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FINAL ESSAY

Quantifying Accessibility Inequality in Milan's Sustainable Transport Network

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Abstract

This study investigates disparities in access to sustainable transportation across socioeconomic and demographic groups in Milan, with the aim of assessing transportation equity at the neighborhood level. We construct a *Milan Accessibility Index (MAI)* that integrates spatial and service-based metrics—such as proximity to public transit, density of public transports, and infrastructure coverage for cycling and walking. Using a combination of GTFS transit data, cycling infrastructure maps and detailed neighborhood-level socioeconomic statistics, we conduct a geospatial and statistical analysis of accessibility patterns.

Preliminary hypotheses suggest that lower-income and socially vulnerable populations face lower accessibility to sustainable mobility options, despite having a higher dependency on them. Our methodology applies spatial mapping and regression modeling to identify the social groups systematically underserved by sustainable transport infrastructure. By leveraging Milan’s extensive open data repositories, we aim to provide policy-relevant insights into the structural inequalities shaping urban mobility, contributing to the broader discourse on just and inclusive transportation systems.

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1 Introduction to the topic

1.1 Transportation equity: a today's problem

Transportation equity has emerged as a critical urban justice issue, particularly as cities pursue sustainable mobility transitions, representing a fundamental challenge in contemporary urban planning where the benefits and burdens of transport systems are unevenly distributed across different social groups. Contemporary transport systems are characterized by systematic injustices that favor motorized transport while placing environmental and social burdens on sustainable alternatives and vulnerable populations, creating what scholars term "transport injustices" that manifest across three key dimensions: exposure to traffic risks and pollutants, distribution of space, and valuation of transport time (Schwanen, 2023) [1]. The importance of addressing these inequalities cannot be overstated, as transportation provides access to opportunity and serves as a key component in addressing poverty, unemployment, and equal opportunity goals, with mobility disparities directly impacting human behavior, economic mobility, and urban sustainability (Schwanen, 2023) [1].

Smart city mobility approaches have increasingly recognized the need for comprehensive accessibility measurement, with cities worldwide adopting standardized approaches to ensure better comparability of key mobility indicators such as affordability and accessibility (European Commission, 2024) [2].

However, the implementation of smart city technologies, particularly sensors and digital mobility systems, can potentially affect socio-economic and spatial inequalities, creating "sensor deserts" and "mobility divides" that disproportionately impact vulnerable populations (Turing Institute, 2018) [3].

Recent research has highlighted the potential risk of smart cities exacerbating social inequality and diminishing quality of life, particularly as digital mobility infrastructure often prioritizes affluent, mobile populations. This dynamic can intensify gentrification and the proliferation of short-term rentals, which displace long-term residents and erode local communities, disproportionately affecting those who are less digitally competent and more place-dependent (Cocola-Gant et al., 2023) [4].

The development of innovative data-driven approaches for mapping sustainable transport equity has become increasingly important, with researchers developing two-dimensional urban indicator approaches that assess both the supply of transport infrastructure and the actual demand for these services by local residents, providing more accurate pictures of where transport inequality exists (Liverpool City Council and the University of Sydney, 2024) [5].

1.2 Why Milan?

Milan stands out as a leading European city in advancing transportation equity, thanks to its comprehensive policy commitments and innovative initiatives that make it an ideal case study for urban mobility research. The city's Sustainable Urban Mobility Plan (PUMS) [6] explicitly prioritizes "**equity, security, and social inclusion**" as core strategic objectives, aiming to ensure that all residents, regardless of socioeconomic status, have equitable access to mobility services. This commitment is further demonstrated by the "**Full Electric 2030**" [7] initiative, which plans to convert the entire public transport fleet to electric vehicles, deploying 1,200 electric buses and building new depots to reduce emissions and improve air quality. Additionally, Milan's Area C congestion charge has successfully decreased city center traffic by around 30%, with revenues reinvested into sustainable transport infrastructure. The city's multimodal transport network—including metro, tram, bus combined with open-access spatial and demographic data, offers researchers a robust platform to study how mobility systems can either alleviate or reinforce social exclusion.

1.3 Objectives of the Project

Transportation equity has emerged as a critical urban justice issue, particularly as cities pursue sustainable mobility transitions. This study investigates disparities in access to sustainable transportation across socioeconomic groups in Milan, Italy, examining how infrastructure availability translates to actual accessibility for different populations.

We develop a novel **Milan Accessibility Index (MAI)** that integrates multiple mobility modes through spatial analysis of GTFS data, cycling infrastructure networks and neighborhood-level socioeconomic statistics from ISTAT and Milan's open data portal.

Using a **500m² spatial analysis grid**, we construct accessibility metrics for 406 analysis cells across Milan, calculating cycling infrastructure availability, and multimodal connectivity. Our methodology addresses critical gaps in transportation equity research by measuring actual access rather than merely mapping infrastructure presence, while incorporating newer mobility options often overlooked in equity assessments.

2 Related work

2.1 Transport Equity: Theoretical Frameworks and Dimensions

Equity in transport refers to the fair distribution of transport resources and opportunities among different societal groups, addressing disparities in access to mobility. Scientific frameworks approach transport equity from two complementary perspectives (Bruzzone et al., 2023)[8]:

Horizontal Equity (Spatial Equity) ensures transportation resources are evenly distributed across geographical areas. (Welch and Mishra 2013)[9] analyzed spatial equity through transit connectivity measures, while (Monzón et al. 2013)[10] investigated territorial accessibility using population/GDP and travel time metrics along transport corridors. (Kim and Sultana 2015) [11] examined spatial equity impacts of high-speed rail extensions across different geographical regions.

Vertical Equity (Social Equity) focuses on fair distribution based on socio-economic factors, supporting vulnerable populations including low-income communities, elderly, and disabled individuals. (Camporeale et al. 2019) [12] developed mathematical models addressing both dimensions with emphasis on vulnerable categories, while (Litman et al. 2021) [13] distinguished vertical equity into "equity in mobility" (addressing need and ability) and "socioeconomic equity" (focusing on income disparities).

Recent research adopts integrated approaches considering both dimensions simultaneously. (Martens et al. 2019)[14] developed multidimensional equity assessment across income, ethnicity, gender, age, and mode choice, while (El-Geneidy et al. 2016)[15] examined "the cost of equity" using total travel cost to bridge spatial and social dimensions.

2.2 Policy Interventions and Effectiveness

Urban transport policies fundamentally shape mobility patterns and can inadvertently "enhance existing, and create new, inequalities in both realized everyday mobility and opportunities for such mobility" (Schwanen et al. 2022, p.3)[16]. The Capability Approach framework (Sen et al. 2009)[17] provides an analytical lens for assessing policy measures based on their potential to expand individuals' real mobility opportunities.

Policy effectiveness demonstrates strong context-dependency, with comprehensive policy packages combining regulatory constraints and incentive mechanisms proving more effective than isolated interventions (Givoni et al., 2009 [18]; Kotilainen et al., 2020 [19]). Contemporary interventions encompass three categories with varying effectiveness:

Enabling Command-and-Control and Economic Measures demonstrate the strongest potential for reducing mobility inequalities. City-center ciclovias effectively increase mobility options for disadvantaged populations (Sarmiento et al., 2017 [20]; Mejia-Arbelaez et al., 2017 [21]), while fare-free public transport policies show substantial promise in improving accessibility among vulnerable groups (Cats et al., 2020 [22]; Kbowski et al. 2019 [23]).

Planning and Design Interventions present complex equity outcomes. Bus Rapid Transit (BRT) systems and cycling infrastructure typically generate the greatest benefits for middle-range mobility distributions, potentially leaving most vulnerable populations less affected (Venter et al., 2018 [24]). Moreover, BRT systems can displace informal transport services serving low-income groups through flexibility and affordability (Ehebrecht et al., 2014 [25]). Transit-oriented densification carries gentrification and displacement risks without careful affordable housing protection measures.

Information and Education Measures offer targeted capability enhancement. Personalized Travel Planning (PTP) effectively improves mobility capabilities, particularly when combined with complementary incentives such as temporary fare-free access (Chatterjee, 2010 [26]; Tørnblad et al., 2014 [27]).

The fundamental policy challenge involves implementing dual strategies that simultaneously lift up the bottom of the capability distribution while constraining excessive mobility consumption at the top end, recognizing that high mobility levels enjoyed by privileged minorities often occur at the expense of opportunities for less privileged groups (Schwanen, 2022 [16]).

3 Variables and Index

3.1 Infrastructures

The goal of this section is to describe the data used in the analysis in a way that helps the reader understand the context and how the different variables are related. The focus is not on technical details, but on giving a clear picture of the data and its role in the study.

3.1.1 Network Infrastructure and Scale

Milan's transit network is large, well-connected, and combines several types of transport to move people efficiently across the city. It includes **4,690 surface stops** served by **423 routes** across **142 lines**, along with 5 metro lines that run underground. Buses cover the most ground, with 121 lines stretching over 1,100 kilometers, while trams and filobuses cover add another 188 kilometers of electric service. The city also has 475 kilometers of cycling paths that fill in the gaps and support short-distance travel.

