Transportation Research Part D 128 (2024) 104087

Contents lists available at ScienceDirect

Transportation Research Part D

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

Comparing urban form influences on travel distance, car ownership, and mode choice

Peter Berrill[a,b,*], Florian Nachtigall[a,b], Aneeque Javaid[b,c], Nikola Milojevic-Dupont[a,b], Felix Wagner[a,b], Felix Creutzig[a,b]

[a] *Sustainability Economics of Human Settlements, Technische Universität Berlin, Str. des 17. Juni 145, 10623 Berlin, Germany*
[b] *Land Use, Infrastructure and Transport Working Group, Mercator Research Institute on Global Commons and Climate Change, EUREF Campus 19, Torgauer Str. 12-15, 10829 Berlin, Germany*
[c] *International Institute for Applied Systems Analysis, Schlosspl. 1, 2361 Laxenburg, Austria*

A B S T R A C T

Steady growth in global greenhouse gas emissions from transport is driven by growing demand for car travel. A sizable body of research investigates influences of urban form on travel behavior, but few European studies illustrate variation of these influences across multiple cities and countries using disaggregated data. Here, we compare car ownership and mobility patterns, and we use gradient boosting decision tree and regression models to investigate urban form influences on travel distances, vehicle ownership, and mode choice across nineteen diverse European cities. Residential proximity to the city center is the urban form feature with greatest predictive importance for trip distances, car ownership and car mode choice. The exponential reduction of car use with higher population density is clearly demonstrated with aggregate city data. We detect nonlinear relationships between urban form and modelled outcomes, identify urban form thresholds for sustainable mobility, and suggest targeted policy interventions.

1. Introduction

Global greenhouse gas (GHG) emissions from transport grew 73 % between 1990 and 2019, and constituted 27 % of 2019 energy-related emissions (Minx et al., 2021). Emissions from transport are challenging to mitigate. The sector has been singled out as a 'roadblock' to climate change mitigation (Creutzig et al., 2015), and in Europe, transport is the only sector where emissions continue to rise (European Environment Agency, 2022; Sporkmann et al., 2023). Decoupling of transport emissions from GDP in Germany and France, Europe's largest economies, has stalled or reversed since 2010 (Tsoi et al., 2021). Not all transport emissions are equally difficult to mitigate. Emissions from urban mobility, responsible for about 40 % of transport emissions (Creutzig et al., 2016), are easier to address than other transport emissions, mainly because transport modes with low emissions per passenger-km, such as active travel and public transport, are more feasible and accessible in cities. Urban areas usually have lower car mode shares (Pucher & Renne, 2005; Tao et al., 2019; Ton et al., 2020), and lower travel distances, (Holz-Rau et al., 2014; Pucher & Renne, 2005) as origins and destinations are usually closer together. Emissions from urban mobility can be reduced further by identifying and leveraging the spatial and infrastructural features of cities conducive to lower travel distances and sustainable mode choice.

Reducing GHG emissions from urban mobility brings benefits beyond climate change mitigation. Less car trips and shorter travel distances bring strong health co-benefits from reduced air pollution exposure and increased active travel (Cao et al., 2023; Stevenson et al., 2016), as shorter trips are more likely to involve active modes. Despite compelling health and environmental benefits of lowering

* Corresponding author at: Sustainability Economics of Human Settlements, Technische Universität Berlin, Str. des 17. Juni 145, 10623 Berlin, Germany.

E-mail address: peter.berrill@aya.yale.edu (P. Berrill).

https://doi.org/10.1016/j.trd.2024.104087
Received 31 August 2023; Received in revised form 19 December 2023; Accepted 22 January 2024
Available online 2 February 2024

car travel, and the greater feasibility of alternative modes in urban contexts, cars still account for the majority of distance traveled in cities worldwide (Verbavatz & Barthelemy, 2019).

Global comparisons show that European cities tend to have lower mobility energy use or emissions per capita than in other developed regions (Ewing et al., 2018; Li et al., 2019). However, there is still a lot of variation within Europe, and relatively little research explores the varying influence of urban form on mobility across European cities and countries. Our study is the first to use gradient boosting decision tree (GBDT) methods to compare effects of urban form on several mobility outcomes across multiple cities in Europe. We assemble and harmonize urban mobility survey data from nineteen cities in France, Germany, Spain, and Austria, including the capital and largest cities in each country, and a mix of small and medium-sized cities in France and Germany. The combined dataset consists of around 674,000 trips by 187,000 individuals from 107,000 households. We enrich the harmonized mobility data with descriptions of urban form generated for this study using openly available data, at the 'disaggregate' level of local administrative units used in each survey (postcode or similar). The paper addresses the following research questions, considering how the results differ between cities and countries:

1. How do aggregate measures of mode share, vehicle kilometers traveled, and car ownership rates vary with density, distance to city centers, and household income?
2. Which urban form features have important linear or nonlinear influences on car ownership, average and commute trip distances, and mode choice at disaggregate levels, and how do these influences vary across cities and countries?
3. Which demographic and trip characteristics are influential for mobility practices, and which population subgroups need additional support to enable sustainable mobility?

To address the first question, we compare and analyze correlations at city-level and local level. For the second and third questions, we use explainable machine learning and regression methods to model associations of urban form, demographic, and trip characteristics with four outcome variables – average trip distances by administrative units, individual commuting trip distance, household car ownership, and individual trip mode choice. We select these outcome variables because they together determine the energy demand and environmental impacts from urban mobility. Our findings identify policy challenges and potential solutions to promote sustainable urban mobility. The results of this study have important implications for urban areas of all sizes in Europe and other similar regions.

2. Literature review

Many studies have assessed connections between urban form (also termed 'built environment') and sustainable mobility outcomes including travel distances, mode choice, and car ownership. Researchers increasingly apply GBDT models to detect nonlinear relationships between urban form features and outcome variables. Table S1 in the Supplementary Information (SI) provides a summary of such studies. GBDT models have been used (sometimes alongside other models) to investigate urban form effects on car ownership in Beijing (Zhang et al., 2020); mode choice in the Netherlands (Hagenauer & Helbich, 2017), Delaware valley (Wang & Ross, 2018), Xiamen (Liu et al., 2021), Seoul (Kim, 2021), and Beijing (Ding et al., 2022); driving distances in Olso (Ding et al., 2018) and Berlin (Wagner et al., 2022); transit ridership in Washington DC (Ding et al., 2019); travel related CO_2 emissions in Minneapolis-St. Paul (Wu et al., 2019) and Guangzhou (Yang, 2023); and driving distances, frequency of car commuting, and car ownership in Stavanger (Tao & Næss, 2022). Distance to center is often reported as the most important urban form feature for travel distances, and travel distance is commonly the most important feature for mode choice. Urban form features found important to car ownership include distance to center, accessibility to shops, services and employment, and intersection density, while income and household size are influential sociodemographic variables (Sabouri et al., 2021; Tao & Næss, 2022; Zhang et al., 2020).

To investigate mobility patterns and influences of urban form across locations, researchers have compared aggregated city-level data from many cities (Ingvardson & Nielsen, 2018; Li et al., 2019; Newman & Kenworthy, 1989). Others have gathered results from previous studies and used *meta*-regression analysis to estimate average urban form elasticities on vehicle distance traveled (Ewing & Cervero, 2010; Stevens, 2017). Such *meta*-regression analyses have predominantly used studies of cities in the USA, and have attracted critiques of bias due to the inclusion of studies with poorly (or differently) specified models (Næss, 2022). Other studies gather consistent mobility and urban form data from multiple locations for use in a multi-city model (Christidis et al., 2022; Engebretsen et al., 2018; Ewing et al., 2015; Sabouri et al., 2021). Multi-city models have the advantage of using consistently defined urban form features and the same model specifications, addressing one concern expressed by Næss (2022). However, due to the extensive data requirements, the sample of cities is usually smaller than in *meta*-regression analyses.

