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Three-dimensional transport poverty and its socio-demographic and urban density predictors: Spatial regression analyses of neighborhoods in the Amsterdam metropolitan area

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ABSTRACT

Reducing transport poverty can improve well-being and expand employment opportunities. This study investigates the relevance of socio-demographic and urban density predictors in relation to transport poverty contributor metrics for neighborhoods in the Amsterdam metropolitan area. Utilizing a spatial econometric framework, we assess the relevance of these predictors across three dimensions of transport poverty: mobility, accessibility, and affordability. Contrary to existing literature, our findings indicate that the demographic factors of gender and younger age are not significant predictors at the neighborhood level. Furthermore, the research identified a correlation between higher urban density and transport poverty. While higher urban density is associated with decreased car ownership rates and increased accessibility, it simultaneously correlates with higher public transport costs relative to income. Additionally, the method revealed a high cumulative spatial effect of income in connection with transport affordability, indicating spatially extensive income-related transport affordability disparities. Our research offers new insights into factors related to neighborhood-level transport poverty. The observed spatial dynamics call for targeted strategies that address the unique challenges for implementing equitable transport policies in both densely populated urban areas and less urbanized regions.

1. Introduction

One of the primary objectives of transportation policy is to facilitate people's access to jobs, amenities, and social connections (Bastiaanssen and Breedijk, 2022), as inadequate access to opportunities is associated with significant individual and societal costs (United Nations, 2016).

Transport poverty arises when transport disadvantage—including elements such as expensive, unreliable, or inconvenient transportation options—is compounded by social disadvantage, where individuals or communities face socioeconomic challenges like low income, unemployment, or limited mental or physical abilities. Those already at a disadvantage due to income, health, or abilities can be further marginalized by inadequate transportation, reducing their access to jobs, education, medical care, and social networks (Lucas, 2012).

Our main contribution is determining the relevance of several distinct and commonly used socio-demographic and urban density predictors for identifying transport-poverty-susceptible neighborhoods in a more holistic manner by considering three dimensions of transport poverty in conjunction. We quantitatively evaluate their relevance using regression coefficients, significance, and cumulative spatial effects statistics obtained from standardized spatial regression analyses.

Our approach, as visualized in Fig. 1, starts with reviewing the literature to discover the relevant socio-demographic and urban density predictors to include in our analyses. In conjunction with the selection of the predictors, the methodology includes a combination of spatial regression and spatial visualization. We rely on data from a study-area-specific transportation model: socio-demographic and urban density input data, and transport poverty output data. After collecting and preprocessing the required data, we conducted standardized spatial regression analyses while eliminating any insignificant predictors through backward elimination and correcting for heteroskedasticity. Our analyses provides regression coefficients, their significance, and cumulative spatial effects results as well as spatial distributions of special interest. We discuss these results and their implications, and then discuss limitations and provide recommendations for further research.

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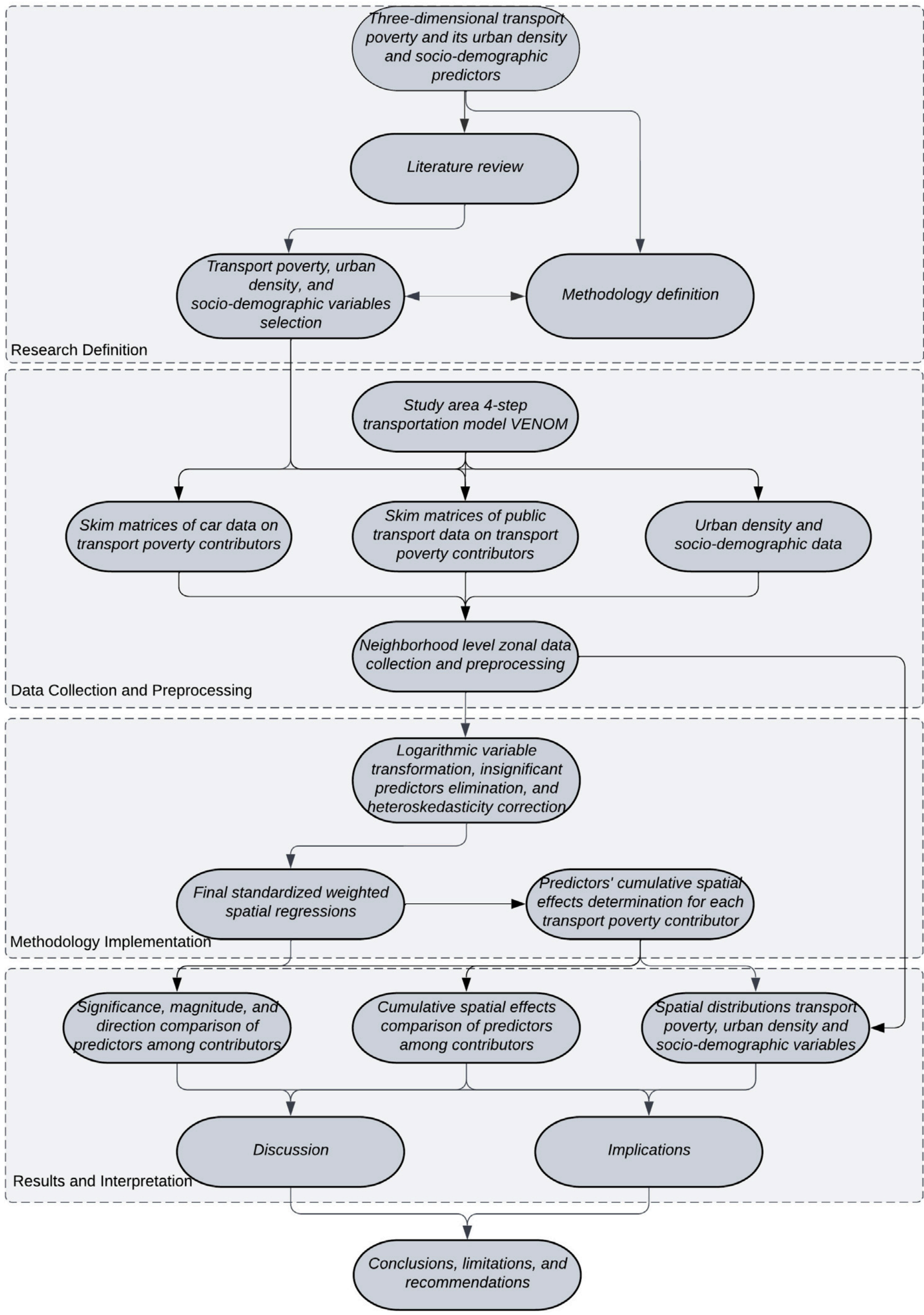


Fig. 1. Research workflow.

2. Literature review

Previous studies have extensively examined the difficulties that various population groups might experience in fulfilling their transportation needs to access jobs, amenities, and social contacts. These challenges have been described under the theoretical constructs of accessibility poverty (Martens and Bastiaanssen, 2019), transportation affordability (Fan and Huang, 2011), transport poverty (Lucas, 2012) leading to transport-related social exclusion (Church et al., 2000) or mobility-related exclusion (Kenyon et al., 2002), transport equity (Martens et al., 2019), and transportation disadvantage (Lucas, 2012), among others.

We focus on transport poverty because a higher level of transport poverty has been shown to negatively affect well-being (Awaworyi Churchill and Smyth, 2019; Awaworyi Churchill, 2020; Delbosc and Currie, 2011), employment levels (Bastiaanssen et al., 2020), and social inclusion (Luz et al., 2022). We use three of the four dimensions of transport poverty as given by Lucas et al. (2016) (see Table 1): mobility poverty, accessibility poverty, and transport affordability, with exposure to transport externalities outside the scope of this study.

In Table 1, we lay out the contributor metrics for quantifying contributions to three out of the four aspects of transport poverty (as used in Lucas et al., 2016). They include cars per household, the level of (job) accessibility, and the financial cost of accessibility relative to income, with the latter two being evaluated for both car and public transport. These metrics highlight potential sources of transport poverty: a shortage of private vehicles in a household, difficulty in accessing essential services within a reasonable time, and the inability

Table 1
A lexicon of definitions for transport poverty.
Source: Adapted from Lucas et al. (2016).

Transport poverty: a broad, overarching notion, which identifies a research/policy field and encompasses the following sub-concepts		
Notion	Definition	Contributor metric
Mobility poverty	A systemic lack of (usually motorized) transport that generates difficulties in moving, often (but not always) connected to a lack of services or infrastructures	Cars per household
Accessibility poverty	The difficulty of reaching certain key activities—such as employment, education, healthcare services, shops and so on—at reasonable time, ease and cost	Number of jobs within average trip time as a proxy for general accessibility, considering both car and public transport modes.
Transport affordability	The lack of individual/household resources to afford transportation options, typically with reference to the car (in developed countries) and/or public transport	Percentage of daily income required to cover the travel cost of a single trip needed to meet the benchmark accessibility level. This benchmark is represented by the median number of jobs (across all study area zones) that can be accessed within an average trip duration. Considering both car and public transport modes.
Exposure to transport externalities	The outcomes of disproportionate exposures to the negative effects of the transport system, such as road traffic casualties and chronic diseases and deaths from traffic related pollution. Often considered within the US literature from an environmental justice perspective	Outside of the scope

to afford access to destinations. This framework allows for analyzing transport poverty from an economic perspective; however, it is also somewhat narrow.

The reason for excluding exposure to transport externalities, such as road traffic casualties and pollution-related health issues, is due to their significant variability within neighborhoods, unlike the more consistent patterns observed in accessibility, affordability, and mobility metrics. This study focuses on these latter aspects because they provide a clearer and more uniform basis for assessing transport poverty predictor relevance across different areas, allowing for more actionable and relevant policy recommendations.