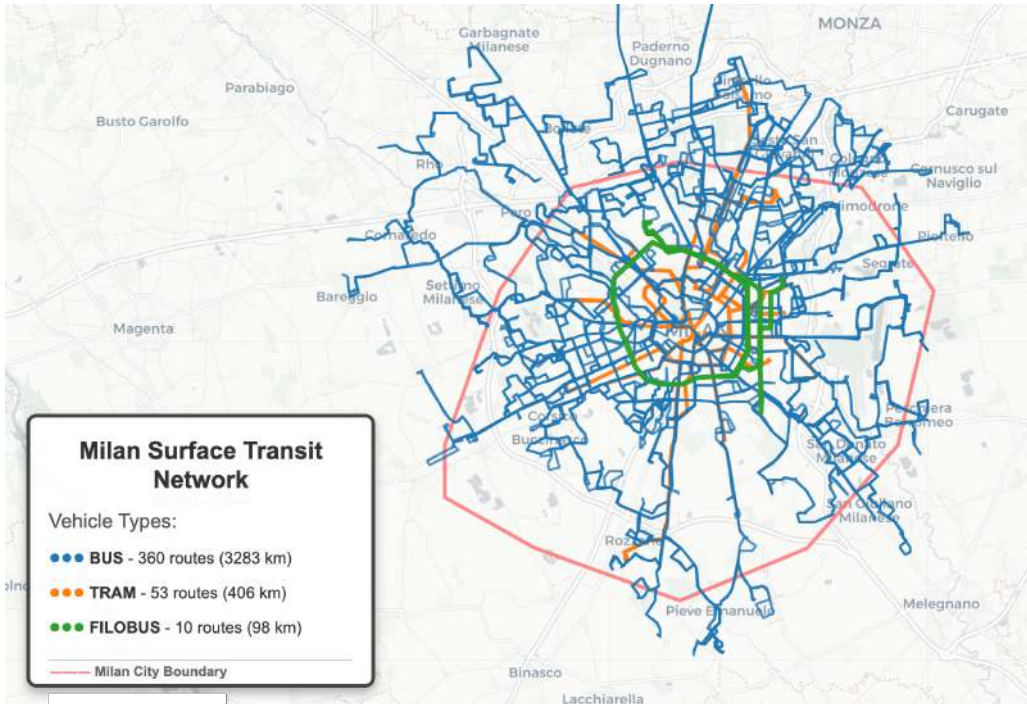


Figure 1: Milan Surface Transit Network. Bus (blue), tram (orange), and filobus (green) routes overlaid on the city boundary (red), illustrating the city's multimodal surface transport coverage.

Over one-third of all stops (1,752 locations) serve multiple lines, creating natural transfer points that enable seamless journeys across the city. The most connected node, "Via Comasina", accommodates eight different lines, exemplifying the system's efficiency.

Service density varies across the network. Lines average 49.5 stops each, with overall density reaching 6.1 stops per kilometer. The longest routes, such as Line 903 connecting Linate Airport to San Donato over 25 kilometers, serve intercity and airport functions, while highly dense local services like Line 201 provide 18.4 stops per kilometer in suburban Rozzano.

3.1.2 Bus Network: Comprehensive Urban Coverage

Milan's bus network forms the system's backbone, providing extensive coverage that reaches every corner of the metropolitan area. With **121 lines** handling **83.7% of all transit connections**, buses ensure universal accessibility while maintaining operational flexibility that allows rapid route adjustments to meet changing urban demands.

The network's flagship route, Line 151 connecting Cairoli to Quartiere Olmi, serves 112 stops and exemplifies comprehensive urban coverage. Similarly, Line 78 with 83 stops and Line 220 with 82 stops demonstrate how buses bridge diverse neighborhoods while maintaining frequent service. Strategic routes like Line 901 provide crucial airport connectivity, linking San Donato metro station to Linate Airport.

3.1.3 Tram Network: High-Capacity Urban Corridors

Milan's tram system, while representing only **11.1% of total network length**, provides high-frequency service along the city's most demanding corridors. Seventeen lines serve **973 stops** with superior density of **7.06 stops per kilometer**, reflecting their role in dense urban areas where frequent boarding is essential.

The tram network's efficiency becomes evident through lines like Line 14, which serves **87 stops** between Cimitero Maggiore and Lorenteggio, and Line 19, connecting Castelli to Lambrate with 84 stops. These routes traverse Milan's historic center and high-density residential areas, providing rapid transit along dedicated tracks that bypass street congestion.

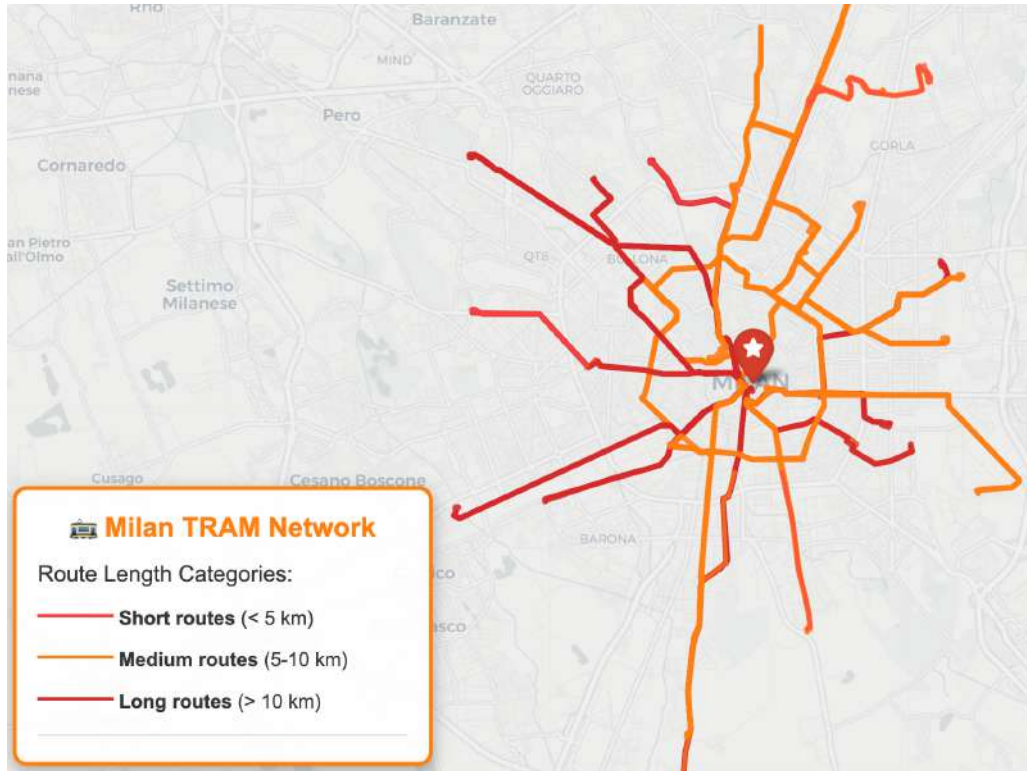


Figure 3: Milan Tram Network by Route Length. Tram lines are categorized as short (5 km, red), medium (5–10 km, orange), and long (10 km, dark red)

3.1.4 Bus and Tram: A Comparison

The relationship between buses and trams reveals complementary service strategies. Buses provide geographic coverage and flexibility, reaching every area of the metropolitan region with 1,105 kilometers of routes. Trams concentrate on high-demand corridors, achieving superior service density and passenger capacity along 144 kilometers of dedicated infrastructure.

Table 1: Bus vs Tram Network Comparison

Metric	Bus Network	Tram Network	Advantage
Network Coverage	1,105 km (85.4%)	144 km (11.1%)	Bus
Service Density	5.95 stops/km	7.06 stops/km	Tram
Average Route Length	9.1 km	8.5 km	Bus
Stops per Line	48.1 stops	57.2 stops	Tram
Geographic Reach	Comprehensive	Urban core	Bus
Service Frequency	Variable	Generally higher	Tram

This division enables buses to handle diverse mobility needs from suburban connections to airport links, while trams focus on high-volume urban corridors where dedicated infrastructure justifies the investment. Trolleybuses

fill specific gaps with electric operation and high capacity, averaging 58.5 stops per line despite comprising only four routes.

3.1.5 Metro and Trains

Milan’s integrated metro and train network forms the other part of the backbone of the city’s public transportation system, providing essential connectivity across the metropolitan area. Our analysis examined the walkability and accessibility of this combined network through a comprehensive spatial analysis of **468 stations** (444 metro access points + 24 train stations).

Network Infrastructure Characteristics The Milan metro network spans **683.36 km** of total track length across **5 main lines** (M1-M5), with an average station spacing of 1.54 km. A high station density of 1.11 per square kilometer reflects a well-developed and concentrated urban transit network.

The integration of **24 strategic train stations** enhances regional connectivity, particularly for longer-distance commutes and inter-city travel. This combined network creates a comprehensive public transportation grid that serves both local and regional mobility needs.

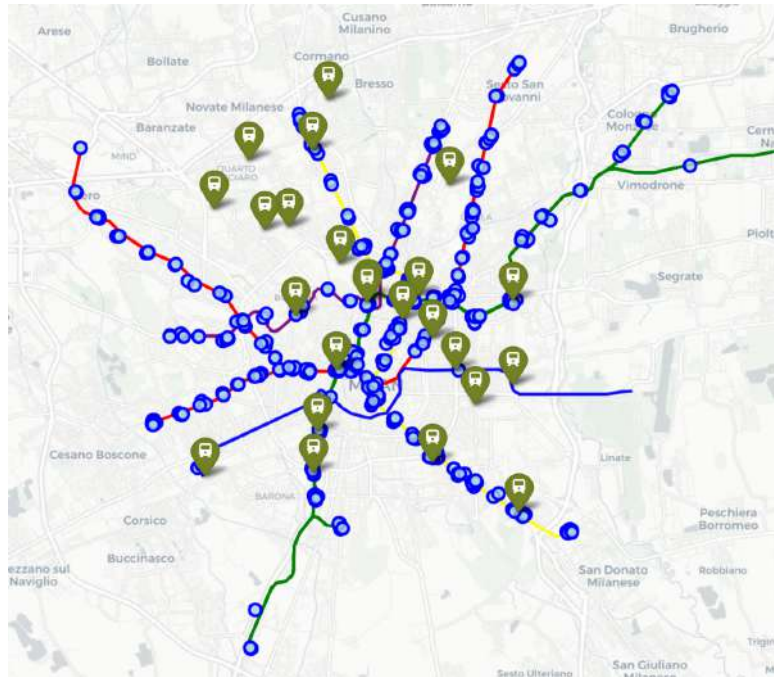


Figure 4: Milan Metro and Train Network Coverage with Station Locations

To evaluate the practical accessibility of Milan’s metro and train network, we employed a dual-methodology approach comparing **Euclidean** (direct distance) and **network-based** (actual walking routes) accessibility measurements.

The Euclidean buffer analysis provides theoretical accessibility under ideal conditions, while the network-based analysis accounts for real-world constraints such as street layouts, barriers, and routing inefficiencies. For the network analysis, we implemented a simplified model using a 75% scaling factor (following suggested Pedestrian Route Directness range from ”Measuring Network Connectivity for Bicycling and Walking - Jennifer Dill, Ph.D. Portland State University” [28]) to account for street network constraints when full routing analysis proved computationally intensive.