Multi-city studies in Europe using disaggregated data are most comparable to the scope of this paper and are summarized in SI Table S2, alongside single-city and national level European studies. Charreire et al. (2021) modelled mode choice in five cities, and found lower likelihood of walking and using public transit in low density neighborhoods. Mertens et al. (2017) studied the same five cities, and found higher cycling rates in neighborhoods with low speed limits and more bike lanes. Christidies et al. (2022) used a GBDT approach to model increased car use during the Covid-19 pandemic in 20 European cities and found minor a importance of public transport availability and residential distance from workplace. Engebretsen et al. (2018) find high relevance of distance to center and combined density measures and a moderate influence of distance to subcenters on travel distances and car mode choice in four Norwegian cities. Tennøy et al. (2022) found a negative correlation between walking time to transit and the likelihood of traveling by transit in two Norwegian cities. Few of the studies surveyed claim to identify causal determinants of mobility outcomes. Most approaches to assess causality are based on qualitative research seeking to better understand 'transport rationales' via interviews. Such rationales (the background, motivation, and justification for transport decisions) are inferred from interview responses to explain, for example, why residents living further from city centers tend to have longer travel distances and choose car more frequently (Næss et al., 2018; Tao & Næss, 2022). Quantitative approaches revealing causal connections have been sparsely applied to urban form analysis. Wagner et al. (2023) use a causal discovery framework to discover a directed acyclical graph considered to represent causal influences between urban form and vehicle kilometers travelled.

Several research gaps become apparent when surveying the existing literature on urban form and mobility. First, as indicated by the studies in Table S1 and S2, there is little precedent for applying GBDT to investigate urban form influences on mobility outcomes across multiple locations. Christidis et al (2022) and Hagenauer & Helbich (2017) use GBDT models for multiple locations, but neither study compares location effects or illustrates linear or nonlinear urban form influences. Second, few studies use disaggregated data to assess urban form influences over several cities and countries in Europe (Charreire et al., 2021; Christidis et al., 2022; Mertens et al., 2017), and multicity studies with detailed representation of urban form mostly focus on cities in Norway (Engebretsen et al., 2018; Næss et al., 2019; Tennøy et al., 2022). Finally, the disaggregated influences of urban form on mobility outcomes have not been analyzed in any of the cities in our study except Berlin (Wagner et al., 2022). We address these gaps, using GBDT and regression models to investigate influences of urban form on trip distances, car ownership, and mode choice across nineteen diverse cities in France, Germany, Spain, and Austria. We assess which effects are consistent across the locations studied, identify differences by country and city type, and demonstrate important nonlinearities and urban form thresholds relevant to sustainable urban mobility.

3. Material and methods

3.1. Data

We gather and harmonize urban mobility surveys describing trip diaries, household characteristics, and personal characteristics from nineteen cities in Germany, France, Spain, and Austria, and enrich them with measures of local urban form calculated using open-source data. Mobility data for German cities are from the 2018 'system of representative traffic surveys' (SrV) administered by TU Dresden (Hubrich et al., 2019). French mobility surveys are accessed from the Réseau Quetelet platform (ADISP, 2022), and were carried out by local authorities with technical assistance from *CEREMA*. Mobility data from Vienna is extracted from the 'Österreich unterwegs 2013/2014′ survey (Tomschy et al., 2016). Additional Austria cities were considered, but only Vienna had sufficient disaggregate data below the city level. Mobility data for Madrid comes from the 2018 *Encuesta de Movilidad de la Comunidad de Madrid* (EDM2018) (Consorcio Regional de Transportes de Madrid, 2019).

Although many common variables are gathered in each survey, some important variables, such as household income, are only available in certain cities. In Table 1 we describe the survey and urban form variables used. Table 2 summarizes trip distances, mode

Table 1
Household, personal, trip, and urban form features used in models.

Features	Description
<u>Household Characteristics</u>	
Residential location	Local administrative unit
Household Size	Number of members per household
Household Monthly Income	In income bands which vary across surveys
Household Vehicle Ownership*	For cars, bicycles, and motorbikes/mopeds
Household Weight	Weighting factor by household (not used as a model feature)
<u>Personal Characteristics</u>	
Age	Numeric
Sex	Male; Female
Occupation	Categorical, harmonized
Education	Categorical, harmonized
Person Weight	Weighting factor by person (not used as a model feature)
<u>Trip Characteristics</u>	
Trip Distance*	Reported or measured trip distance in km
Mode Choice*	Categorical, aggregated to five modes: walk, bike, car, public transit, motorbike/moped/scooter (2–3 wheel)
Origin/Destination Purpose	Categorical. Aggregated to: Home, Work, School, Companion, Shopping, Personal, Other
Origin/Destination location	Local administrative unit
Season	Defined by month, Spring starting March 1, etc.
Trip Weight	Weighting factor by trip (not used as a model feature)
<u>Urban Form Features</u>	*Calculated per local administrative unit unless stated otherwise*
Distance to City Centre	City centers manually defined for each city, distance measured in km
Distance to Closest Subcenter	City subcenters identified as described in methods, distance measured in km
Population Density	Residents per urban land area in per/ha (=0.01 * per/km^2)
Built-up Density	Building volume per urban land area m^3/m^2
Street Intersection Density	Number of street intersections per land area N/km^2, within 1.25 km buffer of spatial unit centroid
Average Street Length	Mean length of all streets (m)
Cycle lane share	Ratio of length of cycle lanes to length of motor traffic lanes, within 1.25 km buffer of spatial unit centroid
Transit accessibility	Departures per minute in a postcode, weighted by distance of population to transit stations
Land-use Mix	Summarized to % commercial, % urban fabric

*modelled outcome variables.

choice, and car ownership for the cities studied. Section 2 of the SI summarizes the spatial units used for each city, the city spatial boundaries, and the size distribution of spatial units. Spatial extents of cities were defined for each city based on available survey official city boundaries, including medium/high-density peripheries within commuting distance where possible. Ten variables common to all cities are used to describe urban form features. Summary values of each metric are shown in SI Table S4. A detailed description of urban form feature estimates including all relevant data sources and methods is given in section 3 of the SI.

3.2. Methods

We first compare summary correlations of metrics of interest (mode share, car ownership, daily car travel) with density and household income at city-aggregate and disaggregated resolutions. We then use disaggregated data to model four outcome variables using GBDT models and regression methods: average trip distance per residential postcode, individual trip distance for commute trips (home to work and work to home), car ownership per household, and mode choice for trips starting at home. We only use features which are consistently available across all cities (Table 1). For models of car ownership, we only include cities which have household income data. In our average trip distance model, we examine how urban form and summary statistics of age and trip purpose influence average trip distance per spatial unit, averaging trip distances based on residential location, as that is a primary determinant of overall travel demand (Næss et al., 2018; Srinivasan & Ferreira, 2002). The model explores how urban form at the residential location affects all trips, including those that do not start or finish at home. To investigate influences of a larger set of variables (including household and personal features) on individual trip distances, we model individual commute trips, which are generally the longest distance trips (Fig. S7). We restricted trip distance models to trips longer than 50 m and shorter than 50 km. We exclude the features ‘Cycle lane share’ and ‘Transit accessibility’ from models of trip distance, as we do not consider there to be a direct relationship between these variables and trip distance. We test for correlation and variance inflation factor of each urban form feature and remove correlated features where necessary to make the interpretation of model results more reliable (c.f. SI Section 5).