By considering only low income as a social disadvantage, the analysis may miss other elements that might contribute to transport poverty, such as education level, employment status, health conditions, and physical or digital abilities, which can also influence an individual's mobility options and needs. Additionally, transport disadvantages are not solely about ownership or costs; they also include the quality, reliability, and safety of transport modes, which the current metrics might not fully capture. Therefore, while our contributor metrics in relation to socio-demographic and urban density predictors provide a valuable structure for understanding the economic interactions between social and transport disadvantages, it is important to recognize that we are examining a segment within the broader framework of transport poverty. This examined segment is visualized in Fig. 2.

Several studies have analyzed the relevance of socio-demographic and urban density predictors in relation to transport poverty. For example, Lucas et al. (2018) use individual-level trip frequency as a proxy for transport poverty and highlight the exploratory nature of their geographically weighted regression approach rather than a robust causal analysis of transport and social disadvantage. Allen and Farber (2019) define transport poverty as the coexistence of low transit accessibility and low income, finding it most apparent in very dense, low-income neighborhoods or low-density suburban areas in Canadian cities.

Similarly, Lowans et al. (2023) find no significant association between self-reported transport poverty and demographic factors in Irish survey participants. Alonso-González et al. (2017) identify relevant socio-demographic and urban density predictors of transport affordability and accessibility poverty among Spanish households. Verhorst et al. (2023) show that the significance of socioeconomic predictors varies depending on the transport poverty definition used.

This study makes a unique contribution by analyzing and juxtaposing three separate transport poverty dimensions and their socio-demographic and urban density predictors, using objective indicators as contributors to these dimensions.

For the included set of socio-demographic and urban density predictors and their direct relation to the incorporated contributor metrics to each of the transport poverty dimensions, Table A.4 provides an overview of the available empirical evidence on their interplay. Table A.4 draws insights mainly from studies in a European, Canadian, and in particular in a Dutch setting. These studies provide quantifiable measures, differing widely in terms of statistical tools, included predictors, and considered dimensions of transport poverty, to uncover the complex relationships that exist between predictors such as household size, age distribution, and job density, and the dimensions of transport poverty used in this study—mobility, accessibility, and affordability.

3. Methodology

We evaluate the relevance of nine socio-demographic and two urban density predictors. To this end, we incorporate them as independent variables in each spatial regression analysis. The predictors are inhabitant density, job density, household size, five age cohorts (0–18, 18–34, 35–54, 55–64, and 65^+), gender, cars per household, and income.

Car ownership is often grouped with other socio-demographic predictors as a determinant of or predictor relating to transport poverty (e.g., Jomehpour Chahar Aman and Smith-Colin, 2020). However, as we have done, car ownership may be used to directly represent mobility poverty contributions as it influences available transport options. To illustrate, public transport service varies considerably throughout the day, whereas household car ownership provides much greater time flexibility. In the case of forced car ownership (Banister, 1994), car ownership may result from a lack of viable alternatives, suggesting affordability or accessibility issues for public transport options. Therefore, we use cars per household both as a predictor of contributions to mobility poverty and transport affordability and the contributor metric of mobility poverty.

Cars per household is used as a predictor in the four spatial regression analyses where cars per household is not the transport poverty contributor metric. Additionally, cars per household is the dependent variable in a spatial regression analysis where the remaining ten socio-demographic and urban density predictors form the set of predictors.

The data for our spatial regression analyses originates from the Amsterdam metropolitan area; Fig. 3 shows the constituent neighborhood zones of the study-area-specific transportation model. The socio-demographic and urban density predictors and the transport poverty contributor metrics are all computed on the level of these neighborhood zones.

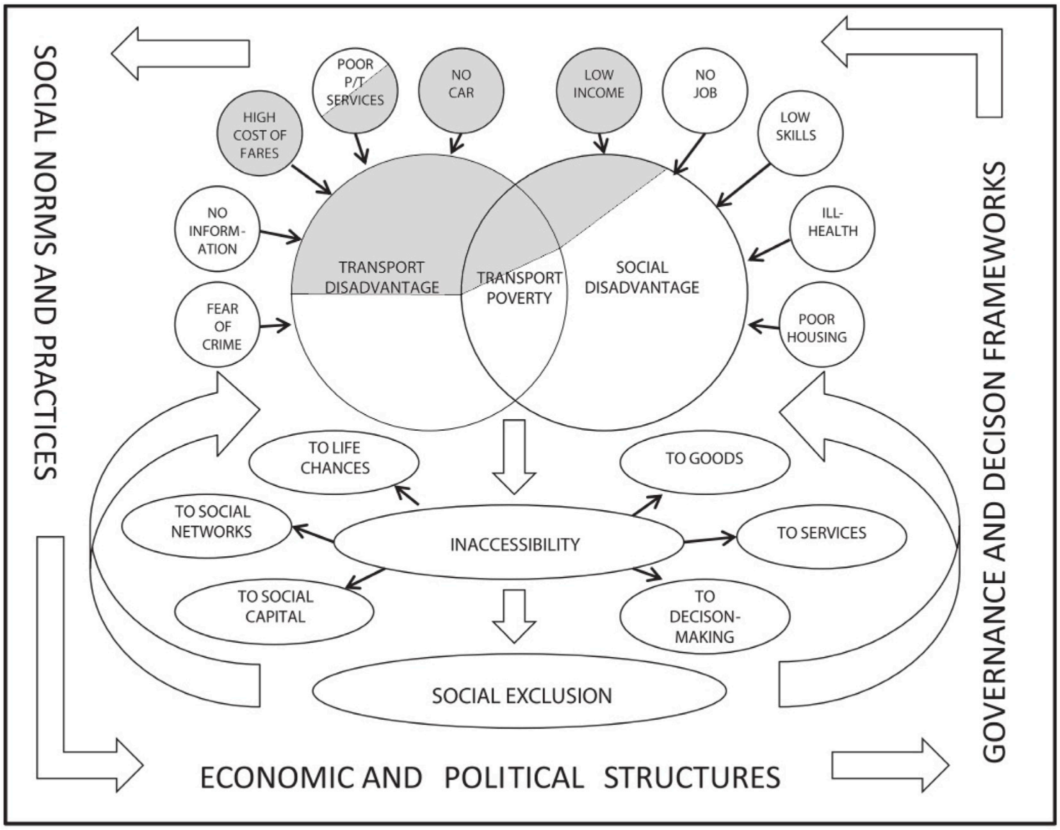


Fig. 2. Diagram to illustrate the relationship between transport disadvantage, social disadvantage, and social exclusion. The light gray shaded area depicts the focus of this study. *Source:* Adapted from Lucas (2012).

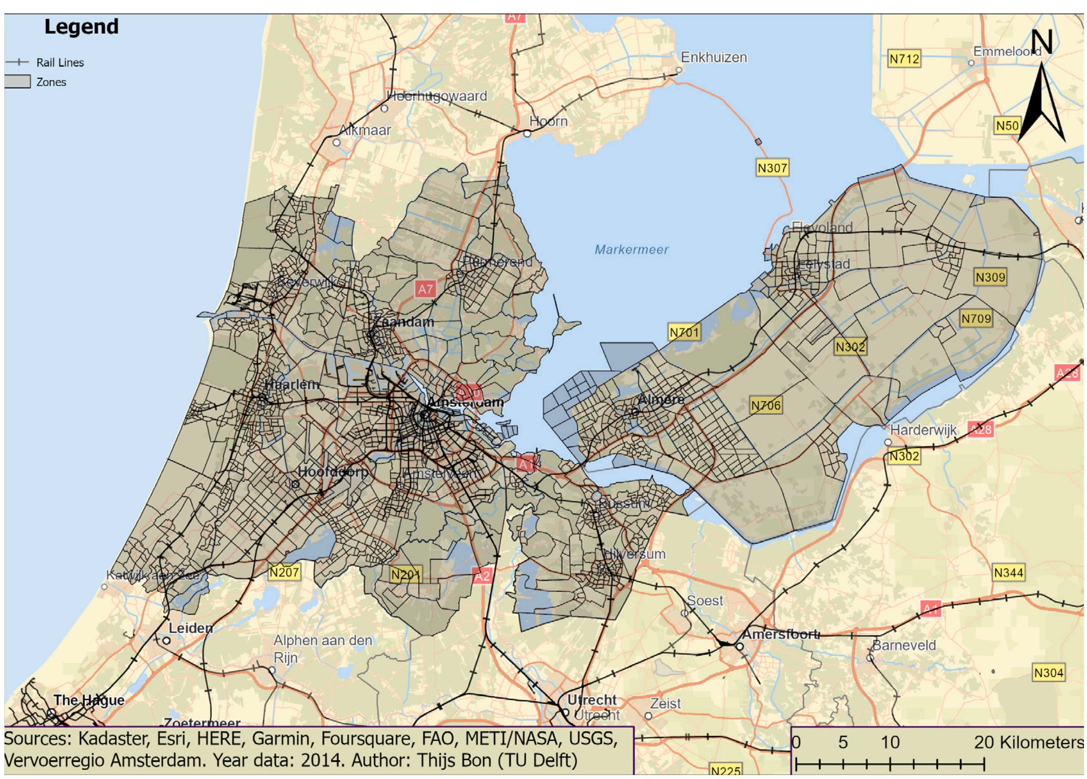


Fig. 3. Amsterdam metropolitan area neighborhood zones overview.

3.1. Transport poverty contributor metrics

The contributor metrics outlined in Table 1 provide a suitable quantitative framework to assess contributions to various facets of transport poverty, particularly by operationalizing the abstract concepts of mobility, accessibility, and affordability into measurable contributing entities.

For instance, considering cars per household as a contributing metric for mobility poverty captures the basic general level of motorized transport availability, which is a crucial factor in enabling mobility. This metric is straightforward and quantifiable, reflecting the direct connection between car ownership and the capacity to move freely, which can be representative of the overall mobility level of a household.