Accessibility Results and Spatial Patterns Our walkability analysis reveals significant spatial disparities in metro and train accessibility across Milan. Using Euclidean distance measurements, 13.2% of the analyzed area (221 grid cells, 55.3 km²) demonstrates excellent walkability with stations accessible within a 5-minute walk, this area is represented by the Milan Inner Circle and North Center areas. An additional 15.2% (255 cells, 63.8 km²) shows good accessibility with stations reachable within 10 minutes. However, the majority of the study area—71.7% (1,204 cells, 301.0 km²)—exhibits poor walkability, requiring more than 10 minutes to reach the nearest station.

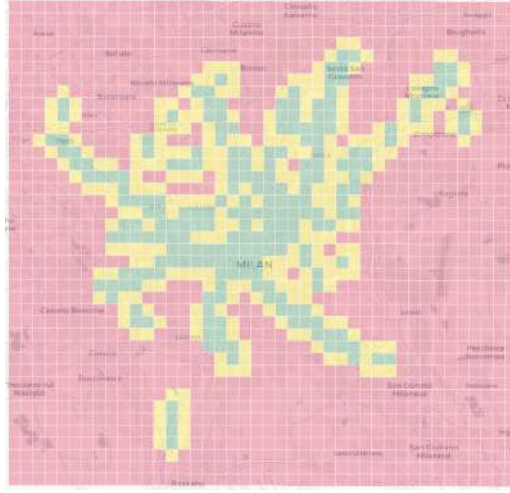


Figure 5: Metro and Train Station Walkability Classification across Milan

The network-based analysis, which better reflects real-world walking conditions, shows more conservative results: 9.8% excellent accessibility, 12.1% good accessibility, and 78.1% poor accessibility. This 6.4 percentage point increase in poorly accessible areas highlights the impact of street network constraints on actual transit accessibility.

Geographic Distribution and Accessibility Hotspots High-accessibility areas are mostly found near the historic city center, major transfer stations such as Milano Centrale and Cadorna, and along busy transit lines, especially the M1 and M2. The radial structure of Milan's metro system creates spoke-like patterns of high accessibility extending from the center.

In contrast, significant accessibility gaps persist in the southeastern and northwestern quadrants of the metropolitan area. These underserved zones represent strategic opportunities for network expansion and infrastructure development. The analysis identified approximately **328.0 km²** of area with poor network-based accessibility, indicating substantial portions of Milan's population may face barriers to sustainable transit use.

Although **28.3%** of the analyzed area enjoys good or excellent transit accessibility, the substantial majority of Milan's urban space remains poorly served by walkable transit infrastructure. This spatial distribution suggests that residents in peripheral areas may face systematic disadvantages in accessing sustainable transportation options.

The 6.4% difference between Euclidean and network-based accessibility measurements underscores the importance of considering real-world walking conditions in transportation planning. Street network constraints, physical barriers, and routing inefficiencies significantly impact actual accessibility, particularly affecting vulnerable populations who may have limited mobility options or resources for alternative transportation modes.

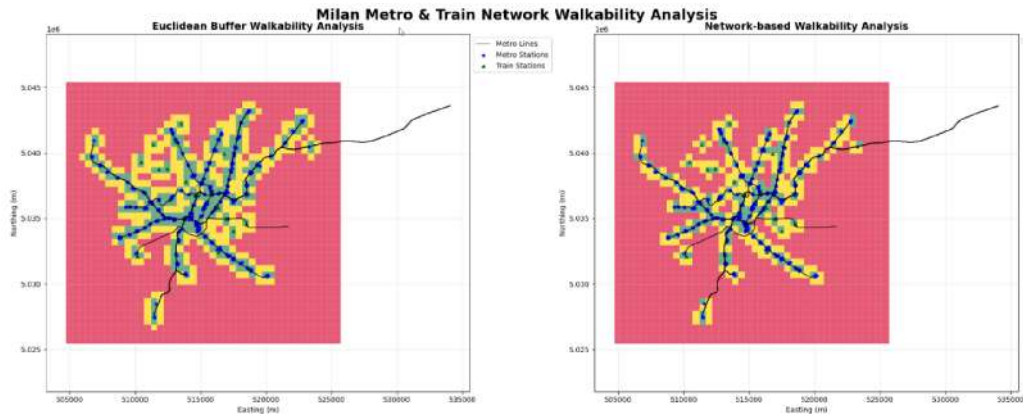


Figure 6: Comparison of Euclidean vs Network-Based Accessibility Analysis

Implications for Transportation Equity These findings contribute directly to our MAI calculation by providing precise spatial measurements of metro and train accessibility across Milan’s urban grid. The integration of both theoretical and practical accessibility measures ensures our composite index accurately reflects the lived experience of Milan residents while identifying priority areas for infrastructure investment and policy intervention.

Table 2: Milan Metro and Train Network Accessibility Summary

Accessibility Category	Euclidean Analysis	Network Analysis	Difference
Excellent (5min walk)	13.2%	9.8%	-3.4%
Good (5-10min walk)	15.2%	12.1%	-3.1%
Poor (10min walk)	71.7%	78.1%	+6.4%
Total Well-Served Area	28.3%	21.9%	-6.4%

3.1.6 Bike

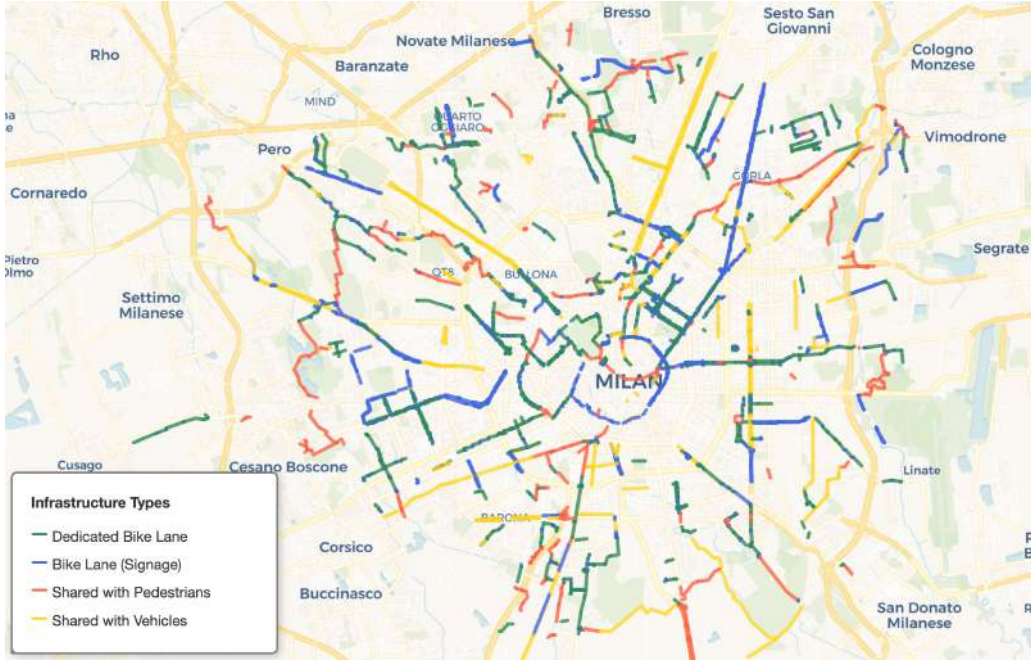


Figure 7: Geographical distribution bike lanes

Milan’s cycling network includes **4,062 segments**, covering **332.8 km** across the metropolitan area.

There is a clear difference in quality across the network. Only 36.2% (120.4 km) are high-quality bike lanes (“ciclabile sede propria”) that have full physical separation from traffic. These high-quality lanes also tend to be longer on average (83.3 m) compared to medium-quality lanes marked only by signs (40.9 m), indicating more continuous and better-connected cycling routes.

Table 3: Infrastructure quality analysis with category counts, lengths, and distribution.

Quality Category	Count	Total Length (m)	Avg Length (m)	Total Length (km)	Percentage (%)
High Quality	1.445	120 368	83.30	120.368	36.2
Medium Quality	1.942	79 419	40.90	79.419	23.9
Mixed Traffic	270	71 532	264.93	71.532	21.5
Shared Space	405	61 444	151.71	61.444	18.5

The remaining infrastructure presents accessibility challenges: 23.9% consists of medium-quality signage-only bike lanes (“ciclabile segnaletica”), while a substantial 40% combines mixed traffic situations (“promiscuo veicoli”) (21.5%) and shared pedestrian (“promiscuo pedoni”) spaces (18.5%).

These shared arrangements, while extending nominal coverage, may compromise cycling safety and accessibility, particularly for vulnerable users including elderly cyclists and families with children.

However, most bike lane segments are quite short, with a median length of just 27 meters. This suggests possible gaps in connectivity that could interrupt the flow of cycling and make longer trips less efficient. The large difference between the longest segment (2.35 km) and the average segment lengths highlights an uneven development of the cycling infrastructure across the city.

3.2 Milan Accessibility Index (MAI)

3.2.1 Introduction

The **Milan Accessibility Index (MAI)** is a comprehensive transportation accessibility metric that adapts the proven **Public Transport Accessibility Level (PTAL)** [29] methodology to Milan’s multimodal urban context. Developed in 1992 by the Borough of Hammersmith and Fulham in London, PTAL evaluates public transport accessibility based on walking distances to transit stops and service frequencies during peak hours, assigning scores from 1a (poor) to 6b (excellent).

In our work, we **extend the original PTAL framework** by incorporating cycling infrastructure as a distinct accessibility layer, using a methodology based on infrastructure density rather than service frequency. This addition enables the MAI to capture the role of bike networks in shaping urban accessibility, providing a more holistic and mode-inclusive evaluation.

Traditional accessibility measures focus solely on proximity to transit stops—essentially answering “how long it takes me to be on public transport?” MAI goes beyond this simple distance-based approach by integrating four critical factors: service frequency, walking distances, mode reliability, and cycling infrastructure. This comprehensive methodology provides a realistic assessment of mobility options available to residents.

The index addresses a fundamental limitation in urban mobility assessment: the difference between theoretical access and practical accessibility. MAI quantifies not just *where* transportation services exist, but *how usable* they are in practice, accounting for real-world factors such as service frequency, waiting times, and the integration of multiple transportation modes.