GBDT models are estimated using the *XGBoost* python library (Chen & Guestrin, 2016), and regression models are specified using the *statsmodels* library (Seabold & Perktold, 2010). GBDT models are well suited to our analysis as they can detect non-linear dependencies (Ding et al., 2019), their predictions are robust to multicollinearity of input features (Ding et al., 2018), and they can identify local variations in urban form influences (i.e., how an urban form feature influences the target variable at different locations in a city) (Wagner et al., 2022). Regression models provide estimates of the size and statistical significance of linear effects, which is useful for hypothesis testing and assessing linear relationships. To facilitate easier comparison of model results, we estimate individual models for the four largest and capital cities (Berlin, Paris, Madrid, and Vienna) and combined models for small and medium-sized cities in Germany and France, hereafter referred to as ‘rest of Germany’ and ‘rest of France’. We also run models with pooled data for all cities, enabling estimation of country effects. In the pooled models, distance to center is calculated as percentage of mean for each city, as the variation of travel behaviors with distance to center can vary substantially by city size.

Feature contributions to GBDT model predictions are assessed using Shapley additive explanation (SHAP) values (Lundberg et al., 2020), which estimate the local influence of a feature on model outcomes for every observation in the data. Overall feature importance is calculated by summing absolute SHAP values for each feature and observation, while local explainability scatter and line plots

Table 2
Household, personal, trip, and urban form features collected for each city and city groupings.

City	Year	Avg. trip dist. (km)		Avg. daily km/cap		Mode share (dist. weighted)					HH. car ownership
		Commute	*All trips*	*All trips*	*Car*	*Car*	*2–3 W*	*Bike*	*Foot*	*Transit*	
Berlin	2018	10.2	5.2	15.1	6.2	41 %	1 %	12 %	5 %	41 %	57 %
Dresden	2018	8.2	4.4	13.4	7.6	57 %	1 %	14 %	5 %	23 %	71 %
Düsseldorf	2018	11.1	5.5	16.2	9.7	60 %	1 %	9 %	4 %	26 %	72 %
Frankfurt	2018	9.7	5.2	15.3	8.7	57 %	1 %	11 %	5 %	26 %	74 %
Kassel	2018	8.2	4.2	13.4	8.5	63 %	0 %	9 %	7 %	20 %	73 %
Leipzig	2018	9.1	4.7	14.0	8.3	59 %	1 %	12 %	5 %	22 %	63 %
Magdeburg	2018	7.3	4.3	13.1	8.8	67 %	0 %	12 %	6 %	15 %	72 %
Potsdam	2018	14.8	6.7	19.0	9.7	51 %	0 %	10 %	3 %	36 %	70 %
DE, other	2018	9.9	5.0	15.0	8.9	59 %	1 %	11 %	5 %	24 %	71 %
Clermont	2012	7.5	4.4	17.4	14.4	82 %	1 %	1 %	6 %	10 %	81 %
Dijon	2016	6.6	4.0	14.5	11.0	76 %	0 %	1 %	6 %	16 %	77 %
Lille	2016	10.4	5.1	20.3	15.9	78 %	0 %	1 %	4 %	16 %	74 %
Lyon	2015	9.2	4.9	16.5	10.7	65 %	1 %	1 %	6 %	27 %	71 %
Montpellier	2014	8.2	4.5	16.8	12.6	75 %	2 %	2 %	5 %	16 %	78 %
Nantes	2015	9.1	4.9	20.1	15.1	75 %	1 %	2 %	4 %	18 %	82 %
Nimes	2015	7.5	3.8	12.3	9.7	79 %	1 %	1 %	9 %	10 %	74 %
Paris	2010	7.5	3.3	11.7	4.7	40 %	3 %	1 %	6 %	50 %	61 %
Toulouse	2013	10.2	5.8	20.3	15.2	75 %	2 %	1 %	3 %	19 %	82 %
FR, other	~	9.3	5.0	17.1	12.7	74 %	1 %	1 %	5 %	19 %	78 %
Madrid	2018	8.9	5.1	13.1	7.2	55 %	1 %	0 %	5 %	39 %	71 %
Vienna	2014	10.2	7.0	20.9	10.1	48 %	1 %	2 %	4 %	44 %	66 %

HH. car owners. = Household car ownership. Includes presence of company cars in household. 2–3 W = 2/3 wheelers. DE, other = rest of Germany, FR, other = rest of France.

visualize the relationship between feature values and predicted outcomes. An advantage of SHAP values for explaining model results is that we can estimate and visualize how the influence of a feature varies across the distribution of values of that feature, facilitating detection of nonlinear influences and spatial variation of influences.

Model accuracy scores are calculated for all models using cross validation algorithms, and these are summarized in SI Table S7. In cross validation, a 'fold' is a random subsample of the entire data selected as a test set, and the remainder of the sample serves as the training set. The model is run on the training set, and its accuracy (r^2 for regression, F1-score for classification) is calculated based on the actual vs predicted values of the outcome variable in the test set. This is repeated for k unique folds until all the data has been used as training data, with the number k set by the modeler. For models of average trip distance, we use repeated k-fold cross validation for the average trip distance model with 5 folds and 10 repeats. Repeating the cross validation with (randomly) different folds helps to improve robustness of results, and we do this for the average trip distance models due to the lower sample sizes involved (Table S8). For car ownership we used k-fold cross validation with 9 folds, and for trip level models of mode choice and commute trip distance we used grouped k-fold cross validation with 9 folds and grouping by person. The grouped k-fold approach helps to mitigate against hierarchical data leakage (e.g. where trips by persons within the same household can be influenced by household characteristics beyond those captured in the modeled features) (Hillel et al., 2021). Using this for the mode choice and commute trip distance models ensures that different trips by the same person are never present in both training and test data. Feature importance (SHAP) values are estimated as the mean SHAP value for each observation across all validation folds. We used a grid search method to identify hyper-parameters which gave the best model accuracy, varying the number of estimators, maximum tree depth, and learning rate.