The number of jobs within average trip time as a contributor metric for accessibility poverty may be used to (roughly) express relative differences in general accessibility poverty, as jobs are typically distributed throughout urban areas, where other kinds of activities such as health care, shopping, leisure and social activities also typically exist, and thus access to jobs can be a reasonable indicator of overall accessibility (Martens and Bastiaanssen, 2019). Considering both car and public transport accessibility, this metric gives a rounded view of differential abilities to access essential services. While job accessibility is used as a proxy of overall accessibility, the methodology allows for this to be replaced with other forms of accessibility for researchers working with different data or different ways of measuring accessibility.

While the number of jobs in a neighborhood directly contributes to its accessibility—given that job accessibility serves as a proxy for overall accessibility—it is important to note that residents can reach many zones beyond their own within the average trip time. Therefore, the direct contribution of the number of jobs in a neighborhood to its accessibility level is limited and the neighborhood's job density remains a meaningful predictor of general accessibility.

The metric of percentage of daily income required to cover the travel cost of a single trip that would be needed to meet the benchmark median accessibility level for transport affordability directly ties the economic burden of transportation to financial capacity. By relating travel costs to daily income, it provides insights into how transport expenses weigh against other daily expenditures and the affordability of reaching essential services.

Given that affordability has been operationalized as a cost-to-income ratio, it is expected that lower incomes will correlate with reduced affordability. The relationship between income and affordability nonetheless highlights the relative importance of income in predicting transport affordability.

The car and public transport metrics for both accessibility and affordability are influenced by the average trip time. The computation of average trip times combines data on the average travel time per trip with the daily per capita trip rate for each transportation mode and includes all travel motives. We only use data from the province of North-Holland as the vast majority of the study area neighborhood zones are located in this province. We use the year 2019 to avoid the impact of COVID-19-related disruptions that persisted into 2022. The average travel times and trip rates follow from the Dutch national travel diary survey (CBS, 2023b,a) and are collected for each self-reported main mode of transport: car (driver), car (passenger), train, and bus/tram/metro. The travel times are weighted by the respective trip rates for each mode to determine a composite average trip time for car travel (29.3 min) and public transport (59.8 min).

The quantitative contributor metrics are valuable in that they offer a foundation for empirical analysis of transport poverty. They serve as tools for identifying transport-poverty-susceptible areas and can be instrumental in guiding policy decisions and targeted interventions to mitigate transport poverty. They represent a starting point that can be complemented by additional analysis for a more comprehensive understanding of transport poverty.

3.2. Spatial regression analyses

Our spatial regression analyses consist of six sequential steps. First, we evaluate the normality of each regressant's data using histograms and Jarque–Bera tests for both raw and log-transformed values, selecting the dataset with the lowest chi-squared statistic in the Jarque–Bera test for subsequent analysis. Second, all data is standardized using the standard score to impose the same scales for all variables, facilitating a meaningful comparison of standardized regression coefficients and cumulative spatial effects. Third, we perform an initial elimination of insignificant predictors through backward elimination in a non-spatial, ordinary least squares estimated standard linear regression.

Fourth, after testing for homoskedasticity using the White test (White, 1980) at a five percent significance level and rejecting it, we employ weighted least squares to effectively address the detected heteroskedasticity in the error terms. Fifth, we conduct a Moran's I test on the residuals of the backward eliminated weighted least squares model and on the original regressant values to check for spatial independence. If both tests reject spatial independence at a five percent significance level, we proceed to the final step. In this step, we estimate a Spatial Autoregressive Combined (SAC) model (Kelejian and Prucha, 1998) using the 'sacsarlm' function from the 'spatialreg' package in R (Bivand, 2023). This final estimation includes a backward elimination process, excluding any predictors that become insignificant, thus refining our model to include only spatially relevant predictors.

A range of studies have utilized spatial autoregressive models to explore (transport) poverty. Putri et al. (2018) and Pratama et al. (2021) both found significant spatial dependencies in their respective studies on poverty in Soppeng and Lampung Province, Indonesia. Lunke (2022) used a spatial Durbin model in the context of transport poverty, identifying disparities in public transport accessibility in Oslo, particularly in less affluent neighborhoods. Ayadi and Mohamed (2009) similarly highlighted the importance of considering neighborhood effects and spatial heterogeneity in the analysis of poverty in Tunisia. These studies collectively underscore the value of spatial autoregressive models in understanding (transport) poverty.

While spatial autoregressive models offer significant advantages in capturing spatial dependencies, they also present several challenges. One notable disadvantage is the complexity of model estimation and interpretation. The inclusion of spatial lag terms and spatial error structures requires sophisticated computational techniques and a deep understanding of spatial econometrics, which can be a barrier. Additionally, the spatial autoregressive models are sensitive to the specification of the spatial weight matrix, which dictates the spatial relationships among data points. Incorrectly specifying this matrix can lead to biased and inconsistent parameter estimates, undermining the validity of the model's conclusions.

The SAC model, also known as the Spatial Autoregressive Model with Autoregressive Disturbances (SARAR) (Kelejian and Prucha, 1998), is a sophisticated spatial econometric model that integrates two types of spatial dependencies: the spatial lag of the dependent variable and the spatial autocorrelation in the error terms.

This SAC model is particularly useful in transport studies to assess transport poverty dimensions. Its robustness allows for the identification of both the direct connection of various predictors in relation to the transport poverty contributor metrics and the influences arising from spatial interdependencies among regions. By taking these spatial relationships into account, the model helps to prevent potential endogeneity biases and reduce the risk of underestimating the variance in the estimates of predictor coefficients, ensuring a more accurate and reliable analysis of predictor relevance (Getis, 2010).

The SAC model can be represented as follows:

$$y = \rho W y + X\beta + \epsilon$$

$$\epsilon = \lambda W \epsilon + u,$$

where

- y is the dependent variable, representing the contributor metric of the dimension of transport poverty considered, with $n = 1704$ observations.
- ρ is the spatial autoregressive coefficient for the dependent variable, indicating the influence of the transport poverty contributor metric in neighboring locations.
- W is the spatial weights matrix, which defines the spatial structure of the data, for which we followed a first-order queen contiguity row-standardized approach. It is an $n \times n$ matrix.
- X is the matrix of predictors, with dimensions $n \times k$ where k is the number of predictors.
- β is the vector of coefficients for the predictors, quantifying the connection of each predictor with the transport poverty contributor metric. It has k elements.
- ϵ is the vector of error terms, representing unexplained variation after accounting for the effects of both the predictors and the lagged transport poverty contributor metric. It has n elements.
- λ is the spatial autoregressive coefficient for the error term, measuring the degree of spatial correlation in the error terms.
- u is a vector of white noise error terms, capturing random effects that are not spatially autocorrelated. It has n elements.

The spatial weight matrix W is constructed using a first-order queen contiguity method, ensuring each zone is connected to its neighbors based on shared boundaries or corners. This matrix is then row-standardized, equalizing the influence from each neighboring zone. Such standardization is crucial for our spatial regression analysis, as it ensures that zones with many neighbors do not disproportionately influence the results simply due to the number of connections they have (Getis, 2010).

In terms of applicability, a significant ρ coefficient suggests a spatial spillover effect in the SAC model, where the level of the transport poverty contributor metric in one area is influenced by and influences neighboring areas. This effect is particularly relevant for understanding the dynamics of gentrification and transport infrastructure improvements. For example, improved transport facilities in a gentrifying area might inadvertently elevate transport poverty in adjacent neighborhoods due to resource reallocation or increased living costs, reflecting a direct spatial dependency. This highlights the necessity of comprehensive transport planning that accounts for the effects of local developments on neighboring areas, ensuring equitable distribution of resources.

On the other hand, a significant λ coefficient indicates spatial autocorrelation in the error terms, suggesting that transport poverty is influenced by spatially structured, unobserved factors. This is crucial in contexts where historical segregation or uneven development patterns have shaped the transport infrastructure landscape. Understanding these underlying spatial processes is essential for developing targeted interventions that address the root causes of spatial inequalities.

3.2.1. Cumulative spatial effects

Cumulative or total effects in spatial econometrics (Golgher and Voss, 2015), particularly in models like the SAC model, conceptually arise from the interdependence of spatial units, without implying any causal direction. These cumulative spatial effects illustrate the correlation between changes in one area and variations in others. This means that a change observed in one location is often correlated with changes in neighboring areas and by extension in neighboring areas of neighboring areas, both directly and indirectly. Cumulative spatial effects capture the broader network of interconnections across the spatial framework, emphasizing that the overall pattern observed in the data is a result of interconnected and correlated changes across multiple locations, rather than isolated, independent events.

The computation of cumulative spatial effects is implemented in R, utilizing the 'spatialreg' package (Bivand, 2023), which facilitates the estimation of spatial econometric models. The process begins with the extraction of key coefficients from the SAC model, specifically the spatial autoregressive coefficient ρ and the spatial error coefficient λ. The coefficients β of the predictors are also retrieved. All these coefficients are crucial in determining the extent to which changes in one spatial unit can relate to others.

To compute the cumulative total effects, we construct a matrix M as follows:

$$M = (I - \rho W)^{-1}(I - \lambda W)^{-1},$$

where M is a derived $n \times n$ matrix crucial for computing cumulative spatial effects, representing the combined influence of both the spatial lag and error components of the model and thereby encapsulating the full spectrum of spatial dependencies in our analysis. I is the $n \times n$ identity matrix.

The cumulative total effect vector of length k is then calculated by multiplying the scalar mean of matrix M, the coefficients of the predictors β, and the number of observations n. Mathematically, it is represented as:

$$CumulativeTotalEffect = mean(M)\ \beta\ n.$$

The SAC model offers an aggregated view of spatial interactions, which is crucial for understanding how changes in one area are connected to others within a spatially interdependent context. By incorporating both spatial lags of the dependent variable and spatial autocorrelation in the error terms, the SAC model allows us to discern relationships not only at the local level but also across a broader spatial scale. For instance, it helps in identifying how a change in one region might influence adjacent areas, and how these changes can, in turn, affect further adjacent areas. This cascading effect shows how spatial factors interact and propagate through the entire study area, offering a holistic view of the interconnected spatial dynamics.