3.2.2 Theoretical Framework

The fundamental principle is elegant: transform the complex relationship between location, service frequency, and accessibility into a single, comparable score ranging from 0 (no access) to 40+ (exceptional access).

This transformation process operates through four interconnected components:

1. **Spatial discretization:** Systematic analysis using a regular grid at neighborhood scale
2. **Service accessibility:** Distance-weighted access evaluation for each transportation service
3. **Frequency integration:** Incorporation of real-time service availability during peak periods
4. **Modal aggregation:** Synthesis of accessibility across all transportation modes

3.2.3 Calculation Methodology

Step 1: Spatial Grid Framework The analysis begins by systematically dividing Milan into a regular **500m × 500m grid system**, creating approximately **1,500 analysis points** across the metropolitan area. This grid-based approach ensures consistent spatial resolution and enables comprehensive coverage of the urban area. Each grid cell G_i represents a neighborhood-scale area where accessibility is evaluated from the geometric center:

$$G_i = \{(x, y) : i \in \{1, 2, \dots, n\}\}$$

where n represents the total number of grid cells covering Milan’s urban area. The 500-meter resolution provides sufficient detail for neighborhood-level planning while maintaining computational efficiency for city-wide analysis.

Step 2: Service Access Point Identification For each grid point G_i , the algorithm identifies all accessible Service Access Points (SAPs) within mode-specific walking catchments:

$$SAP_{mode}(G_i) = \{s \in S_{mode} : d(G_i, s) \leq C_{mode}\}$$

where:

- S_{mode} is the set of all stops/stations for a given transportation mode
- $d(G_i, s)$ is the Euclidean distance between grid point and service access point
- C_{mode} is the catchment distance specific to each mode

The catchment distances are based on acceptable walking times and mode characteristics:

Table 4: Mode-Specific Catchment Distances

Transportation Mode	Catchment (m)	Walking Time
Bus	640	8 minutes
Tram	640	8 minutes
Metro	960	12 minutes
Rail	960	12 minutes
Cycling Infrastructure	1,200	15 minutes

Step 3: Total Access Time Calculation For each accessible service s from grid point G_i , the Total Access Time (TAT) combines three components:

$$TAT(G_i, s) = WT(G_i, s) + SWT(s) + RP_{mode}$$

where:

$$WT(G_i, s) = \frac{d(G_i, s)}{v_{walk}} \quad (\text{Walking Time}) \quad (1)$$

$$SWT(s) = \frac{0.5 \times 60}{f_s} \quad (\text{Scheduled Waiting Time}) \quad (2)$$

$$RP_{mode} = \text{Reliability Penalty by mode} \quad (3)$$

Parameters:

- $v_{walk} = 80$ m/min (standard walking speed)
- f_s = services per hour during peak period (8:15-9:15 AM)
- $RP_{bus/tram} = 2.0$ minutes, $RP_{metro/rail} = 0.75$ minutes

The scheduled waiting time assumes passengers arrive randomly at stops, resulting in an average wait of half the service interval. Reliability penalties are applied because scheduled times assume perfect service adherence, while real-world transit experiences delays and irregularities that effectively increase total access time.

Step 4: Equivalent Doorstep Frequency The Total Access Time is converted to an Equivalent Doorstep Frequency (EDF), which represents the theoretical service frequency that would be required if a transit service were hypothetically located directly at the grid point origin:

$$EDF(G_i, s) = \frac{30}{TAT(G_i, s)}$$

This transformation enables standardized comparison across different services and locations by normalizing the accessibility measure. The EDF value quantifies how accessible a service is relative to an ideal baseline: higher EDF values indicate greater accessibility, as they correspond to shorter total access times. The constant 30 represents a benchmark frequency (30 services per hour, equivalent to 2-minute intervals) derived from PTAL methodology, establishing a reference point for high-quality transit service.

Step 5: Modal Accessibility Aggregation Within each transportation mode (bus, tram, metro, rail), multiple services may be accessible from a single grid point. These individual service EDFs must be combined into a single modal accessibility score. The aggregation follows PTAL weighting methodology that accounts for the diminishing marginal utility of multiple services:

$$AI_{mode}(G_i) = EDF_{max} + 0.5 \times \sum_{j=2}^n EDF_j$$

Where:

- EDF_{max} : The highest EDF value for that mode receives full weight (represents the primary service)
- $\sum_{j=2}^n EDF_j$: All remaining EDFs (ranked in descending order) receive 50% weight
- The 0.5 weighting factor reflects diminishing returns from additional services

This weighting scheme recognizes that while multiple transit options increase accessibility, each additional service provides progressively less benefit. The primary service delivers the full accessibility advantage, while supplementary services contribute primarily through enhanced service reliability, reduced vehicle crowding, and backup options during service disruptions. The mathematical formulation ensures that areas with multiple services receive appropriate accessibility credits without overestimating their practical advantage over single-service areas.

Step 6: Cycling Infrastructure Integration Cycling accessibility is calculated using a fundamentally different approach compared to public transit modes, as it is based on infrastructure density rather than service frequency. This methodological distinction reflects the unique characteristics of cycling as a transportation mode:

$$AI_{cycling}(G_i) = \min(2 \times \rho_{bike}(G_i), 20)$$

where $\rho_{bike}(G_i)$ represents the bike lane density (km/km²) within the cycling catchment area around grid point G_i .

Where:

- $\rho_{bike}(G_i)$: Bike lane density measured as total kilometers of cycling infrastructure per square kilometer (km/km²)
- $2\times$: Scaling factor that converts infrastructure density to accessibility equivalent units (e.g., 5 km/km² becomes accessibility score of 10)
- $\min(\cdot, 20)$: Maximum cap of 20 to ensure cycling accessibility remains proportional to other modes

Unlike public transit, which operates on fixed schedules and routes, cycling accessibility depends primarily on the availability and density of safe, dedicated infrastructure. The scaling factor of 2 establishes an empirically-derived equivalence where each km/km² of bike lane density contributes 2 points to the accessibility score, calibrated so that moderate cycling infrastructure density (5 km/km²) achieves comparable scores (10 points) to moderate-frequency public transit areas. Milan's cycling infrastructure density typically ranges from 0-10 km/km², producing scaled contributions of 0-20 points before the maximum cap. Higher bike lane density indicates better connectivity, reduced conflict with vehicular traffic, and enhanced safety for cyclists. The scaling factor and cap ensure cycling accessibility scores remain proportional to public transit scores while recognizing the practical limits of cycling network accessibility.

Step 7: Total MAI Score The final Milan Accessibility Index combines all modal contributions:

$$MAI(G_i) = AI_{bus}(G_i) + AI_{tram}(G_i) + AI_{metro}(G_i) + AI_{rail}(G_i) + AI_{cycling}(G_i)$$

3.2.4 Classification and Interpretation

MAI scores are classified into nine accessibility bands adapted from PTAL standards:

Table 5: MAI Accessibility Bands

Band	Score Range	Description
0	0	No Access
1	0.01 - 2.50	Very Poor
2	2.51 - 5.00	Poor
3	5.01 - 10.00	Moderate
4	10.01 - 15.00	Good
5	15.01 - 20.00	Very Good
6	20.01 - 25.00	Excellent
7	25.01 - 40.00	Outstanding
8	40.01+	Exceptional

3.2.5 Interpretation and Applications

MAI scores enable direct comparison of accessibility levels across Milan’s diverse neighborhoods. High scores ($MAI > 20$) typically indicate central areas with overlapping transit services and good cycling infrastructure, while low scores ($MAI \leq 5$) suggest areas that may face mobility challenges requiring targeted transportation improvements.

The modal breakdown component of MAI allows planners to identify whether accessibility gaps stem from specific transportation modes (e.g., limited bus frequency vs. inadequate cycling infrastructure), enabling targeted interventions where they will have maximum impact on citywide mobility equity.

This methodology provides a standardized, reproducible framework for monitoring accessibility changes over time and evaluating the effectiveness of transportation investments in improving urban mobility.

3.2.6 Mapping Mobility: Spatial and Modal Analysis

Our analysis of 1,500+ grid points across Milan reveals significant accessibility disparities:

- **Coverage Gap:** 25% of Milan’s urban area lacks adequate transit accessibility ($MAI \leq 2.5$)
- **Central Concentration:** Exceptional accessibility ($MAI > 25$) concentrated in central Milano and major transit hubs
- **Median Performance:** 75% of accessible areas score below MAI 10.0, indicating predominantly moderate accessibility levels

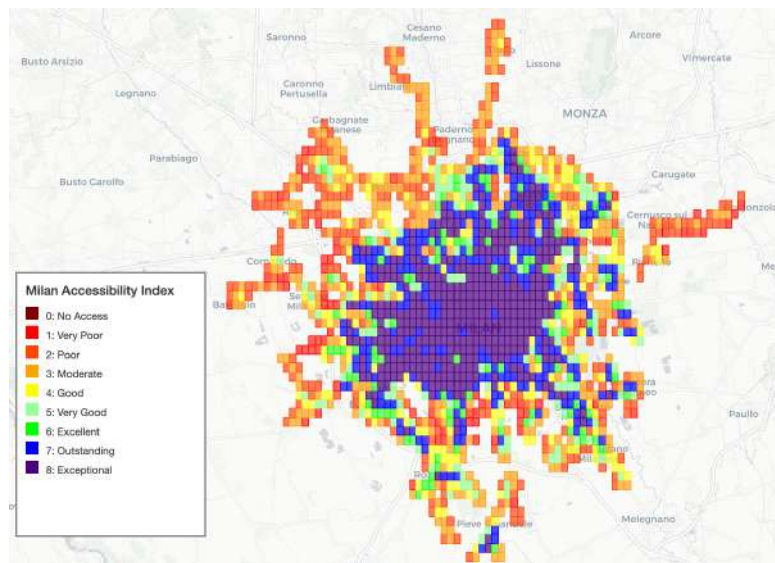


Figure 8: Milan Accessibility Index spatial distribution showing accessibility bands across the metropolitan area.