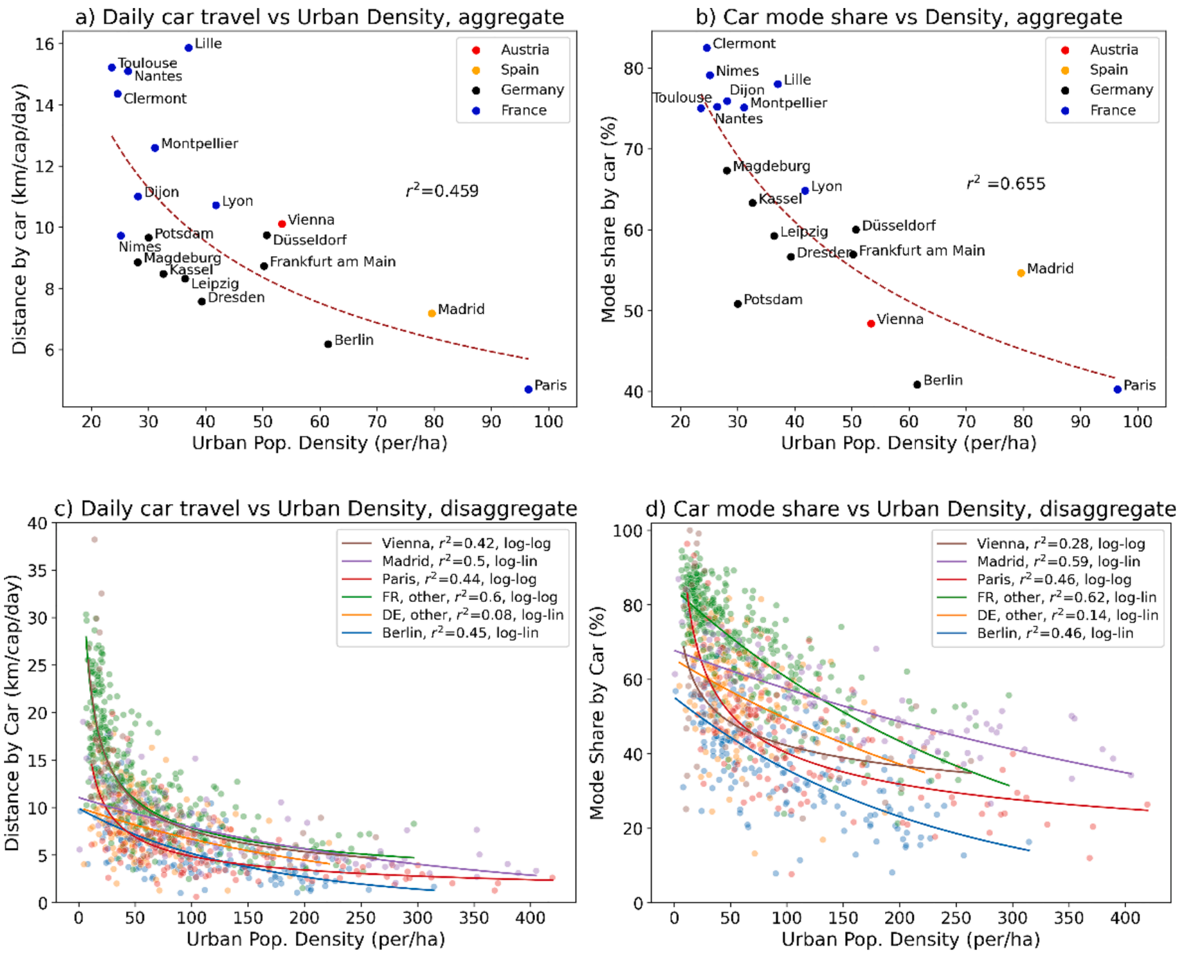

Fig. 1. Variation of daily car travel per person and car mode share vs population density, (a-b) at aggregate level (one data point per city) and (c-d) disaggregate level (one data point per postcode or similar spatial unit). Exponential decay curves are shown for all relationships, log–log for aggregate figures, and either log–log or log-lin for disaggregate figures, whichever has a better fit. Coefficients of determination (r^2) are shown within the panel in Fig. 1a-b, and in the legend for each city/grouping in the legend of Figure c-d, along with the model type.

3.3. Limitations

Several limitations apply to our analysis. The identified effects from GBDT and statistical models do not imply causality, so interpretation of effects must consider whether an underlying causal mechanism might exist. One barrier to distinguishing causal relationships and spurious correlations in mobility data is residential self-selection, where households may decide to locate in areas that support their mobility preferences (Stevens, 2017). A lively debate exists on this topic (Cao, 2014; Naess, 2014). Several studies suggest that the magnitude and relevance of self-selection effects may be overstated for several reasons, including the higher relevance of criteria other than mobility preferences when choosing residential location (Chatman, 2014; Wolday et al., 2018). Our models include income and demographic variables when applicable, which represent some of the socioeconomic drivers of residential location (Ding et al., 2018). Causality of urban form features is discussed further in the Interpretation section. The modelled feature effects can be affected by inter-feature correlations, which we take some steps to mitigate (c.f. Methods and SI Section 5).

The mobility surveys are not all collected in the same year (Table 2). Although the German cities and Madrid refer to 2018, the surveys from Vienna and French cities range from 2010 to 2016. While we strive to collect urban form features which match the year of the city survey as best as we can, it is possible that omitted variables which fluctuate with time and place (e.g. fuel prices) account for some of the variation between cities. Further, differences in survey collection methods and sampling approaches could influence survey responses, but we are unable to assess the magnitude of this potential effect. Other differences including historical urban development, or cultural influences on urban development and mobility practices, are outside the scope of our formal analysis. We highlight areas where we think local culture may be relevant when interpreting our results.

Some relevant aspects of urban form are excluded here (e.g., road widths and grade, parking availability and cost), as it was not possible to obtain consistent metrics for all cities due to data availability. Studies on fewer cities may allow more comprehensive consideration of urban form, including additional features. The modifiable unit area problem can affect our results, both on the city aggregate scale and for disaggregated spatial units. We address this at a disaggregated scale by calculating urban form features based on buffers around central points where appropriate. Finally, in our classification models for car ownership and mode choice the data are not well balanced – in some cities car ownership is very high and bike trips are a very low share of all trips (Table 2), leading bike trips to have low prediction accuracy.

4. Results

4.1. Comparison of car use, mode shares, and car ownership

Substantial differences in daily travel, car use, and mode shares are evident across the cities studied. Daily car travel per person ranges from 5 km/cap/day in Paris to 16 km/cap/day in Lille (Table 2, Fig. 1a), and car mode shares range from 40 % in Paris to 82 % in Clermont (Table 1, Fig. 1b). The exponential decline of transport energy use with increasing aggregate population density was famously demonstrated by Newman and Kenworthy (1989). Ewing et al. (2018) argued that density tends to be more relevant using aggregate data than disaggregate data, but that both resolutions have useful applications. In our sample, a log–log model of daily car travel vs population density is quite effective at capturing the exponential relationship at aggregate city level ($r^2 = 0.46$, Fig. 1a). Similar models (log–log or log-lin depending on which has the better fit) using disaggregated data generally perform well. Only the pooled data for rest of Germany has a low accuracy (Fig. 1c). A log-log models of car mode share vs population density shows a very good fit with aggregate city data ($r^2 = 0.66$, Fig. 1b), and log–log or log-lin models show a wide range of fits by city/region ($r^2 = 0.14$ –

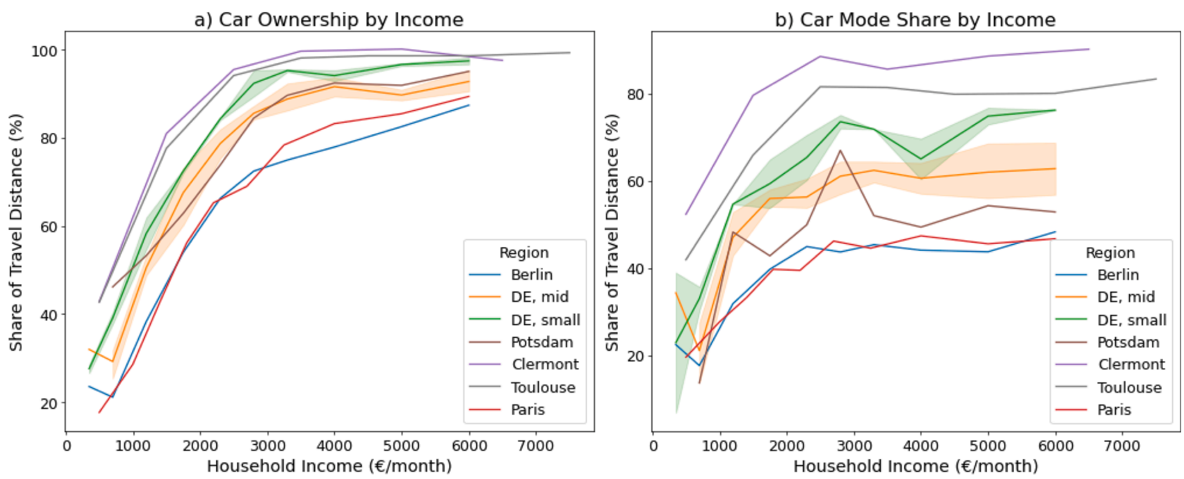

Fig. 2. A) car ownership and b) car mode share vs household monthly income for cities with income data. 'DE, mid' refers to mid-sized german cities (frankfurt, dusseldorf, leipzig, and dresden). 'DE, small' refers to small german cities (kassel and magdeburg). potsdam is a small german city, but is plotted separately as the data for potsdam differ considerably from kassel and magdeburg.