4. Data

In this section, the data are discussed, starting with the socio-demographic and urban density data and followed by the transport poverty data. The spatial resolution of both is at a neighborhood level and the data stems from the year 2014, the most recent available year. A more extensive data description is given in the more elaborate report on which this paper is based by Bon (2023).

There are 1941 neighborhood zones situated in the Amsterdam metropolitan area. After filtering out observations with incomplete data, 1704 neighborhood observations remain. Furthermore, there are 1959 zones situated outside the study area, of which 159 are located outside the Netherlands. Some of the zones outside of the study area influence the transport poverty contributor metrics within the study area, dependent on their number of jobs and travel times to the study area zones. Table 2 describes the study area neighborhood zonal data (directly or indirectly) used as input for our regression analyses.

The raw socio-demographic and urban density data consists (for each zone) of inhabitant age cohort totals, inhabitant gender (female and male) totals, total inhabitants, total number of households, area in hectares, number of jobs in seven sectors (agriculture, industry, retail, services, government, self-employed, and other), number of cars registered, and average income level. Most of the socio-demographic data originate from Statistics Netherlands. Additionally, there are some other sources and a research agency (ABF Research) made some modifications. For a complete description of this dataset see Groenemeijer et al. (2022).

Table 2
Descriptive statistics of the 1704 study area neighborhood zones.

	Mean	SD	Median	Min	Max	Description
Area	1.47	4.44	0.44	0.03	65.6	In square kilometers
Inhabitants	1.55	1.84	1.00	0.00	13.9	Number of people ($\times10^3$)
Jobs	0.77	1.42	0.30	0.00	14.5	Number of jobs ($\times10^3$)
Cars per household	1.05	0.33	1.06	0.00	2.10	Cars divided by households
PT accessible jobs	305	273	197	0.00	1241	Jobs within average trip time ($\times10^3$)
Car accessible jobs	706	279	788	85	1171	Jobs within average trip time ($\times10^3$)
PT costs-to-income	2.73	1.19	2.50	0.36	11.92	% daily income for benchmark accessibility[a]
Car costs-to-income	3.53	1.34	3.19	1.34	13.15	% daily income for benchmark accessibility[a]
Inhabitant density	3.97	4.23	3.25	0.00	27.8	Inhabitants ($\times10^3$) divided by area (km^2)
Job density	1.97	3.74	0.75	0.00	44.26	Jobs ($\times10^3$) divided by area (km^2)
Household size	2.30	1.23	2.24	1.00	36.6	inhabitants divided by households
Age 0–18	0.19	0.08	0.19	0.00	0.85	Fraction relative to all inhabitants
Age 18–34	0.20	0.13	0.18	0.00	1.00	Fraction relative to all inhabitants
Age 35–54	0.29	0.09	0.29	0.00	1.00	Fraction relative to all inhabitants
Age 55–64	0.13	0.07	0.13	0.00	1.00	Fraction relative to all inhabitants
Age 65$^+$	0.18	0.12	0.17	0.00	1.00	Fraction relative to all inhabitants
Male	0.51	0.07	0.50	0.00	1.00	Fraction relative to all inhabitants
Yearly income	38.4	9.53	37.2	11.4	101	Yearly income (€$\times10^3$) per capita

[a] The percentage of daily income required to cover the travel cost of a single trip needed to meet the benchmark accessibility level. This benchmark is represented by the median number of jobs (across all study area zones) that can be accessed within an average trip duration. PT: Public transport.

4.1. Socio-demographic data

Age, gender, income, cars per household, and household size are included as socio-demographic predictors in the regression analyses. Income is reflected by the average yearly income in Euros among the inhabitants of a zone, whereas cars per household is represented by the average number of registered passenger cars per household. For the potential relation between household size and transport poverty, we include the average household size in the analysis. A household is defined as one or more persons who provide in their livelihood for themselves as a single unit, and either share or do not share a dwelling with one or more other households (CBS, 2022).

To limit multicollinearity, we aggregate seven age cohorts into two age cohorts; all cohorts below 18 years, and all cohorts above 64 years. These ranges are chosen based on previous research, see Table A.4. We include the other three age cohorts in the raw data (18 to 34 years, 35 to 54 years, and 55 to 64 years) as separate cohorts in our analysis. For all cohorts, we use fractions relative to the total number of inhabitants of the respective neighborhood.

Regarding gender, we use the fraction of males among all inhabitants, which means that we do not account for gender and age combinations but instead focus solely on the direct correlations between transport poverty contributor metrics, and age and gender. This aggregation of all the male age cohorts allows for improved parameter estimates by limiting multicollinearity.

4.2. Urban density data

We use job density and inhabitant density to reflect the relationship between urban density and transport poverty contributor metrics at the neighborhood level. To obtain job density, we first aggregate all seven job sectors (agriculture, industry, retail, services, government, self-employed, and other) by computing the total number of jobs for each zone to limit multicollinearity. This way we can accurately determine the relationship between job density and the transport poverty contributor metrics when multiple job sectors display similar spatial distributions.

4.3. Transport poverty data

The transport poverty data consists of cars per household as a contributor metric for mobility poverty, and a separate car and public transport contributor metric for both the transport poverty dimensions of accessibility and affordability see Table 1 and Section 3.1. At the foundation of these contributor metrics lie skim matrices of travel times and travel costs between zones, and the total number of jobs attributed to each zone. The considered period for the skim matrices is a morning rush hour (7:00–9:00) on an average workday.

The skim matrices result from a traditional 4-step transportation traffic model used by transportation planners for the Amsterdam metropolitan area, see Smits (2011) for more details. The skim matrices for financial costs and travel times consist of the respective values between every zonal pair, where costs only concern single-trip costs. Since car ownership, insurance, and road taxes costs are not included, car usage costs would be higher in reality. In contrast, the single-trip public transport costs do reflect the experienced costs.

5. Results and discussion

The standardized regression coefficients of the socio-demographic and urban density predictors for each transport poverty contributor metric, as summarized in Table 3, reveal significant associations that improve our understanding of transport poverty dynamics. Fig. 4 provides an overview of the predictors' cumulative spatial effects in relation to each of the transport poverty contributor metrics.

This section is structured as follows: first, we explain the validity and explanatory power of our model, and the interpretation of its parameters. This is followed by a detailed discussion of each transport poverty contributor metric, examining their individual correlations and cumulative spatial effects while relating those to potential explanations and implications for planning strategies. Finally, we explore the overarching policy implications of our findings, particularly focusing on the impact on individuals dependent on public transport, as well as those with access to a car.

Overall, the models exhibited substantial improvements in Akaike Information Criterion (AIC) values compared to non-spatial linear models (AIC_{lm}), reinforcing the importance of accounting for spatial dependencies.

The Variance Inflation Factor (VIF) values obtained in our spatial regression models, as presented in Table 3, provide key insights into the collinearity among predictors. Generally, a VIF value greater than 5 or 10 is indicative of problematic collinearity (Akinwande et al., 2015). In our models, the highest observed VIF value is 1.72, which is well below these thresholds. This low VIF value across all predictors suggests that collinearity is not a concern in our dataset, affirming the reliability of the regression coefficients and cumulative spatial effects obtained.

The spatial coefficients ρ and λ in these models highlight the extent of spatial dependence within each transport poverty contributor metric. A significant ρ indicates spatial spillover effects, where transport poverty levels in one area are influenced by those in neighboring areas.

Table 3
Spatial regression results summary: normalized weighted spatial autoregressive combined models of the five transport poverty contributor metrics.

Dependent variable				Public transport						Car					
	Cars per household			Accessibility			Costs-to-income†			Accessibility			Costs-to-income†		
	Estimate	t value	VIF	Estimate	t value	VIF	Estimate	t value	VIF	Estimate	t value	VIF	Estimate	t value	VIF
Inhabitant density†	−0.037** (0.013)	−2.89	1.57				0.046*** (0.011)	4.19	1.14						
Job density†	−0.043*** (0.014)	−3.14	1.66	0.139*** (0.010)	14.16	1.28				0.048*** (0.009)	5.49	1.00	−0.044*** (0.007)	−6.30	1.27
Household size													−0.014* (0.006)	−2.44	1.04
Age 35–54							−0.029*** (0.008)	−3.67	1.13				−0.016*** (0.005)	−3.41	1.14
Age 55–64†				−0.027** (0.009)	−3.00	1.04									
Age 65+†							−0.023* (0.009)	−2.41	1.17	0.014* (0.007)	2.14	1.00	−0.026*** (0.005)	−4.96	1.17
Cars per household				−0.039*** (0.010)	−3.87	1.26	0.093*** (0.015)	6.03	1.65				−0.079*** (0.008)	−9.71	1.72
Yearly income†	0.152*** (0.013)	11.69	1.09				−0.634*** (0.014)	−46.28	1.50				−0.587*** (0.006)	−93.19	1.51
ρ	0.835*** (0.016)	52.19		0.835*** (0.015)	54.83		−0.191*** (0.033)	−5.76		−0.435*** (0.044)	−9.90		−0.029 (0.016)	−1.78	
λ	−0.395*** (0.053)	−7.45		−0.070 (0.053)	−1.32		0.926*** (0.009)	102.30		0.979*** (0.003)	282.55		0.946*** (0.007)	144.59	
σ^2		0.931			0.402			0.264			0.104			0.157	
AIC		5113			3637			3077			1676			2228	
AIC_{lm}		6240			5642			5711			5600			5741	

N = 1704; † Logarithmically transformed variable. Standard errors are given in brackets underneath the respective coefficient estimate.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

In contrast, a significant λ points to spatial autocorrelation in the error terms, suggesting the influence of unobserved, spatially structured factors (Kelejian and Prucha, 1998).

The variance values σ^2 in these models range from 0 to 1, with values closer to 0 indicating less error variance and thus a better model fit. Higher values, approaching 1, suggest greater variability not explained by the model. The variations in σ^2 across different models reflect the unique characteristics and challenges in modeling contributions to each dimension of transport poverty.