Table 6: Modal Accessibility Contributions

Mode	Average AI Score	% of Total
Bus	4.2	42%
Tram	2.8	28%
Metro	1.9	19%
Rail	0.8	8%
Cycling	0.3	3%

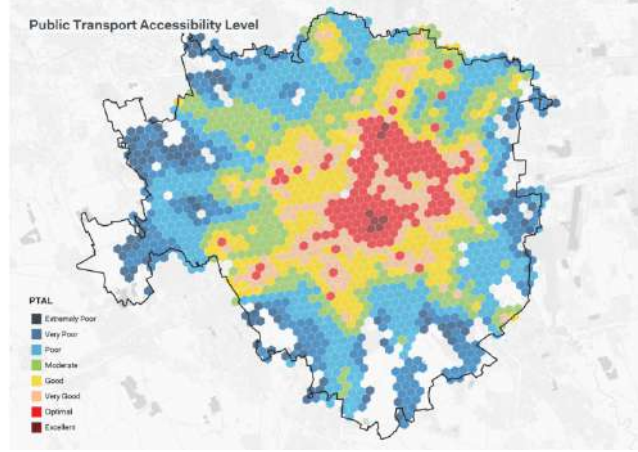


Figure 9: Figure representing the Public Transportation Accessibility Level for comparison purposes

Transportation mode analysis reveals critical dependencies and opportunities:

Bus networks provide the dominant accessibility contribution (42%), making Milan vulnerable to bus service disruptions while highlighting the high-impact potential of bus system improvements.

3.2.7 Comparison with PTAL

As shown in Figure9, the reference PTAL map and our accessibility analysis share similar patterns in the spatial concentration of high and low accessibility areas. Both approaches identify a dense, well-connected central zone surrounded by peripheral areas with limited public transport service. However, our method highlights a broader central area of good accessibility, suggesting that the multimodal nature of our analysis captures more extensive service coverage than the original PTAL methodology. This further supports the importance of integrated network analysis in accurately depicting urban accessibility landscapes.

3.3 A look into Milan’s population - Milan’s Socioeconomic overview

3.3.1 Introduction to Socioeconomic Context

Understanding Milan’s socioeconomic geography is crucial for assessing transportation equity, as income disparities directly influence mobility choices, accessibility needs, and transportation affordability. This analysis examines IRPEF (Imposta sul Reddito delle Persone Fisiche) tax data for 2022, providing insights into income distribution patterns across Milan’s 37 postal codes. The dataset is publicly available on Milan’s data website [30].

Milan’s economic data includes **1,007,644 taxpayers** with a total taxable income of **€35.8 billion**, distributed across 181.7 km² of urban area. This socioeconomic analysis provides the foundation for understanding how income-based differences differentiate the accessibility index across neighborhoods, directly relating to the MAI index and related economic levels.

3.3.2 Income Distribution and Spatial Patterns

Overview of Income Inequality Milan exhibits substantial income inequality across its postal codes, with a dramatic **5.1:1** ratio between the highest and lowest income areas. The city-wide average income of €36,903 per

taxpayer masks significant disparities: the affluent Centro Storico area (CAP 20121) commands **€94,369 per taxpayer**, while the peripheral Quarto Oggiaro district (CAP 20157) averages only **€18,509 per taxpayer**.

Table 7: Milan Income Distribution Key Statistics

Metric	Value
Total Taxpayers	1,007,644
Total Taxable Income	€35.8 billion
Average Income	€36,903
Median Income	€29,745
Highest Income Area (CAP 20121)	€94,369
Lowest Income Area (CAP 20157)	€18,509
Income Inequality Ratio	5.1:1
Geographic Coverage	181.7 km ²
Average Taxpayer Density	8,149 per km ²

The distribution demonstrates a right-skewed pattern (clearly visible in Figure 10), with the median income (€29,745) significantly lower than the mean, indicating that a substantial portion of Milan’s population earns below the average income. This skewness reflects the concentration of high earners in specific geographic areas and suggests that transportation affordability challenges may affect the majority of Milan residents.

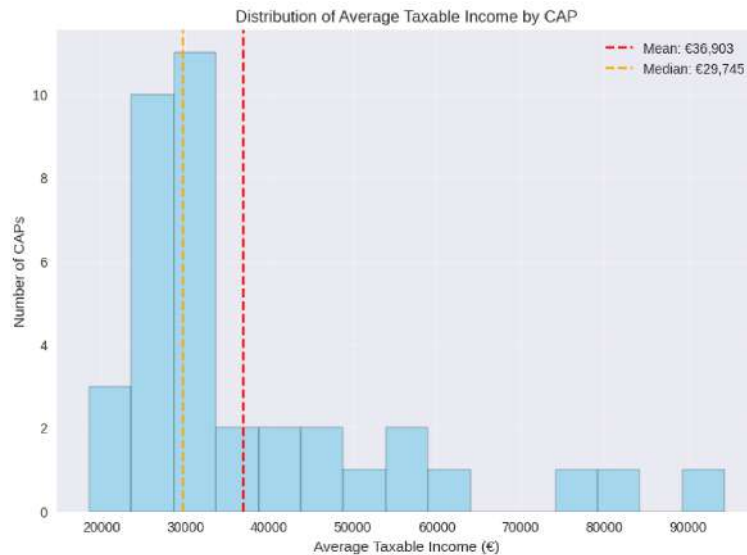


Figure 10: Distribution of Average Taxable Income by Postal Code - Histogram showing frequency distribution of income levels across Milan’s 37 postal codes, with mean and median lines clearly marked, demonstrating right-skewed distribution pattern.

High-Income Geographic Concentration Milan’s highest-income areas cluster in the historic center and select upscale districts, creating distinct zones of economic advantage with superior access to services and urban facilities. The top five income areas demonstrate clear spatial concentration:

1. **CAP 20121 - Centro Storico/Duomo** (€94,369): Historic center with luxury retail, business headquarters, and premium residential properties
2. **CAP 20145 - Magenta/San Vittore** (€83,768): Upscale residential area adjacent to Castello Sforzesco and major cultural institutions
3. **CAP 20123 - Centro/Brera** (€74,232): Artistic district combining cultural amenities with high-end residential properties
4. **CAP 20122 - Porta Nuova/Isola** (€59,924): Modern business district featuring skyscrapers and contemporary developments

5. **CAP 20129 - Città Studi/Porta Venezia** (€56,142): University area attracting professionals and academics

These areas benefit from superior urban infrastructure, excellent public transportation connectivity, and proximity to employment centers, cultural facilities, and premium services. The concentration of high incomes in central areas creates a spatial advantage that extends beyond individual wealth to encompass superior accessibility to urban opportunities (Figure 11).

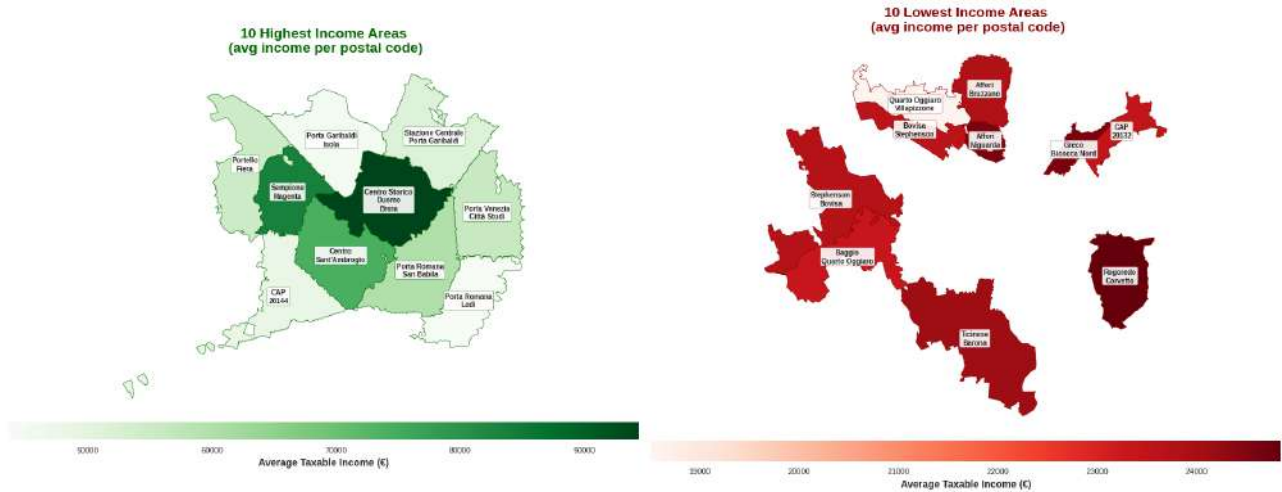


Figure 11: Choropleth maps showing the top 10 highest and lowest average income areas in Milan, aggregated by postal code. The highest income areas (left) are all concentrated in a cluster of central districts, zones such as Duomo, Brera, and Magenta, show average taxable incomes above €70,000, with peaks over €90,000. In contrast, the lowest income areas (right) are predominantly located in the city's periphery, such as Quarto Oggiaro, Barona, and Rogoredo, with average incomes mostly below €23,000. This spatial polarization highlights the socioeconomic divide between the city center and outlying districts.

Low-Income Peripheral Distribution Conversely, Milan's lowest-income areas concentrate in peripheral zones, often coinciding with areas of limited transportation accessibility and reduced urban facilities. The five lowest-income postal codes reveal systematic spatial disadvantage:

1. **CAP 20157 - Quarto Oggiaro/Villapizzone** (€18,509): Peripheral residential area with social housing concentrations
2. **CAP 20152 - Dergano/Bovisa** (€23,319): Former industrial area transitioning to mixed residential use
3. **CAP 20132 - Crescenzago/Adriano** (€23,424): Eastern peripheral area with limited connectivity to city center
4. **CAP 20156 - Stephenson/Bovisa** (€23,602): Northwestern district with industrial heritage and working-class population
5. **CAP 20161 - Affori/Bruzzano** (€23,820): Northern suburban area with high population density but limited amenities

These areas face compound disadvantages: lower average incomes reduce transportation affordability, while peripheral locations often correlate with reduced public transportation frequency and limited sustainable mobility options. This spatial-economic pattern creates potential barriers to accessing employment, education, healthcare, and cultural opportunities concentrated in higher-income central areas (Figure 12).

3.3.3 Center-Periphery Economic Gradient

Spatial Economic Patterns Milan exhibits a pronounced center-periphery income gradient, with average incomes systematically decreasing with distance from the historic center. This pattern reflects classic urban economic theory while creating specific challenges for transportation equity and sustainable mobility access.