0.62, Fig. 1d). Country effects appear strong - German cities have consistently lower car travel and car mode shares at given density levels (Fig. 1a,b, Fig. S4).

We plot daily car travel and mode share against distance to city center using disaggregated data, and linear models are better are capturing this relationship. Both car travel and mode share increase approximately linearly with distance to city center, with wide variation in slopes (Fig. S5, Table S5). In Paris, living 1 km further from the city center correlates with a linear increase of 0.52 km in daily car travel, but such increases are much higher in other French cities (1.09 km increase) and Vienna (1.46 km increase). For mode share, living an additional 1 km from the city center correlates with an increase of 1.8 – 2.4 percentage points in car mode share, except for Madrid, where a weaker increase of 1.1 percentage points is observed. Car travel and mode share are less sensitive to density and distance to center in Madrid than in other cities assessed, possibly due to the polycentric structure of Madrid (Fig. S2). Variation in mobility practices within and across cities cannot be explained just by population density and spatial distribution (Ewing et al., 2018). Local contexts including prices, policies, mode-specific infrastructure, culturally rooted attitudes all play some role (Javaid et al., 2020). Cultural and other non-infrastructural factors and policies may explain some of the apparent country effects (such as German cities having systematically higher bikeshares and lower car shares (Buehler et al., 2017)).

Car ownership is a key variable for understanding and predicting mobility patterns (Sabouri et al., 2021), and a Gompertz sigmoid (S-shaped) relationship is usually observed between car ownership and income (Dargay et al., 2007). We observe sigmoid relationships of car ownership and mode share with income in all cities where income data was collected (German cities, Paris, Clermont, and Toulouse), but the saturation rates differ by country and city size (Fig. 2). Car ownership and mode share tend to saturate or grow much slower above household incomes of 2,500–3,000 €/month. Car ownership and particularly mode share saturate at considerably lower levels in Berlin and Paris compared to smaller cities. Within Germany, ‘small’ cities (Kassel and Magdeburg) have higher car ownership and mode shares than ‘medium’ cities (Frankfurt, Düsseldorf, Leipzig, and Dresden). Potsdam is a small city, but perhaps due to its proximity to Berlin, its car ownership and mode share trends are comparable to medium-sized German cities. The growth of car ownership and mode share with income is very similar in Berlin and Paris (Fig. 2). Between countries, car ownership and mode share at

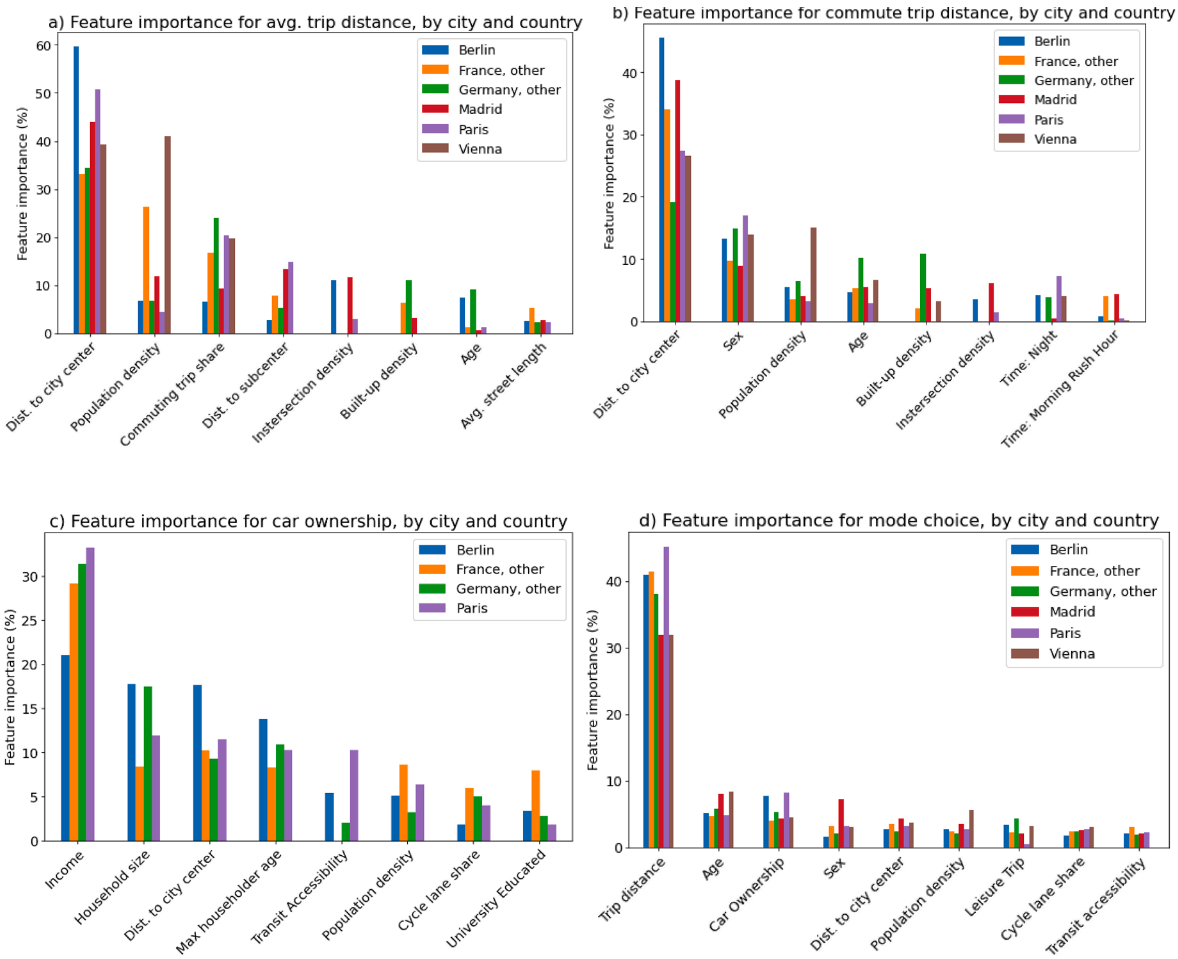

Fig. 3. Ranking of feature importance from models of a) average trip distance, b) commute trip distance, c) car ownership, and d) trip mode choice. Feature importance is calculated as mean absolute influence on model predictions. Some features have 0 importance because they were excluded from models due to correlation issues (SI Section 5).

each income level are higher for French cities compared to similarly sized German cities, although the small number of cities hinders the generalizability of this finding to the country level. At incomes of 2,500 €/month, 95 % of households in Clermont own a car, and 88 % of p-km traveled are by car. At similar incomes in Magdeburg (comparable to Clermont in size and density), 86 % of households own a car, and cars fulfill 73 % of p-km traveled.

4.2. Overall model summaries

To summarize the importance of urban form and other features for each outcome, Fig. 3 demonstrates the contribution of the most important features (those with greatest influence on model predictions) in GBDT models in different locations. Distance to city center emerges as the urban form feature of greatest importance to each outcome variable, followed by population density. Distance to center is the most important of all features (urban form or other) for average and commute trip distances (Fig. 3a,b). Distance to subcenters is important for average trip distances in Madrid and Paris, possibly due to more polycentric urban forms. Distance to center is highly relevant for car ownership, especially in Berlin (Fig. 3c). Densities of population, and to a lesser extent buildings and street intersections, make meaningful contributions to predictions of trip distances. Trip distance is clearly the most important variable for trip mode choice, followed by age, car ownership (especially in Berlin and Paris), sex, and distance to center (Fig. 3d). The availability of biking lanes and accessibility to transit have moderate importance for car ownership and mode choice. While we mitigate correlation issues by removing some variables in some models, some results may still be influenced by inter-feature correlations (c.f. SI section 5, Table S6). Therefore, the rankings shown in Fig. 3 are indicative, with potential for correlation-induced errors. Overall, the high ranking of distance to center for trip distance and car ownership, the relatively high ranking of population density across all models, and the prominence of trip distance for models of mode choice are consistent results which we believe are robust to correlation-induced errors.