In our analysis, we opted to use the variance value σ^2 as an accuracy metric for the SAC model because, in the context of spatial econometrics, the interpretation of traditional goodness-of-fit metrics like R^2 and pseudo-R^2 can be problematic due to the inherent spatial dependencies and autocorrelation present in the data. These metrics are designed primarily for non-spatial regression models and do not adequately capture the spatial structure and complexity addressed by the SAC model. The σ^2 value, on the other hand, provides a direct measure of the error variance, offering a straightforward assessment of the model's ability to minimize unexplained variability in the data.

In our spatial regression models, the variance values σ^2 highlight the extent to which socio-demographic and urban density predictors, along with the spatial dependencies captured by the lags of the transport poverty contributor metric and the error term, may explain the variability in transport poverty metrics. A lower σ^2 indicates a model that effectively captures the interplay of these factors, as seen in the model for car accessibility. This suggests that the combination of chosen predictors and the spatial structure of the model adequately accounts for the factors influencing car accessibility within the study area.

On the other hand, the higher σ^2 value in the model for cars per household indicates that significant variability in car ownership remains unexplained, even after considering socio-demographic factors, urban density, and spatial dependencies. This suggests that car ownership is influenced by additional factors not captured in the model, possibly including broader socioeconomic factors than just income, such as cultural norms or personal preferences.

5.1. Mobility poverty

Fig. 5 shows the spatial distribution of car ownership across the Amsterdam metropolitan area. Areas with lower car ownership per household are predominantly centralized within the urban core, particularly in Amsterdam itself, where high urban density and diverse transport options likely influence this trend. As one moves outward from the city center, the number of cars per household appears to increase, highlighting the potential interplay between suburban or rural living and reliance on personal vehicles. This spatial pattern reflects the relationship between socio-demographic and urban density predictors, which we will further analyzed through regression coefficients and cumulative spatial effects.

As displayed in Table 3, the number of cars per household shows a negative correlation with both inhabitant and job densities, indicating an association with lower car ownership in areas of higher urban density. In contrast, a positive correlation with yearly income suggests that higher income levels are associated with increased car ownership. The positive ρ coefficient implies a spatial spillover effect, where car ownership in one area is positively influenced by that in neighboring areas. The negative λ estimate indicates that the spatial error terms are inversely correlated, suggesting a latent balancing effect where high car ownership rates in one area are associated with low values in adjacent areas and vice versa.

The regression coefficients indicate a direct relationship between densities and car ownership and the cumulative spatial effects, depicted in Fig. 4, also support this finding. The cumulative spatial effect of inhabitant density (−0.162) and job density (−0.187) in relation to cars per household reveals a broader spatial connection, where high-density areas not only directly correlate with fewer cars but also relate to surrounding areas in a similar pattern. The positive cumulative spatial effect of yearly income (0.662) reaffirms its strong spatial connection to car ownership, suggesting that this relation extends beyond immediate local areas.

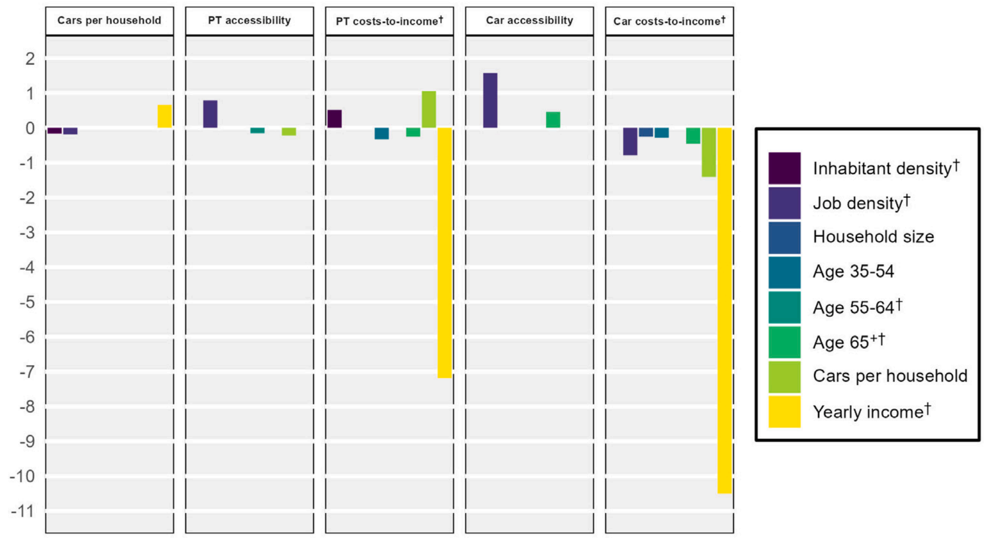


Fig. 4. Cumulative spatial effects for all transport poverty contributor metrics: normalized weighted spatial autoregressive combined models of the five transport poverty contributor metrics. † Logarithmically transformed variable.

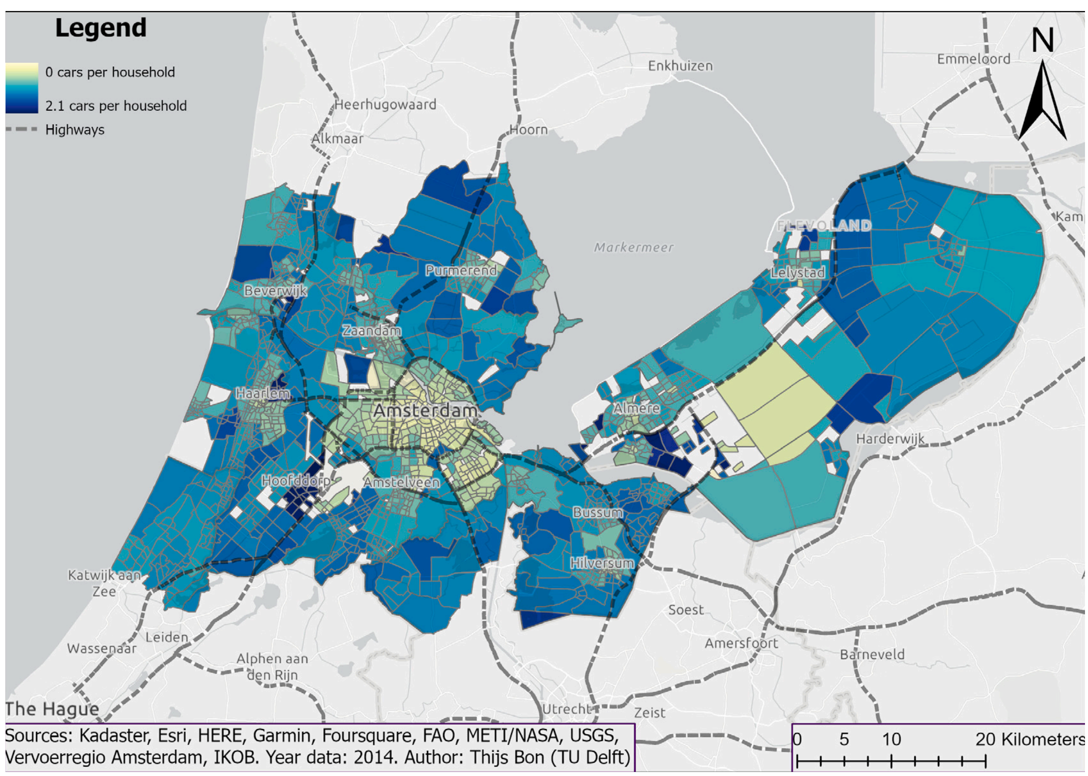
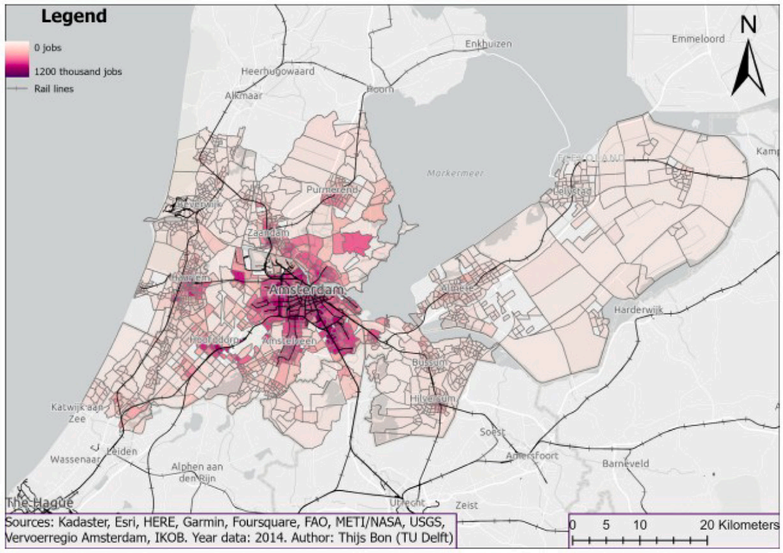


Fig. 5. Spatial distribution of cars per household.

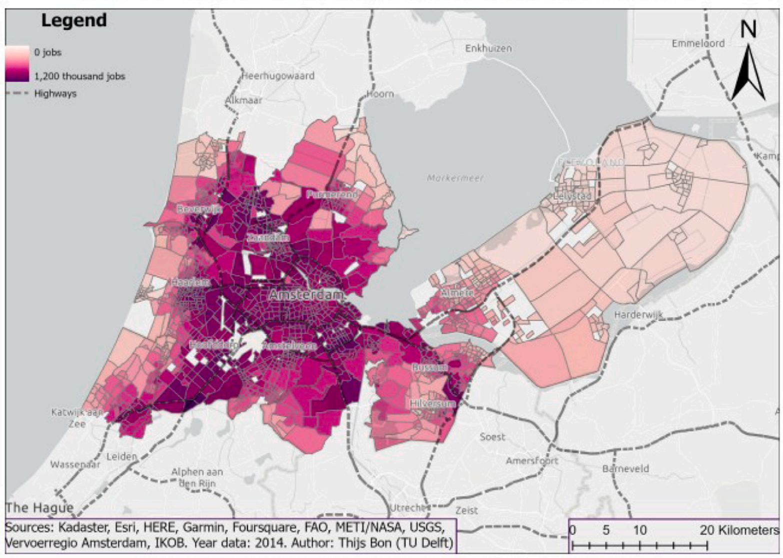
5.2. Accessibility poverty

The comparison of job accessibility (as a proxy for general accessibility) by public transport and by car, as shown in Fig. 6(a) and in Fig. 6(b) respectively, reveals contrasting spatial trends. For public transport, higher accessibility seems to be concentrated around rail lines and urban centers, underscoring the role of public transit infrastructure in destination connectivity. In contrast, car accessibility to jobs is more uniformly distributed, with less dense regions appearing to benefit from similar levels of accessibility as those near urban cores. These observations suggest differing degrees of reliance on public and private transport modes across the region, influencing how residents connect with destinations.