The analysis reveals three distinct socioeconomic zones:

High-Income Core (more than €50,000 average): Central areas including Centro Storico, Brera, Magenta, and Porta Nuova, characterized by business districts, luxury residential properties, and cultural centers. These areas benefit from superior public transportation connectivity, walkable urban design, and proximity to employment centers.

Middle-Income Transition (€25,000-50,000): Mixed residential and commercial areas in intermediate zones, including established neighborhoods and emerging districts. These areas experience moderate transportation accessibility with developing sustainable mobility infrastructure.

Lower-Income Periphery (less than €25,000): Outer residential areas and social housing zones, often with industrial heritage and working-class populations. These areas face compound disadvantages of lower incomes and reduced transportation accessibility, potentially limiting access to economic opportunities.

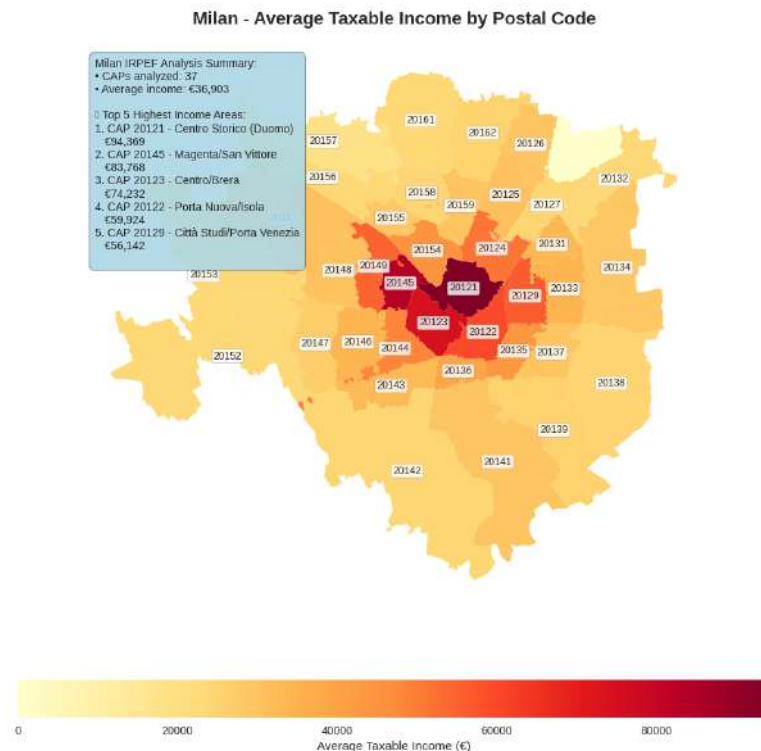


Figure 12: Highest Income Areas Distribution Map - Choropleth map highlighting the top 5 income areas in Milan with color-coded income levels, demonstrating clear center-periphery concentration patterns and spatial clustering of affluent neighborhoods.

Population Density and Economic Relationships The relationship between population density and income levels reveals important patterns for transportation planning. Areas with the highest taxpayer concentrations often occur in middle and lower-income peripheral zones, creating significant demand for affordable and accessible transportation options (Figure 13).

Most Populous Areas by Taxpayer Count:

1. CAP 20146 (Baggio/Forze Armate): 46,452 taxpayers, €30,187 average income
2. CAP 20142 (Ticinese/Barona): 43,104 taxpayers, €31,245 average income
3. CAP 20161 (Affori/Bruzzano): 37,564 taxpayers, €23,820 average income
4. CAP 20151 (Lampugnano/QT8): 36,929 taxpayers, €32,156 average income
5. CAP 20141 (Gratosoglio/Stadera): 36,567 taxpayers, €26,789 average income

These high-population areas represent substantial transportation demand from residents with below-average incomes, highlighting the importance of affordable, accessible, and high-capacity transportation options. The concentration of population in areas with limited economic resources suggests that transportation equity interventions could benefit large numbers of Milan residents.

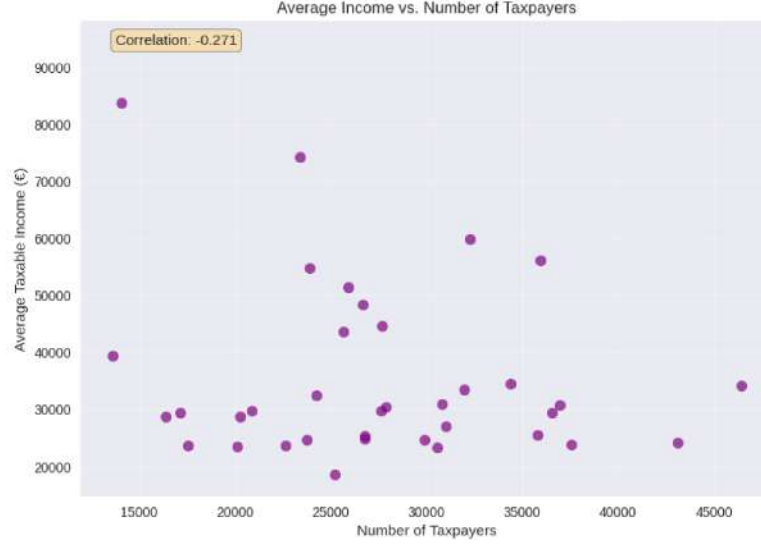


Figure 13: Scatter plot of average income versus number of taxpayers. We observe that the area with the highest average income has a very low number of taxpayers. In general, the majority of the highest income values (more than €40,000) tend to occur in areas with fewer than 30,000 taxpayers, while the most populated ZIP codes (on the right side of the chart) typically show lower average incomes. Most ZIP codes, regardless of population size, are concentrated below the €35,000 average income threshold. The weak negative correlation (approximately -0.27) suggests that higher population areas tend to be associated with slightly lower average incomes.

4 Modeling the Relationship Between MAI and Socio-Economic Indicators

To investigate the relationship between socio-economic conditions and sustainable mobility access in Milan, we combined data on average taxable income with the *Mobility Accessibility Index* (MAI) at both the individual and postal code (CAP) levels. Visualizing the spatial co-distribution of income and accessibility allows us to preliminarily assess whether patterns of correlation or disparity emerge across the urban landscape. This initial inspection serves as a foundation for the more rigorous statistical evaluation presented in the subsequent section.

4.1 Correlation Between MAI and Socio-Economic Data: Statistical Interpretation of Results

The statistical analysis reveals a robust positive relationship between average taxable income and the *Mobility Accessibility Index* (MAI) in Milan (scaled in the regression for a range between 0 and 100), supporting the hypothesis of income-related disparities in sustainable transport access. At the individual data point level ($n = 836$), the Pearson correlation coefficient is $r = 0.468$, indicating a moderate effect size, with income accounting for approximately 21.9% of the variance in MAI ($p < 0.001$). Aggregating the data to the postal code (CAP) level ($n = 38$) strengthens the correlation substantially to $r = 0.718$, explaining 51.5% of the variance and suggesting structural spatial patterns.

To further quantify this relationship, linear regression was applied, modeling MAI as a function of average income. The regression equation is defined as:

$$Y = \beta_0 + \beta_1 X + \varepsilon \quad (4)$$

where:

- Y is the predicted *Mobility Accessibility Index* (MAI),
- X is the average taxable income (in thousands of euros),
- β_0 is the intercept,
- β_1 is the slope (effect of income on MAI),

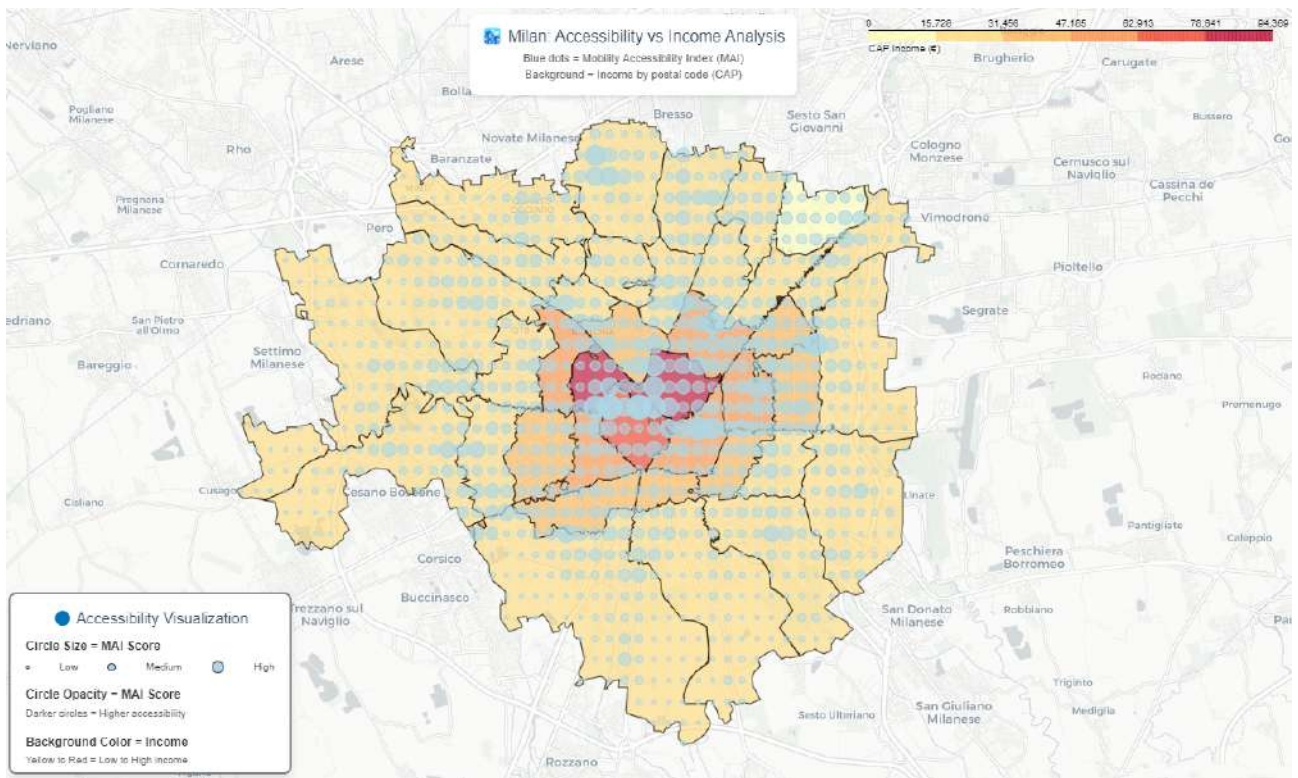


Figure 14: Accessibility vs. Income in Milan: The map visualizes the relationship between mobility access and income across postal code areas. Blue circles represent the Mobility Accessibility Index (MAI), with larger circles indicating higher accessibility. Background colors range from yellow (low income) to red (high income), revealing a central cluster with both high income and high accessibility.