Table 3 presents coefficients for regression models of each outcome variable, using pooled disaggregated data for all cities. Country/city effects arising from the regression models indicate that average trip distances are highest in Vienna and shortest in Germany, while commute trip distances are highest in Vienna and Germany and and shortest in France. Car ownership is less likely in Germany than France, bike mode choice is most likely in Germany and least likely in Madrid, transit mode choice is most likely in Vienna, and walking mode choice is most likely in Germany and Vienna. More detailed descriptions of results for each model are given

Table 3
Regression coefficients for all-city models of average trip distance and commute trip distance (linear regression), household car ownership (logistic regression), and trip mode choice (multinomial logistic regression). Models shown here are use pooled disaggregated data from all cities.

	Avg. trip	**Commute**	**Car**	**Mode choice (ref. = Car)**		
Feature	**Distance (m)**	**Distance (m)**	**Ownership**	*Bike*	*Walk*	*Transit*
Country[¤] *France*	−1616***	−1822***	NA	−1.10***	−0.88***	−0.81***
Country *Germany*	−2096***	*29*	−0.460***	1.45***	*−0.10*	−0.26***
Country *Spain (Madrid)*	−1366***	−675***	NA	−2.95***	−1.27***	−0.46***
Household income (1000€)	NA	NA	0.0006***	NA	NA	NA
Sex = Female	NA	−1383***	NA	−0.14***	0.11***	0.41***
Age[+] (Years)	19.7**	−24.5***	0.014***	*0.000*	−0.003**	−0.01***
Car Ownership	NA	NA	NA	−2.51***	−2.35***	−2.89***
Trip Distance (km)	NA	NA	NA	−0.0003***	−0.0017***	0.00002***
Household size (persons)	NA	*23.0*	0.268***	0.13***	*0.00*	0.03***
Commute share (%)	74.0***	NA	NA	NA	NA	NA
Dist. to center (% of mean)	9.0***	30.2***	0.003***	−0.004***	−0.002***	−0.003***
Dist. to subcenter (km)	61.0**	170***	*−0.013*	*−0.011*	−0.012**	0.013***
Urb. Pop. Density (per/ha)	−3.5***	*−0.6*	−0.007***	0.004***	0.005***	0.004***
Urb. Built density (m^3/m^2)	*−3.6*	−5.6	NA	*−0.002*	0.005***	0.009***
Intersec. density (N/ km^2)	−18.0***	−12.9***	*−0.001*	0.003***	0.007***	0.005***
Avg. street length (km)	*1.8*	6.6	−0.004***	0.004***	0.004***	0.006***
Cycle lane share (%)	NA	NA	*0.257*	0.012***	0.002**	0.004***
Transit access. (dep/min)[‡]	NA	NA	−0.0099***	*−0.0004*	*0.0003*	0.0024***
Urban fabric area (%)	−4.8	−6.7***	0.760***	−0.004***	−0.004***	−0.003***
Commercial area (%)	−18.7***	−14.5***	−0.636***	−0.004**	0.007***	0.006***
Season, Time FE	N	Season	N	Y	Y	Y
Education, Occupation FE	N	Education	Y	Y	Y	Y
Trip Purpose	N	N	N	Y	Y	Y
N	1,754	121,626	39,184	262,499		
r^2 / F1	0.530	0.121	0.758	0.678		

[¤] *Country ref. = 'Austria (Vienna)' for trip distance and mode choice models and 'France' for car ownership. FE = 'Fixed Effects'.*

[‡] *The transit accessibility feature is also weighted/discounted by distance of population to stations.*

[+] *Age refers to average age by administrative units for avg. trip distance models, individual age for commute distance and mode choice models, and* max. *householder age for car ownership.*

*** , **, *and * denote significance at $p < 0.001$, $p < 0.01$, and $p < 0.05$ levels, respectively.*

Coefficients with p-value > 0.1 are shown in italics. 'NA' means that a feature was not included in the model. Coefficients for features measured in % refer to a 1 percentage point increase. N describes the sample size for each model.

in the subsequent sections. Regression results for individual cities and regions are shown in SI Tables S8-S11 and a summary of the prediction accuracy of all models is shown in Table S7.

4.3. *Trip distance*

Fig. 4 maps the combined influence of urban form estimated by GBDT models of average trip distance in Berlin, Madrid, Paris, and Vienna. Blank areas indicate regions where no survey respondents live. The total variation in average trip distances attributed to urban form (comparing locations with max difference in urban form influences) reaches 4–5 km in Berlin and Madrid, 2.5 km in Paris, and 8 km in Vienna (NB this model considers far fewer features due to correlation issues, SI Section 5). In Berlin for instance, the influence of urban form on average trip distance ranges from −1 km (near the center) to + 3 km (on the outskirts). The combined urban form results visually demonstrate the relevance of distance to city center, with urban form contributing to shorter trip distances at the center and larger trip distances further from the center. After distance to the center, different measures of density are also important, depending on the city. Population density is highly relevant in Vienna and rest of France, intersection density is important in Berlin and Madrid, and built-up density is most important in rest of Germany and rest of France (Fig. 3, Fig. S8). Linear regression models of average trip distance show significant effects for distance to center everywhere except Vienna and estimate an increase in average trip distances of 0.12——0.21 km associated with living 1 km further from the city center (Table S8). As commute trips are usually the longest trip type, the commute trip share is an important form feature for predicting average trip distance (Fig. 3, Table 3, Fig. S8, Table S8).

Urban form features have larger magnitude when considering their effects on commute trips (which are longer than average trips), and distance to center is again the dominant feature in models of commute distances (Fig. 3, Fig. S9). Linear regression models estimate increases of 0.34——0.70 km in commute distances associated with living an extra 1 km from the city center (Table S9), while GBDT models reveal strong nonlinear increases in commute trips with distance to center in some locations, e.g. above 11 km from the center in Paris, or 6 km from the center in Vienna and rest of Germany (Fig. S9). The influence of population density is less pronounced for commute distances than for average trip distances. Only in rest of France do we see a significant negative linear effect, and in rest of Germany we see a positive effect (Table S9), although this model has very low prediction accuracy. Nonlinear decreases of commute