The high public transport accessibility levels in central urban areas, particularly Amsterdam, sharply contrast with the east of the study area. The eastern regions exhibit notably lower accessibility, likely due to their relative remoteness from major Dutch urban centers. This distance factor inevitably impacts car accessibility as well, although the effects are somewhat mitigated by the more evenly distributed nature of car accessibility, suggesting that cars may mitigate some of the geographic disadvantages faced by residents in the eastern parts.



(a) Public transport accessibility for average trip time (59.8 minutes).



(b) Car accessibility for average trip time (29.3 minutes).

Fig. 6. Spatial distributions of the number of accessible jobs within average trip time, as a proxy for general accessibility.

5.2.1. Public transport accessibility poverty

From Table 3, we note that public transport accessibility is highly positively correlated with job density, indicating that areas with a higher concentration of jobs are associated with better public transport accessibility. The positive ρ coefficient here signifies a spatial spillover effect, where an area's public transport accessibility is positively influenced by that of its neighboring areas.

The cumulative spatial effect for job density (0.787) on accessible jobs via public transport (see Fig. 4) emphasizes a wider spatial connection. This effect suggests that job density does not only positively relate to local public transport accessibility but also has a wider connection across the metropolitan area. This broader relatedness shows the importance of strategically located job centers and transport hubs in enhancing public transport efficiency. Additionally, the negative correlations of age 55–64 (−0.15) and cars per household (−0.22) with public transport accessibility indicate that areas with a higher proportion of older residents and more cars per household tend to have lower public transport accessibility. This could imply that these demographics either have less reliance on public transport or that public transport services are less prevalent in areas dominated by these groups, highlighting a potential area for policy intervention to improve accessibility.

5.2.2. Car accessibility poverty

As shown in Table 3, the correlation between car accessibility and job density is positive, suggesting that areas with more jobs are associated with better car accessibility. The negative ρ value implies that higher car accessibility in one area might be related to lower accessibility in neighboring areas , possibly due to resource allocation disparities and spatial spillover effects that divert infrastructure investments and increase congestion in adjacent regions. The positive λ coefficient, significantly high in this context, indicates that unobserved factors (e.g., historical development patterns) influencing car accessibility in one area have a similar effect on surrounding areas.

Fig. 4 highlights the positive cumulative spatial effect of job density (1.57) in relation to car-based accessibility. This strengthens the observed direct correlation and suggests a widespread connection. Not only do destination-rich areas directly relate to improved car accessibility, but they also correlate similarly to neighboring regions. This is possibly due to substantially increased accessibility that extends beyond local neighborhood boundaries.

5.3. Transport affordability

Fig. 7 reveals a varied landscape of transport affordability within the Amsterdam metropolitan area. The data shows a non-uniform distribution of transport costs relative to income; notably, residents in peripheral regions, especially in the east, encounter reduced affordability for both public transport and car use. This trend is primarily attributed to their greater distance from central urban hubs, resulting in increased travel costs to achieve the same level of accessibility found in more central locations.

While central Amsterdam shows relatively better public transport affordability, the situation is reversed when it comes to car affordability, possibly due to road congestion often encountered in highly urbanized areas. Interestingly, other urban areas apart from Amsterdam also demonstrate low affordability. These patterns are crucial for understanding the varying challenges faced across different parts of the metropolitan area and underscore the need for a differentiated approach in transport policy to address these disparities.

5.3.1. Public transport affordability

The public transport trip costs relative to income exhibit a positive correlation with inhabitant density and a strong negative correlation with yearly income, as detailed in Table 3. Additionally, there is a notable association between public transport affordability and cars per household, suggesting an interlinked dynamic between personal vehicle ownership and the economic burden of public transport. While the strong negative correlation with income partially arises from its inherent role in the costs-to-income metric, this relationship nonetheless highlights the significant relative importance of income in predicting public transport affordability. The negative ρ coefficient points to a spatial spillover effect, where areas with lower public transport affordability are contrasted by higher costs in adjacent areas, likely due to the localized concentration of public transport hubs. The significantly positive λ value suggests that factors like historical public transport development practices, impacting affordability in one area, resonate similarly in neighboring regions.

The strong negative cumulative spatial effect of yearly income (−7.19) in connection with public transport costs-to-income, as shown in Fig. 4, indicates a widespread spatial relationship. This suggests that while income is a direct predictor of transport affordability, its impact is also felt across the broader spatial network, potentially hinting at systemic economic disparities affecting public transport affordability across regions. The observed positive cumulative spatial effect of population density (0.52) suggests that higher population density areas may require higher costs to reach a certain accessibility benchmark level using public transport due to the increased demand and congestion, as well as the higher operational costs associated with maintaining and expanding public transport services in densely populated regions.

The noteworthy cumulative spatial effect of cars per household (1.05) in relation to public transport affordability reflects the trade-offs between public transport affordability and car ownership. This relationship suggests that in regions where car ownership is prevalent, public transport may be relatively less affordable. This pattern can be indicative of broader socioeconomic dynamics, where high car ownership might not always be a matter of choice but rather a necessity—termed 'forced car ownership' (Banister, 1994). This scenario often arises in areas where public transport options are limited, unreliable, or economically unviable, compelling residents to rely on personal vehicles. Consequently, this forced reliance on cars can impact the affordability of public transport, as the demand and subsequent investment in public transport infrastructure may diminish in car-dependent areas, leading to a cycle where the lack of viable public transport options perpetuates the need for personal vehicle ownership.

5.3.2. Car transport affordability

As presented in Table 3, car-related trip costs as a proportion of income show a consistent negative correlation with various sociodemographic and urban density predictors. This consistent trend across different predictors, including cars per household, job density, and particularly income, suggests that these factors are uniformly associated with a decrease in the relative financial burden of car-related expenses. Additionally, the significantly high positive λ value in the model indicates that spatially correlated, unobserved factors influence car affordability uniformly across the study area. This directionally consistent influence could be reflective of historical patterns, such as road infrastructure development, that have shaped the current landscape of car affordability.

For car-related costs relative to income, the cumulative spatial effect of job density (−0.790), cars per household (−1.41), and yearly income (−10.50), showcased in Fig. 4, brings additional insights. These figures suggest a broader spatial trend, where these predictors do not just relate to car affordability locally but also have a significant connection with surrounding areas. The extent of these effects highlights the importance of considering regional economic and urban planning strategies in improving transport affordability.

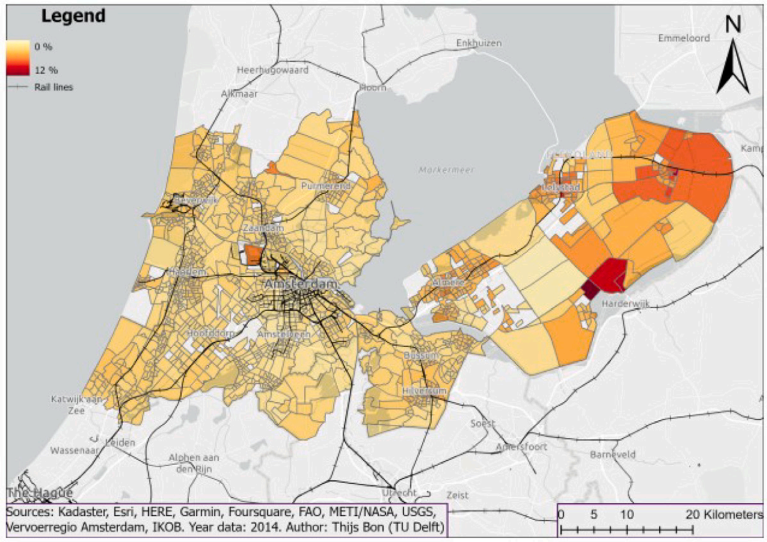
5.4. Overarching policy implications

Our analysis of mobility, accessibility, and affordability contribution dynamics within the Amsterdam metropolitan area could have direct policy implications, particularly for individuals reliant on public transport and those with access to a car. Fig. 4 provides an overview of the predictors' cumulative spatial effects in connection with each of the transport poverty contributor metrics. This summary aids in understanding the broader spatial interactions and influences, thereby guiding effective policy interventions that consider both the unique and shared challenges faced by public transport-dependent individuals and car owners.