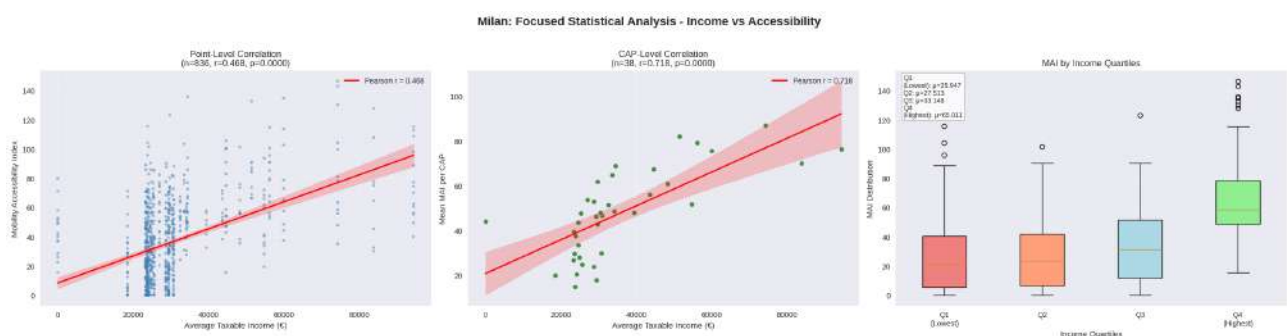


Figure 15: **Statistical Relationship between Income and Mobility Accessibility in Milan.** The figure presents three complementary perspectives on the income-accessibility relationship. **Left:** A scatter plot of individual points ($n = 836$) illustrates a positive correlation between average income and the Mobility Accessibility Index (MAI), with a Pearson coefficient of $r = 0.468$ ($p < 0.001$), along with a linear regression trend. **Middle:** When aggregated by postal code ($n = 38$), the correlation strengthens to $r = 0.718$ ($p < 0.001$), indicating spatial consistency. **Right:** A boxplot of MAI across income quartiles highlights strong disparities; the highest income quartile (Q4) exhibits more than double the mean MAI of the lowest (Q1), underscoring inequalities in mobility access.

- ε is the error term.

At the individual point level, the fitted model is:

$$\hat{Y}_{\text{point}} = 14.43 + 0.925 \cdot X$$

indicating that each €1,000 increase in income corresponds to a 0.925-point increase in MAI.

At the CAP-aggregated level, the model becomes:

$$\hat{Y}_{\text{CAP}} = 16.32 + 0.757 \cdot X$$

also statistically significant ($p < 0.001$), reinforcing the presence of income-driven spatial disparities in accessibility.

A one-way ANOVA confirms significant variation in MAI across income quartiles ($F = 107.51$, $p < 0.001$). The average MAI nearly doubles from the lowest quartile (Q1: 25.95) to the highest (Q4: 65.01), demonstrating marked inequality. Moreover, the overall distribution of accessibility scores is moderately right-skewed (skewness = 0.71), indicating that a subset of high-income areas disproportionately benefits from high accessibility.

In sum, these results quantitatively support the broader narrative that lower-income populations in Milan are systematically underserved by sustainable transport infrastructure, despite their higher reliance on it. This underscores the need for equity-oriented planning in future mobility policies.

5 Policy Recommendations for Reducing Transport Inequalities

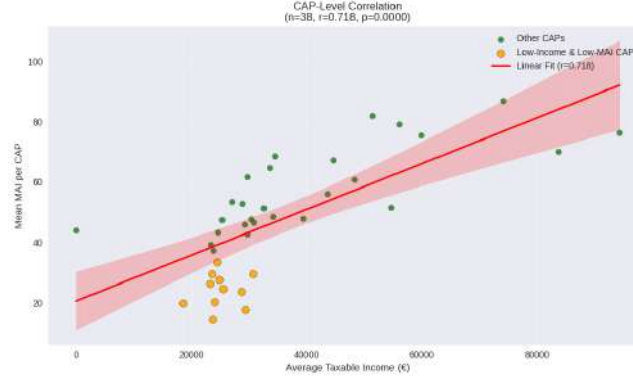


Figure 16: Figure 1. CAP-Level Relationship Between Income and Accessibility. This scatter plot visualizes the correlation between average taxable income and mean accessibility index (MAI) across Milan’s postal code areas (CAPs). The red line represents a linear regression fit, with a 95% confidence interval shaded. The orange-highlighted points indicate a distinct cluster of CAPs characterized by both low income (less than €35,000) and low accessibility (aggregated MAI less than 35), suggesting areas that may benefit most from targeted policy interventions.

Table 8: Recommended Intervention Areas: Low-Income and Low-Accessibility CAPs in Milan

CAP	Average Income (€)	Mean MAI Score
20134	28,680	23.70
20138	24,847	27.65
20139	25,572	24.71
20141	29,400	17.65
20142	24,122	20.29
20151	30,705	29.65
20152	23,319	26.45
20153	23,713	14.60
20156	23,602	29.50
20157	18,509	19.79
20158	24,578	33.41

The Milan Accessibility Index (MAI) analysis, combined with regression findings on the relationship between neighborhood income and accessibility, provides a solid foundation for evidence-based policy interventions. Our research reveals that accessibility disparities correlate significantly with income distribution across Milan’s metropolitan area, with the regression coefficient indicating how accessibility advantages compound with neighborhood wealth. This section proposes targeted interventions designed to systematically reduce these inequalities through strategic infrastructure investments and service enhancements.

5.1 Digital Twin-Based Investment Optimization

The most innovative policy recommendation involves implementing prospective policy evaluation using MAI as a decision-support tool for transport investments. Our regression analysis reveals that the slope coefficient linking neighborhood income to accessibility serves as a quantitative indicator of accessibility-based inequality: a steeper positive slope indicates that income increases correspond to disproportionately larger accessibility gains, systematically disadvantaging lower-income areas.

Simulating Interventions through Ex-Ante Assessment: Before committing to infrastructure projects, their proposed characteristics (routes, stop locations, service frequencies) should be integrated into existing spatial and transport network data, creating comprehensive “what-if” scenarios. The MAI would be recalculated for all affected grid cells under these new conditions and the regression model linking MAI to socioeconomic variables would be re-estimated.

Coefficient-Reduction Prioritization: Interventions that demonstrably reduce or flatten the regression coefficient—making MAI value less dependent on income—should receive investment priority. This approach directly targets systematic inequality reduction by identifying projects that improve accessibility disproportionately in underserved areas, transforming traditional cost-benefit analysis by establishing equity metrics as primary decision criteria.

Scenario Modeling Protocol: Municipal transport authorities should establish standardized procedures for testing infrastructure proposals within the digital twin environment. Each potential intervention requires assessment across multiple scenarios: immediate implementation effects, five-year service maturation impacts, and integration benefits with existing networks. This systematic approach ensures investment decisions maximize equity outcomes while maintaining operational efficiency.

5.2 Mode-Specific Intervention Strategies

Based on MAI findings that bus networks contribute 42% of total accessibility while serving 56.7% of grid points, targeted interventions should prioritize high-impact, cost-effective improvements that address the identified coverage gap, especially in the areas identified in our study.

Bus Network Enhancement: Priority interventions should include: increasing service frequency on routes serving low-MAI areas with high concentrations of vulnerable populations (directly improving the Scheduled Wait Time component); optimizing routes to better connect underserved areas to employment centers, health-care, and education facilities; and implementing dedicated bus lanes to improve reliability and reduce both Walk Time and Reliability Penalty components.

Multimodal Integration Expansion: The analysis reveals that areas with tri-modal service integration (bus, tram, and metro) achieve three times higher average MAI scores compared to single-mode areas. However, only 8.5% of Milan’s grid points currently benefit from such integration. Strategic investments should target neighborhoods where adding a second or third transportation mode would create multimodal hubs, particularly in areas with high concentrations of lower-income residents who would benefit most from increased mobility options and service redundancy.

Cycling Infrastructure as Equity Tool: The weak correlation ($r = 0.15$) between cycling accessibility and total MAI, combined with maximum bike lane density of only 12.3 km/km², indicates substantial untapped potential for cycling infrastructure to address transport inequalities. Unlike traditional transit investments requiring significant capital expenditure, cycling infrastructure represents a cost-effective intervention that can rapidly improve accessibility in transit-sparse areas while providing mobility options independent of service frequencies and fare structures.

5.3 Equity-Focused Implementation Framework

Drawing from Schwanen’s (2022) framework for capability-enhancing interventions, Milan’s transport policy should adopt a dual approach that simultaneously lifts accessibility levels in underserved areas while managing excessive mobility consumption in privileged neighborhoods.

Targeted Service Enhancement: Investment priority should focus primarily on the CPS of Milan’s urban area currently experiencing inadequate transit accessibility, clearly identifiable through spatial mapping analysis. These areas require comprehensive service improvements addressing both horizontal equity (fair geographic distribution) and vertical equity (fair distribution based on socioeconomic factors).