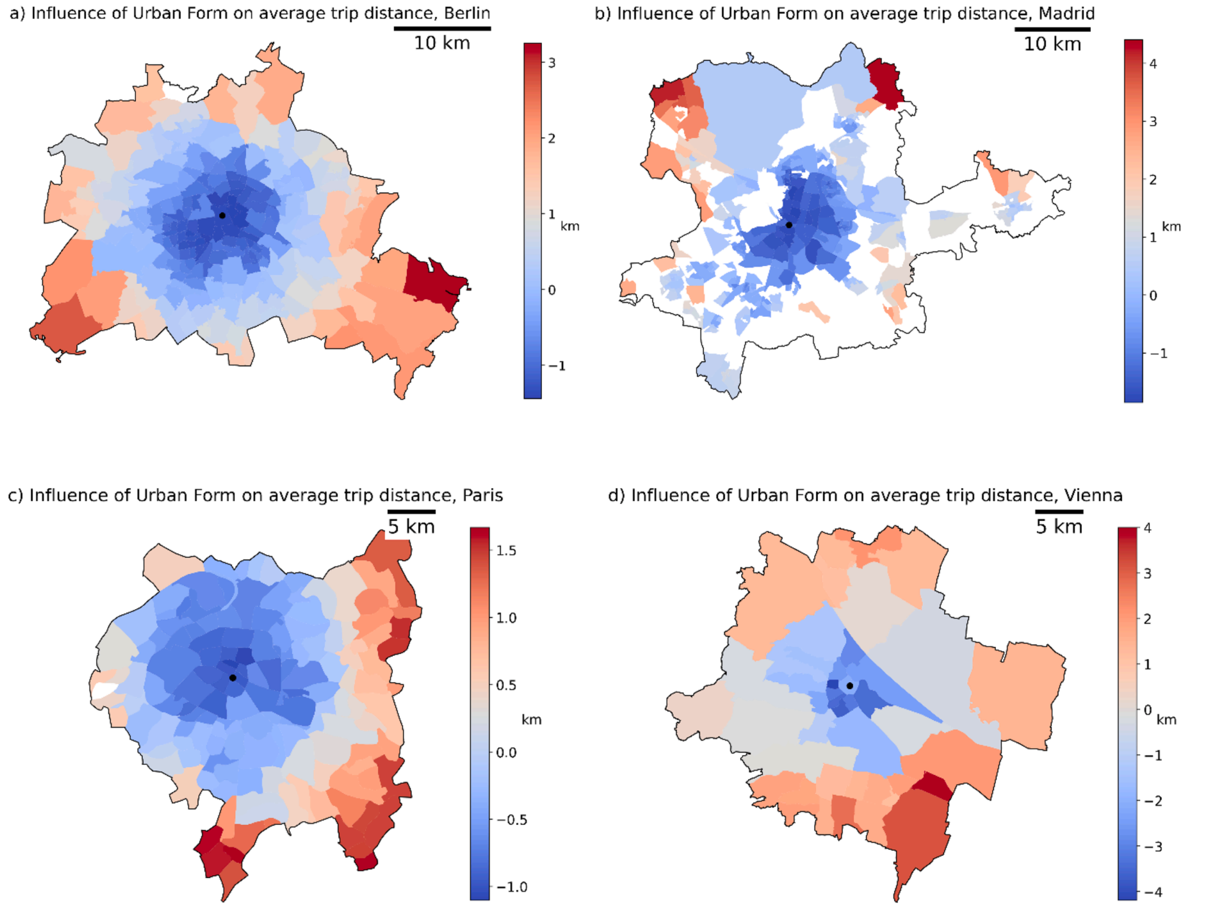

Fig. 4. Influence (SHAP values) of combined urban form features at residential location on average trip distance in four capital cities. Areas without data are marked in white and correspond to areas where no survey respondents live.

trip distances with population density are clearest in Berlin and Vienna (Fig. S9). Distance to subcenter has visible importance in GBDT models and significant positive coefficients in linear models of commute trip distance, especially in Paris, Madrid and rest of France (Table S9, Fig. S9), indicating that living near a subcenter can have a measurable effect on reducing commuting trip distances. Among demographic features, female and older commuters (excluding Paris and Vienna) have shorter commute trips (Table S9).

4.4. Car ownership

Our results indicate that car ownership is most strongly influenced by household income and household size, consistent with previous literature (Dargay et al., 2007; Sabouri et al., 2021; Tao & Næss, 2022; Zhang et al., 2020). Distance to city center has a strong influence, particularly in Berlin, and max householder age is important across regions (Fig. 3, Fig. S10, Fig. S11). Income has lowest importance in Berlin, where it contributes 21 % to GBDT model predictions, compared to 29–33 % in other locations. Non-linear effects and emergent thresholds of increased likelihood of car ownership with increased distance to center are observed (Fig. 5). In Berlin a clear threshold of increasing likelihood of car ownership is seen at 6 km from the city center. In Paris are smaller nonlinear increases in likelihood of car ownership at 5 km and 7 km from the city center. In the rest of France (Clermont and Toulouse) a substantial increase in likelihood of car ownership is seen between 5 and 7 km from the city center, while in the rest of Germany, increased likelihood of car appears more linear, although a small non-linear increase is observed between 4 and 5 km from the city center. Logistic regression models of car ownership estimate that living an additional 1 km from the center is associated with a 9 percentage point increase in car ownership likelihood in Berlin and rest of Germany, and an 5–6 percentage point increase in Paris and rest of France (Table S10). Population density has a significant negative association with car ownership - an additional 10 per/ha is associated with a 3 percentage point reduction in probability of car ownership in Paris, a reduction of 4–6 percentage points in Germany, and a reduction of 9