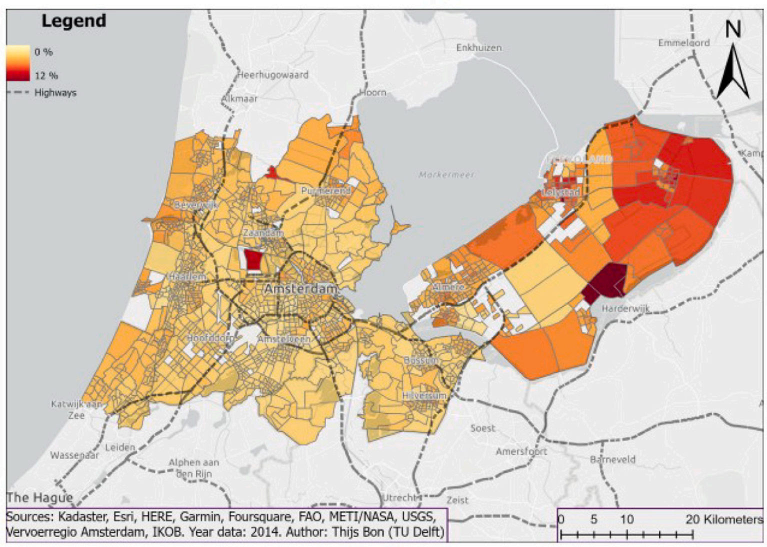
The relationship between urban density and the three transport poverty contributor metrics highlights the need for context-sensitive transport policies. Our analysis shows a clear pattern of lower car ownership in areas of higher urban density, which simultaneously display higher accessibility but lower public transport affordability levels. This suggests that policies increasing the affordability of public transport in dense urban areas are crucial for reducing transport poverty and mitigating the adverse effects of limited car access. Conversely, in suburban and rural areas where public transport options are limited, initiatives to enhance mobility might include on-demand public transport services or offering incentives for car-sharing to address the higher dependence on personal vehicles.

Income is a significant predictor of car ownership, underscoring the need for economic policies that support lower-income groups in accessing personal vehicles where absolutely necessary, and otherwise, improving public transport services and promoting active modes in economically disadvantaged areas to reduce car reliance.

In navigating the challenges of transport poverty, it is crucial to consider the adverse environmental and space use implications of increasing car reliance. While facilitating access to personal vehicles might offer immediate relief in terms of mobility, it could also result in increased emissions and air pollution from urban congestion. Conversely, while improving public transport infrastructure presents a more sustainable solution, it often faces political and practical hurdles, such as funding constraints and reliability issues. This dichotomy highlights the delicate balance required in formulating transport policies that not only address immediate mobility needs but also align with long-term environmental sustainability goals. Efforts should be directed towards creating an integrated transport system that combines the efficiency of public transit with the flexibility and reliability of personal vehicles, ensuring that solutions are both socially inclusive and environmentally responsible.



(a) Public transport



(b) Car

Fig. 7. Spatial distributions of the percentage of daily income required to cover the transport cost of a single trip needed to meet the benchmark accessibility level†. This benchmark is represented by the median number of jobs (across all study area zones) that can be accessed within an average trip duration of the respective mode, as a proxy for general accessibility.

For individuals reliant on public transport, the positive correlation of accessibility with job density highlights better service availability in job-rich, denser areas. However, the positive cumulative spatial effect of inhabitant density in connection with public transport costs relative to income suggests a direct relationship where denser urban areas face lower affordability in terms of public transport. This trend indicates a substantial burden for residents in these denser regions, where despite higher public transport accessibility, the affordability aspect is compromised. To address this, policy measures should concentrate on improving public transport affordability in these urban areas. Potential strategies could include subsidized fares, enhancing service efficiencies, or redesigning fare structures to better align with residents' income levels. Such targeted interventions would help mitigate the disproportionate economic impact of transport costs on lower-income populations in densely populated urban centers.

The spatial dynamics for car users show that while job density is strongly associated with better car accessibility, the negative spillover effect suggests a need for improved regional connectivity. This might involve developing transportation infrastructure that enhances access to employment centers from surrounding areas.

The high positive cumulative spatial effect of job density, cars per household, and income in relation to car affordability underscores the need to balance job distribution and support economic development in areas with fewer jobs. This might alleviate the financial burden of car-related expenses, particularly in regions where car dependency is high due to inadequate public transport options.

For the entire Amsterdam metropolitan area, the interplay between income level, public transport accessibility, and inhabitant density is visually mapped in Fig. 8, which illustrates transport poverty risk at the neighborhood level. It specifically highlights neighborhoods where residents are at an exceptionally high risk of transport poverty. The dark blue areas, marked by inhabitant density bars, represent zones where both public transport accessibility and income level are lowest, falling into the bottom tertile. Lower income levels correlate strongly with both lower mobility and lower affordability. Consequently, residents in these neighborhoods are presumably often dependent on

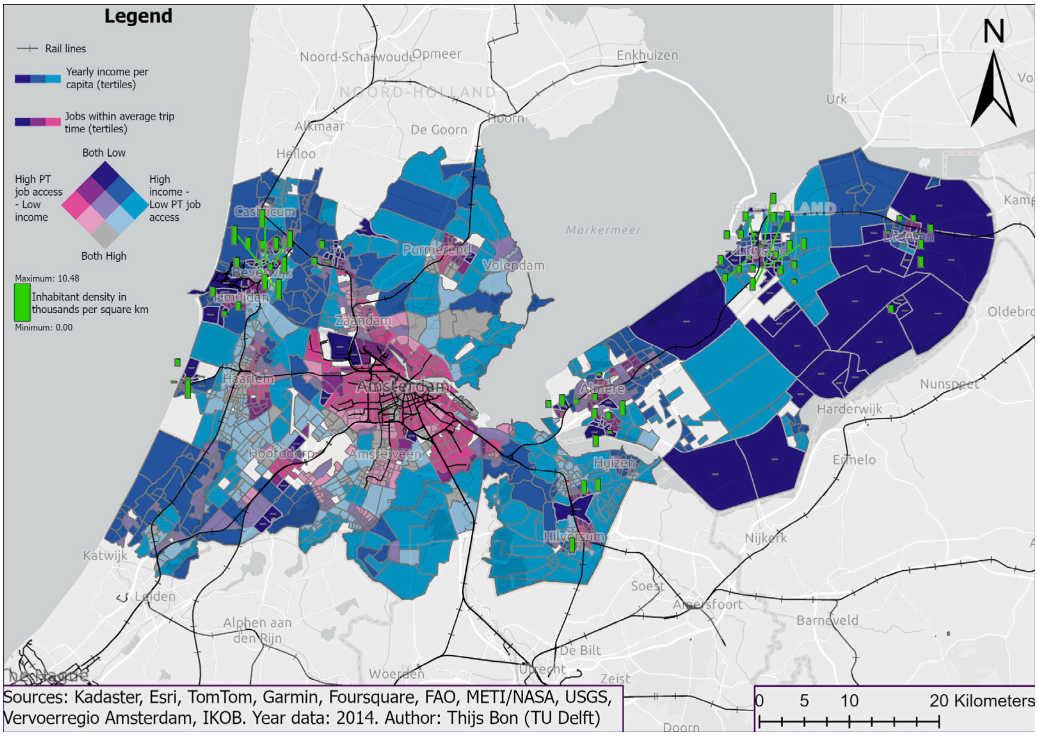


Fig. 8. Income and public transport job accessibility dual spatial distribution, and inhabitant densities of zones that fall in the lowest tertile for both income and public transport job accessibility.

affordable public transport options which provide, paradoxically, the least accessibility.

Fig. 8 underscores the urgent need for targeted policy interventions in those dark blue residential neighborhoods because of the exceptionally high risk of transport poverty along all three considered dimensions. The map suggests areas that could benefit from additional resources to ensure equitable transport opportunities for the most disadvantaged communities within the metropolitan area.

Overall, our findings suggest the need for tailored transport policies that recognize and address the distinct needs of public transport-dependent citizens and those with access to a car. For urban planners and policymakers, this involves a multifaceted approach: in densely populated areas, the focus should be on elevating both the efficiency and affordability of public transport, thereby reducing the economic burden on lower-income residents. In contrast, for less urbanized regions, while improving car accessibility and economic viability may be crucial in certain contexts, alternative strategies should also be considered because of the negative environmental and space-use consequences of increased car reliance. These alternatives may include demand-responsive public transport, encouraging carpooling or ride-sharing initiatives, and promoting sustainable transport options like cycling or walking, where feasible. By acknowledging these spatial disparities and the intricate relationships between socio-demographic factors, urban density, and neighborhood-level transport poverty contributors, policies can be more effectively targeted toward alleviating transport poverty in all its forms.

6. Conclusion

Our study's central contribution lies in determining the relevance of various socio-demographic and urban density predictors for identifying neighborhoods susceptible to transport poverty by considering three dimensions of transport poverty in conjunction—mobility, accessibility, and affordability. To this end, we used a spatial econometric framework, allowing for a more detailed understanding of how each predictor correlates with contributors to different aspects of transport poverty within a spatially interconnected context.

Surprisingly, our results indicate that the demographic factors of gender and younger age were not significant predictors of neighborhood-level transport poverty contributions, which is unexpected given the existing evidence suggesting otherwise. For instance, previous literature often emphasizes gender-specific travel behavior, with studies like Ng and Acker (2018) and Verhorst et al. (2023) highlighting differences in mode choice between men and women. Furthermore, the literature suggests that young adults have distinct mobility patterns that evolve with age (Jorritsma and Berveling, 2014; Matas et al., 2009; Prillwitz et al., 2006), yet our findings did not corroborate this as a significant factor within the context of a neighborhood-level mobility poverty contributor.

Despite significant effects observed for older age groups, it is unlikely that the effects related to younger age are being mirrored by the patterns seen in older age groups. Younger individuals may face unique challenges such as differing employment stability, education commitments, or housing insecurity, which are not entirely reflected in the experiences of older age groups. Consequently, the significant results for older age groups likely reflect different underlying factors, indicating that young-age-related effects are not being masked by older age groups in our analysis.

The finding that gender and younger age were insignificant predictors of neighborhood-level transport poverty contributions in our study area suggests that these factors may not be as universally applicable as previously thought. This underscores the importance of context-specific analyses and cautions against one-size-fits-all assumptions in transport policy.

The markedly strong positive cumulative spatial effect of yearly income in connection with public transport affordability is another particularly notable outcome of this research. It highlights the extent to which income disparities relate to transport affordability across regions, a finding that is in line with general observations from studies like Allen and Farber (2019) , Martens (2013), and Lucas et al. (2018), who discuss the pronounced transport poverty among low-income populations.