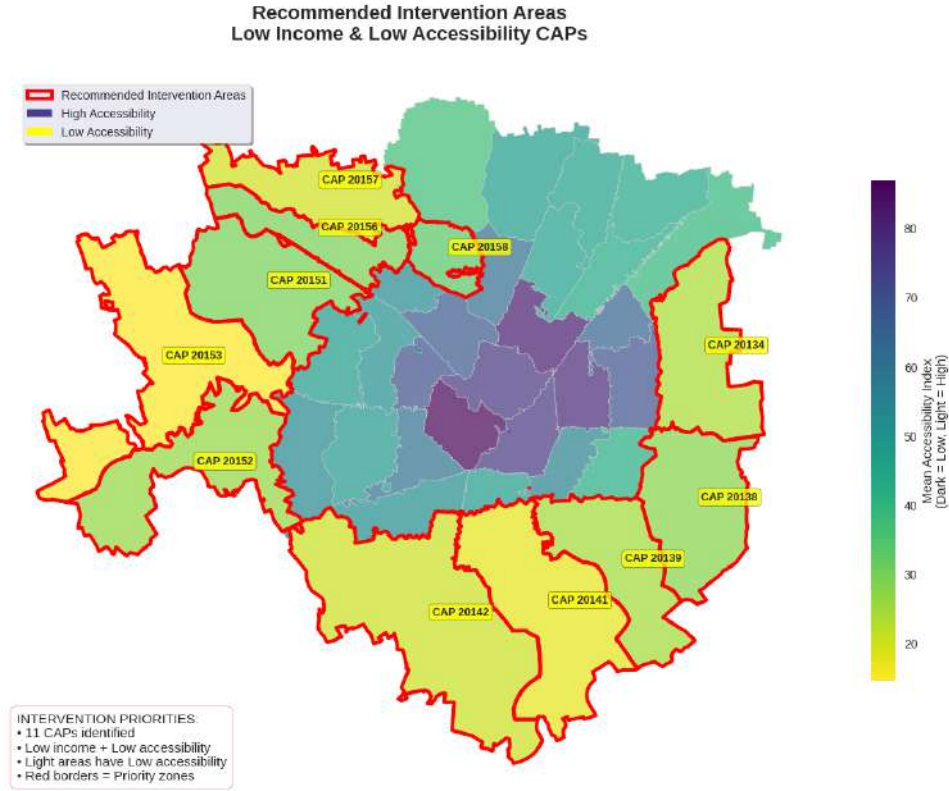


Figure 17: Geographical Distribution of Low-Income & Low-Accessibility CAPs. This map highlights only the CAP areas identified in the bottom-left cluster of the previous scatter plot. These CAPs, shaded in orange, are characterized by both below-average taxable income and limited mobility accessibility. The Milan Accessibility Index (MAI) values are averaged at the CAP level; more precise intervention targets can be identified by consulting the detailed MAI map in Figure 8, which reveals intra-CAP variation.

Anti-Displacement Measures: Transit-oriented development accompanying accessibility improvements must include robust affordable housing protections to prevent gentrification-induced displacement. The regression relationship between income and accessibility suggests that infrastructure improvements in low-income areas may attract higher-income residents unless deliberate measures maintain neighborhood affordability. Policy packages should combine transport investments with inclusionary zoning, community land trusts, and tenant protections.

5.4 Monitoring and Adaptive Management

The MAI methodology provides a replicable framework for ongoing equity assessment, enabling adaptive policy management based on empirical outcomes rather than assumptions about intervention effectiveness.

Continuous Monitoring and Coefficient Tracking: Regular MAI updates incorporating service changes, new infrastructure, and demographic shifts should provide real-time feedback on intervention effectiveness. Quarterly recalculation of the income-accessibility regression coefficient serves as the primary equity metric: coefficient increases indicate growing inequality requiring immediate policy adjustment, while sustained reductions demonstrate successful equity enhancement. This creates a continuous improvement cycle ensuring adaptive policy management based on empirical outcomes rather than assumptions about intervention effectiveness.

Integrated Impact Assessment: Policy evaluation should extend beyond accessibility metrics to incorporate broader social outcomes including employment access, healthcare utilization, educational participation, and social cohesion indicators. The capability approach framework suggests that mobility improvements should translate into expanded opportunities across multiple life domains, making comprehensive impact assessment essential for validating intervention effectiveness.

References

- [1] Tim Schwanen, “Transportation justice,” <http://www.timschwanen.com/archives/827>, 2022, accessed: 2025-05-05.
- [2] European Commission, “New urban mobility indicator fiches released to support sump implementation,” https://commission.europa.eu/index_en, 2024, accessed : 2025 – 05 – 05.
- [3] Alan Turing Institute, “Spatial inequality and the smart city,” <https://www.turing.ac.uk/research/research-projects/spatial-inequality-and-smart-city>, note = Accessed: 2025-05-05, 2018.
- [4] Agustín Cocola-Gant, “The role of the state in the touristification of lisbon,” https://www.researchgate.net/publication/369088004_The_role_of_the_state_in_the_touristification_of_Lisbon, note = Accessed: 2025-05-05, 2023.
- [5] Scott Fitzgerald, “Liverpool sustainable urban mobility study,” <https://imoveaustralia.com/project/project-outcomes/liverpool-sustainable-urban-mobility-study/>, note = Accessed: 2025-05-05, 2024.
- [6] Comune di Milano, “Pums - piano urbano della mobilità sostenibile,” <https://www.comune.milano.it/aree-tematiche/mobilita/pianificazione-mobilita/piano-urbano-della-mobilita/>, note = Accessed: 2025-05-05, 2018.
- [7] Confcommercio Milano , “Atm: dal 2030 sulla strada solo bus elettrici,” https://www.confcommerciomilano.it/it/news/news/impresa_istituzioni/expo_2015nl_1_2017_Atm_FullElectric, note = Accessed: 2025-05-05, 2017.
- [8] F. Bruzzone, F. Cavallaro, and S. Nocera, “Effects of high-speed rail on regional accessibility,” *Transportation*, 2022.
- [9] T. Welch and S. Mishra, “A measure of equity for public transit connectivity,” *Journal of Transport Geography*, vol. 33, pp. 29–41, 2013.
- [10] A. Monzón, E. Ortega, and E. López, “Efficiency and spatial equity impacts of high-speed rail extensions in urban areas,” *Cities*, vol. 30, pp. 18–30, 2013.
- [11] H. Kim and S. Sultana, “The impacts of high-speed rail extensions on accessibility and spatial equity changes in south korea from 2004 to 2018,” *Journal of Transport Geography*, vol. 45, pp. 48–61, 2015.
- [12] R. Camporeale, L. Caggiani, and M. Ottomanelli, “Modeling horizontal and vertical equity in the public transport design problem: A case study,” *Transportation Research Part A: Policy and Practice*, vol. 125, pp. 184–206, 2019.
- [13] T. Litman, “Evaluating transportation equity,” 2021.
- [14] K. Martens, J. Bastiaanssen, and K. Lucas, “Measuring transport equity: Key components, framings and metrics,” in *Measuring Transport Equity*, K. Lucas, K. Martens, F. Di Ciommo, and A. Dupont-Kieffer, Eds. Elsevier, 2019, pp. 13–36.
- [15] A. El-Geneidy, D. Levinson, E. Diab, G. Boisjoly, D. Verbich, and C. Loong, “The cost of equity: Assessing transit accessibility and social disparity using total travel cost,” *Transportation Research Part A: Policy and Practice*, vol. 91, pp. 302–316, 2016.
- [16] T. Schwanen, “Inequalities in everyday urban mobility,” University of Oxford, Tech. Rep. 09, February 2022.
- [17] A. Sen, *The idea of justice*. Cambridge, Mass: Belknap Press of Harvard Univ. Press, 2009.

- [18] M. Givoni, J. MacMillen, D. Banister, and E. Feitelson, “From policy measures to policy packages,” *Transport Reviews*, vol. 30, no. 3, pp. 345–359, 2010.
- [19] K. Kotilainen, P. Aalto, and J. Valta, “From path dependence to policy mixes for nordic electric mobility,” *Energy Policy*, vol. 147, p. 111848, 2020.
- [20] O. Sarmiento, A. Díaz del Castillo, C. Triana, S. Gonzalez, M. Pratt, T. Schmid, and G. Stierling, “Reclaiming the streets for people: Insights from ciclovías recreativas in latin america,” *Preventive Medicine*, vol. 103, pp. S34–S40, 2017.
- [21] C. Mejia-Arbelaez, O. Sarmiento, R. Mora Vega, and M. Pratt, “Social inclusion and physical activity in ciclovía recreativa programs in latin america,” *International Journal of Environmental Research and Public Health*, vol. 14, no. 10, p. E1164, 2017.
- [22] O. Cats, Y. Susilo, and T. Reimal, “The prospects of fare-free public transport: Evidence from tallinn,” *Transport Policy*, vol. 45, pp. 33–44, 2020.
- [23] W. Kębłowski, “Why (not) abolish fares? exploring the global geography of fare-free public transport,” *Transportation*, vol. 46, no. 4, pp. 1051–1069, 2019.
- [24] C. Venter, G. Jennings, D. Hidalgo, and A. Valderrama Pineda, “The equity impacts of bus rapid transit: A review of the evidence,” *International Journal of Sustainable Transportation*, vol. 12, no. 2, pp. 140–152, 2018.
- [25] D. Ehebrecht, D. Heinrichs, and B. Lenz, “Motorcycle-taxis in sub-saharan africa: Current knowledge, policy challenges and the role of regulation,” *Transport Policy*, vol. 35, pp. 124–131, 2014.
- [26] K. Chatterjee, “A comparative evaluation of large-scale personal travel planning projects in england,” *Transport Policy*, vol. 16, no. 5, pp. 293–305, 2010.
- [27] S. Tørnblad, S. Kallbekken, and K. Korneliussen, “Using mobility management to reduce private car use: Results from a large-scale personal travel planning program in norway,” *Transportation Research Part D: Transport and Environment*, vol. 31, pp. 148–153, 2014.
- [28] Jennifer Dill, Ph.D., “Measuring network connectivity for bicycling and walking,” <http://reconnectingamerica.org/assets/Uploads/TRB2004-001550.pdf>, note = Accessed: 2025-05-05, 2004.
- [29] London Government, “Public transport accessibility levels,” <https://data.london.gov.uk/dataset/public-transport-accessibility-levels>, note = Accessed: 2025-05-05, 2017.
- [30] Comune di Milano, “Redditi e variabili irpef su base sub comunale 2023 (a.i. 2022),” <https://dati.comune.milano.it/dataset/ds2734-redditi-e-variabili-irpef-su-base-sub-comunale-2023-a-i-2022>, 2023, accessed: 2025-05-05.