or push traffic to alternative routes that may burden other communities. Effective implementation requires coordinating with logistics operators to develop off-peak delivery programs and investing in freight consolidation facilities at district edges. Critically, these measures would ideally be paired with substantial investments in protected, high-quality alternative pedestrian routes, including buffered sidewalks, pedestrian-priority streets, and traffic-calmed corridors, that provide safe passage to essential services without requiring exposure to industrial traffic. Beijing's ongoing “slow traffic system” improvements in central districts provide a template that could be extended to underserved peripheral areas.

Conversely, for higher-income areas where access quality suffers from intense private car congestion, solutions could center on aggressive demand management. Strategies such as congestion pricing (Brown, Moodie, & Carter, 2015), expansion of car-free zones (Naseri, Ciari, Cloutier, & Patwary, 2025), and enhanced public transit (Jin, Jin, & Zhu, 2019) connectivity can be reframed not merely as traffic reduction tools, but as interventions to reclaim and dignify pedestrian space, fundamentally improving the walking environment. Beijing has piloted car-free streets in select commercial areas (e.g., Wangfujing Pedestrian Street), demonstrating public acceptance of such measures; scaling these interventions to residential neighborhoods would require careful stakeholder engagement and phased implementation. Crucially, equity-focused implementation would need to ensure these measures do not simply displace traffic burdens onto adjacent, often less affluent, neighborhoods. By shifting evaluative focus from proximity to lived experience, from theoretical accessibility to environmental justice, cities can transcend superficial compliance with 15-min city standards and begin constructing walkable, equitable urban environments where the promise of accessible services is fulfilled through comfortable journeys for all residents.

## 6. Conclusions

The successful implementation of the 15-min city paradigm hinges on creating truly walkable environments that provide equitable access to essential services. However, a critical gap exists in conventional assessments, which rely on static, area-based metrics and fail to capture the dynamic, path-specific nature of vehicular exposure that shapes the pedestrian's lived experience. This study addresses this gap by introducing a novel computational framework that integrates large-scale mobility data from mobile phones, trucks, and public transit to reconstruct high-resolution, near-real-time encounters between pedestrians and different vehicle types in Beijing, China. Our results revealed systematic environmental inequities embedded in the urban fabric: higher-income groups face intense car exposure in amenity-rich central areas, while lower-income groups are disproportionately burdened by truck traffic. To quantify how vehicular exposure compromises the equitable accessibility in the 15-min city, we simulated how pedestrian avoidance of high-traffic routes creates an access gap, demonstrating that this exposure acts as an invisible barrier that functionally shrinks the practical reach of the 15-min city. These findings compel a reinterpretation of walkability—from a matter of mere proximity to an experiential quality that demands equitable design.

The framework we developed is designed to be transferable to other urban contexts, though implementation requires certain data conditions: (1) individual-level mobility data with sufficient spatiotemporal resolution to reconstruct walking trajectories (mobile phone data, GPS tracking, or transit smart cards); (2) vehicle movement data or traffic counts that can be disaggregated by vehicle type; and (3) georeferenced service location data. Cities with established mobility data infrastructure, common in East Asian and European contexts, could readily adapt our approach. In contexts with limited data availability, the framework could be modified to use aggregated traffic counts combined with sample GPS trajectories, though this would reduce the precision of individual-level exposure estimates.

Despite its methodological innovations, this study has limitations that open avenues for future research. First, although our exposure index quantifies vehicle presence, it does not directly measure associated health impacts like air and noise pollution. Future work could integrate environmental sensor data to create a more comprehensive, health-based exposure metric. Second, our access gap model, while a powerful quantitative tool, is not a direct simulation of human behavior. It relies on a fixed, hypothetical tolerance threshold to quantify environmental barriers. In reality, a pedestrian's tolerance is elastic and destination-dependent; individuals are more likely to endure high exposure for essential services than for non-essential amenities. Our model quantifies the existence of this conflict (i.e., forced injustice) but does not capture the final behavioral choice. Future research should integrate qualitative methods, such as stated-preference surveys or interviews, to capture the real-world behavioral nuances of traffic avoidance, risk perception, and the actual willingness to walk versus the necessity to endure.

In access gap modeling, we employed a hard-threshold mechanism, in which road segments exceeding $\sigma$ are entirely removed from the network, represents a modeling simplification. In reality, pedestrians may perceive high-traffic streets as undesirable without treating them as completely impassable. Alternative formulations could employ soft penalties (e.g., increased travel time or disutility weights) rather than binary exclusion, which would produce more gradual accessibility degradation. However, the hard-threshold approach offers two methodological advantages: computational tractability when processing millions of individual accessibility calculations, and intuitive interpretation of results as the proportion of services that become unreachable under varying tolerance levels. We interpret our findings as upper-bound estimates of traffic-induced accessibility loss; softer formulations would likely yield smaller but still meaningful access gaps. Future research could explore continuous penalty functions to capture the nuanced trade-offs pedestrians make when navigating high-exposure routes.

Regarding data representativeness and generalizability, while our mobile phone data provides extensive population coverage (approximately 50%), certain demographic groups may be underrepresented, including elderly populations with lower smartphone adoption rates and very young children. Additionally, night-shift workers and individuals with multiple residences may be misclassified despite our filtering criteria. The framework we propose is designed to be adaptable to other location-based services (LBS) data sources, including social media check-ins, transit smart card data, or GPS tracking applications, provided they offer sufficient spatiotemporal resolution to reconstruct individual trajectories. However, each data source carries its own biases. For instance, social media data skews toward younger, more urban populations. Researchers should carefully assess representativeness when applying this framework to alternative datasets.

## Data and code availability

The mobile phone trajectory and truck GPS data were obtained under restricted data use agreements and cannot be shared publicly by the authors; access requests should be directed to the providers. Public transport timetables, route geometries, and points of interest are retrievable from the Amap open API (https://lbs.amap.com/), and neighborhood-level housing prices used as a proxy for socioeconomic status are available from the Lianjia real estate database (https://bj.lianjia.com/). The full computational pipeline is openly available at https://github.com/UrbanMobility-y/dve.

## CRediT authorship contribution statement

**Yitao Yang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Shifen Cheng:** Writing – review & editing, Writing – original draft, Resources, Investigation, Data curation. **Yan Chen:** Writing – review & editing, Writing – original draft, Validation, Software. **Weiming Huang:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization, Formal analysis, Methodology, Supervision, Validation.

## 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.

## Acknowledgements

Shifen Cheng was supported by the National Natural Science Foundation of China (grant number 42371469).

## Appendix A

**Table A1**
Sensitivity analysis of trip detection parameters.

| Parameter set | Spatial radius | Minimum dwell time | Trips detected (M) [Δ%] | Stay–POI alignment (%) |
|---|---|---|---|---|
| **Baseline** | **50 m** | **5** min | **119.3 [−]** | **86.8** |
| Stricter Radius | 30 m | 5 min | 122.6 [+2.8] | 85.9 |
| Looser Radius | 100 m | 5 min | 116.7 [−2.2] | 85.7 |
| Stricter Duration | 50 m | 3 min | 120.8 [+1.3] | 86.2 |
| Looser Duration | 50 m | 10 min | 117.1 [−1.8] | 86.6 |

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