Our spatial analysis also revealed a negative cumulative spatial effect of cars per household in relation to public transport affordability, suggesting a complex dynamic where higher car ownership might negatively impact public transport affordability issues, potentially leading to forced car ownership. This supports the perspectives from Mattioli (2017) , Currie and Senbergs (2007), and Lucas (2009) on the forced reliance on cars in areas with insufficient public transport options.

The spatial distribution of cars per household across the Amsterdam metropolitan area, characterized by an increasing gradient of car ownership rates from the urban core to the periphery, aligns with previous literature (Allen and Farber, 2019; Maltha et al., 2017; Pot et al., 2023), yet our approach adds value by juxtaposing three transport poverty contributing mechanisms. Our study challenges the conventional narrative by revealing that higher urban density is associated with lower car ownership and increased accessibility, yet coupled with higher public transport costs relative to income, underscoring a complex dynamic between mobility, accessibility, and affordability in relation to urban density.

Further research could be conducted to confirm the findings with additional data and methods. Our study's reliance on correlational methods to assess the relationship between socio-demographic and urban density predictors and transport poverty dimensions, while insightful, necessitates caution in inferring causation—especially when deriving policy from a supposed causation structure. For instance, the association between cars per household and public transport affordability does not automatically imply a causal relationship in either direction. Understanding the interplay of these factors requires more intricate methodologies that can dissect causal mechanisms, such as longitudinal studies or natural experiments.

Additionally, our analysis, based on neighborhood zonal averages, potentially masks the diverse experiences of individuals within those zones. Key demographic factors like age and gender, though statistically insignificant at the neighborhood level, could be critical in understanding individual-level transport poverty. Thus, future research should focus on individual-level analyses, allowing for a more granular exploration of transport poverty, including personalized income and car availability metrics. Given that average zonal-level data is often used in transportation models, as opposed to individual-level data, the findings from this study are often helpful for identifying transport-poverty-susceptible areas in practice.

Our study's limited scope in terms of predictor selection also presents a limitation. We did not examine the interactions between predictors or include variables such as mixed land use, race, migration background, employment status, or household structure. These could be significant factors for transport poverty at the neighborhood level that other studies may choose to include.

Moreover, the generalizability of our findings is predominantly relevant to areas that mirror the rural–urban balance and car reliance of our study area. Exploring transport poverty in distinctly different contexts, like car-dependent regions in the U.S. or in economically less developed countries, could offer broader insights into the universality or specificity of our results.

Furthermore, due to the aggregated nature of our data, we do not account for heterogeneity in terms of experienced travel times and affordability measures between people residing in the same neighborhood. The transport modes that we consider are public transport and the car. We do not consider the bicycle as it was shown that this mode plays only a limited role in reducing transport poverty in the Netherlands, especially for accessing job opportunities because the bicycle is generally only used for relatively short trip distances (Martens, 2013).

Lastly, incorporating transport poverty measures that encompass subjective perceptions, outcomes, time restrictions that might result from extreme commutes or inflexible working hours (Geurs and van Wee, 2004), and transport externalities such as air and sound pollution (Lucas et al., 2016) could significantly enhance the comprehensiveness of the research. Such an expansion would provide a richer, more holistic view of transport poverty, supporting the development of inclusive and sustainable transportation policies.

In summary, our research provides a critical examination of the socio-demographic and urban density factors as predictors of contributions to transport poverty along the distinct dimensions of mobility, accessibility, and affordability. The study's results not only corroborate some aspects of the existing literature but also present new insights, particularly regarding the non-significance of certain predictors and the complex spatial interplay between income, urban density, and transport poverty contributors. These findings invite policymakers to consider more context-specific and targeted interventions that are sensitive to the specific needs and dynamics of different neighborhoods, with the ultimate aim of creating more equitable and effective transport policies.

CRediT authorship contribution statement

Thijs Bon: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Matthew Bruno:** Writing – review & editing, Supervision. **Niels van Oort:** Writing – review & editing, Supervision, Project administration.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the first author used ChatGPT-4 in order to improve the readability of sentences and paragraphs by prompting the tool to rewrite the respective texts to improve readability or understanding. After using this tool/service, the first and second author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

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

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Appendix. literature review table

See Table A.4.

Data availability

Data will be made available on request. A more extensive data description is given in the more elaborate report on which this paper is based by Bon (2023).

Table A.4
Existing evidence on the direct connections between the socio-demographic and urban density predictors and employed transport poverty dimensions.

Predictor	Transport poverty dimension*	References
Household size	Mobility, Accessibility	Household size positively influences car ownership and accounted for 35% of the total effect on car ownership among all included economic, socio-demographic, and spatial factors for the Netherlands in 2014 (Maltha et al., 2017). One of the identified key transport-disadvantaged groups in Melbourne, Australia, is described as having, among others, a higher household occupancy and a low public transit supply while being located in outer or remote areas (Currie et al., 2010).
Age 0–18 cohort proportion	Mobility, Accessibility, Affordability	Households with children or dependents are identified as vulnerable to transport poverty in 25% of the articles in a literature review, "for transport poverty, this can mean an increased requirement for journeys and, perhaps more significantly, more reliance on the car" (Simcock et al., 2021).
Age 18–34 cohort proportion	Mobility, Accessibility, Affordability	Dutch young adults use cars less frequently and focus more on bicycles and public transport. However, as they get older, their car usage increases again Jorritsma and Berveling (2014). Young adults are identified as vulnerable to transport poverty in 20% of the articles in a literature review by Simcock et al. (2021).
Age 35–54 cohort proportion	Mobility, Accessibility, Affordability	The number of cars present in a household in Barcelona and Madrid, Spain, initially increases with the age of the head of the household but peaks at the age of 35 and then slowly declines (Matas et al., 2009). Spanish household reference persons who are adults are significantly more likely to have an expenditure-(disposable)-income profile that suggests transport affordability vulnerability ($p < 0.01$) and affordability–accessibility poverty ($p < 0.01$) (Alonso-Epelde et al., 2023).
Age 55-64 cohort proportion	Mobility, Accessibility, Affordability	In Germany, the likelihood of households having more cars grows as the age of the household head increases, peaking at 23.7% for those aged between 35 and 44 years. After this peak, the percentage drops sharply, falling to below 10% for age groups over 55 years old (Prillwitz et al., 2006). Spanish household reference persons who are adults are significantly more likely to have an expenditure-(disposable)-income profile that suggests transport affordability vulnerability ($p < 0.01$) and affordability–accessibility poverty ($p < 0.01$) (Alonso-Epelde et al., 2023).
Age 65^{+} cohort proportion	Mobility, Accessibility, Affordability	One of the identified key transport-disadvantaged groups in Melbourne, Australia, is described as displaying, among others, car-based travel in general, a low to average public transit supply, and low public transit use while generally being older and retired, and located in outer or remote areas (Currie et al., 2010). Spanish household reference persons who are elderly are significantly more likely to have an expenditure-(disposable)-income profile that suggests transport affordability vulnerability ($p < 0.05$) and affordability–accessibility poverty ($p < 0.1$) (Alonso-Epelde et al., 2023).
Male proportion	Mobility, Accessibility, Affordability	The most common trend across Auckland, Dublin, Hanoi, Helsinki, Jakarta, Kuala Lumpur, Lisbon and Manila among women is that they tend to travel shorter distances and prefer public transport to cars more than men (Ng and Acker, 2018). Verhorst et al. (2023) find that Dutch males in urban areas self-report significantly higher scores on accessibility poverty and low income in accordance with the transport poverty definition by Allen and Farber (2019) and significantly higher scores on, among others, accessibility poverty, transport unaffordability, and mobility poverty as measured through a scale developed by Ettema et al. (2022).
Cars per household	Accessibility	Javaid et al. (2020) finds that only street design and accessibility are highly correlated with car use (higher accessibility relates to less car use) from a synthesis of the results from 75 review papers. Low public transport accessibility might induce car ownership (Mattioli, 2021).
Income	Mobility, Accessibility, Affordability	Income is highly positively related to car ownership in the Netherlands (Bastiaanssen and Breedijk, 2022), partly directly defines affordability, and lower-income groups often balance accessibility and mobility (car ownership) (Mattioli, 2017). Canadian low-income households face extreme commute times more often than the population average (Allen et al., 2022).
Inhabitant density	Mobility, Accessibility, Affordability	Residential self-selection in Dutch rural areas strongly relies on access to car mobility, conflicting with social inclusion accessibility planning objectives (Pot et al., 2023). Canadian neighborhoods with a high simultaneous occurrence of low transit accessibility and low income can be described as either very population-dense, low-income, tower-neighborhoods located off of the main axes of transit supply or wherever low income populations live in low population-dense suburban urban forms across the nation (Allen and Farber, 2019). Spanish households in less population-dense areas are significantly more likely to have an expenditure-(disposable)-income profile that suggests transport affordability vulnerability ($p < 0.01$) and affordability–accessibility poverty ($p < 0.01$) (Alonso-Epelde et al., 2023).
Job density	Mobility, Accessibility	For Swiss households, both population and employment densities have a negative impact on the number of owned vehicles. This negative effect grows stronger for a higher number of vehicles. While the impact on the choice to have one vehicle is relatively small, it becomes more significant when considering the choice to have two or more vehicles (van Eggermond et al., 2016). Lower address density is associated with more car ownership and accounted for 15% of the total effect on car ownership among all included economic, socio-demographic, and spatial factors for the Netherlands in 2014 (Maltha et al., 2017). Land use determines the need for spatial interaction, or transport, and transport, by the accessibility it provides, also determines spatial development (Wegener, 2004).

Mobility*: Measured by the number of cars per household.
Accessibility*: Quantified using the number of jobs within average trip time as a proxy for general accessibility, considering both car and public transport modes.
Affordability*: Determined by the percentage of daily income required to cover the travel cost of a single trip needed to meet the benchmark accessibility level. This benchmark is represented by the median number of jobs (across all study area zones) that can be accessed within an average trip duration. Considering both car and public transport modes.

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