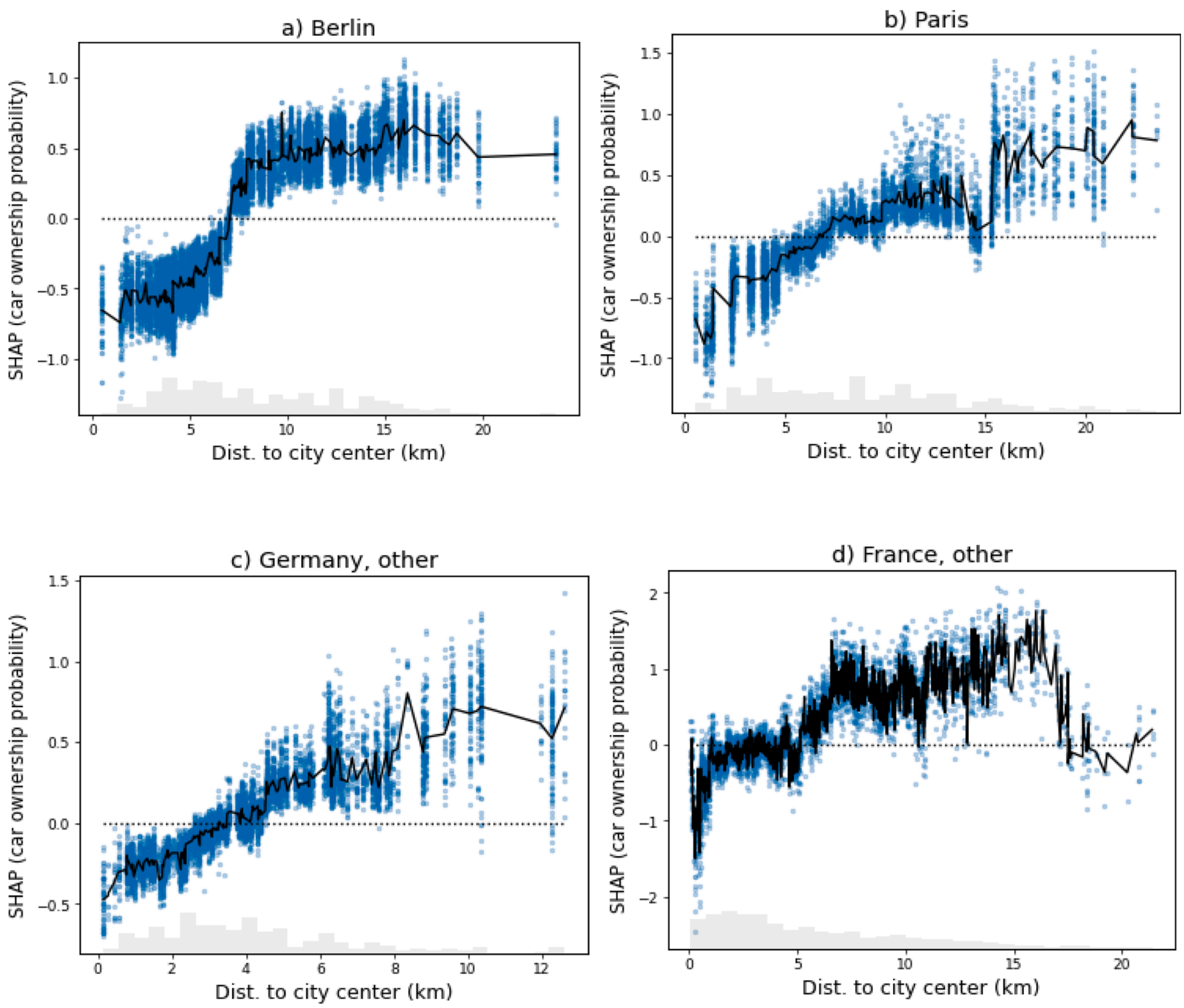

Fig. 5. SHAP values indicating non-linear influences of distance to center in models of car ownership in a) Berlin, b) Paris, c) rest of Germany, d) rest of France (Clermont and Toulouse). Black line indicates mean value for binned values of distance to center, and light-gray bars indicate the distribution of values of distance to center.

percentage points in rest of France. GBDT models show that the likelihood of car ownership increases steeply when population density is less than circa 40 per/ha in Berlin, 90 per/ha in Paris, and 50 per/ha in rest of France (Fig. S11). When pooling data from French and German cities, the importance of distance to center decreases in GBDT models while transit accessibility and population density become more important (Fig. S10). Transit accessibility is a relevant urban form feature for car ownership in Berlin and Paris, while in rest of Germany and rest of France cycle lane share has higher importance (Fig. S10, Table S10).

In Berlin and Paris, households headed by young adults (<40) have lower likelihood of car ownership (Fig. S11). A much weaker version of that relationship is seen in rest of Germany and rest of France. This suggests a possible interaction of age and city size (and perhaps culture), where younger households in bigger cities have lower desire/necessity to own a car. University education is a relevant variable for car ownership, especially in Clermont and Toulouse. The direction of the effect differs by country - in France households with at least one university-educated member have higher likelihood of car ownership, while in Germany such households are less likely to own a car (Table S10).

4.5. Mode choice

Trip distance is by far the most important feature in GBDT mode choice models. Longer trips are more likely to be taken by car or transit, while shorter trips are more likely to be made by foot or bike (Fig. S12, Table S11). Residential distance to the city center is the most relevant urban form feature for mode choice overall, followed by population density, cycle lane share, and transit accessibility (Fig. 3). Trip distance, car ownership, and age are always among the most important features for car mode choice, and trip distance is usually the most important (Fig. 6). The significance of these variables is mostly confirmed by multinomial logistic regression (MNLR) models, although for age a significant effect is not always found (perhaps due to the nonlinear nature of the relationship) (Table S11).

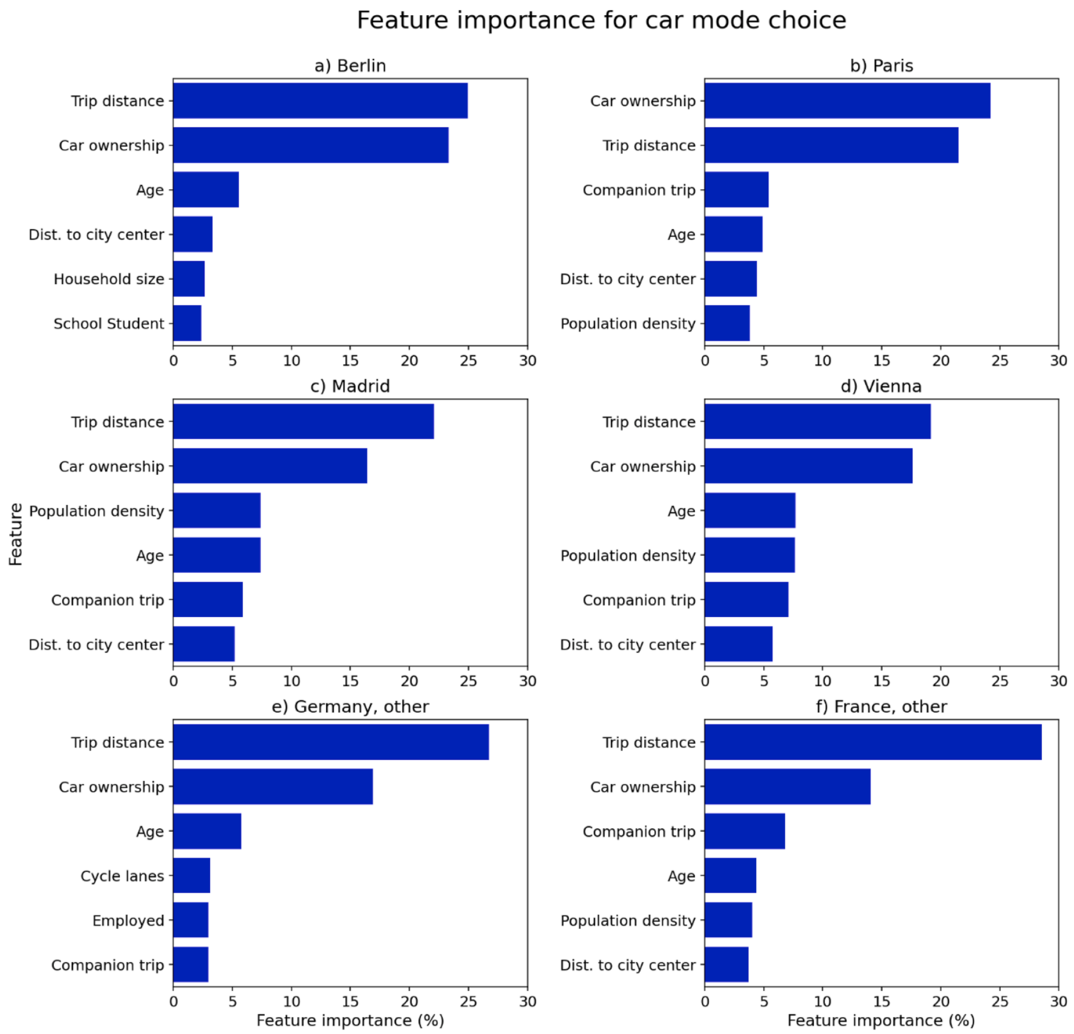

Fig. 6. Feature importance (% contribution to total absolute SHAP values) for most important features influencing car mode choice in a) Berlin, b) Paris, c) Madrid, d) Vienna, e) rest of Germany, f) rest of France.

We show non-linear relationships between important continuous features and car mode choice in Fig. 7. The likelihood of car and transit mode choice increases rapidly with trip distance up to around 3 km and increases more gradually with longer trips (Fig. 7a, Fig S13a). Car mode choice is more likely for children and the elderly, less likely for adolescents and young adults, but for most adults the influence of age on car mode choice is negligible (Fig. 7b). Adolescents and young adults are more likely to travel by transit, while most adults are less likely to travel by transit. The likelihood of biking declines rapidly in older age, but the threshold differs by location; in Madrid people older than 50 are much less likely to bike, while in Berlin the drop-off occurs after ca. 70 (Fig. S13b).

Longer distance to city center and lower population density are associated with higher probability of car mode choice (Fig. 7 c-d). Transit mode choice is less likely with higher distance to center (Fig. S13d). Distance to center thus appears to be relevant in deciding between car and transit for longer trips, while transit accessibility (often correlated with distance to center, SI Table S6) is usually the next most important urban form feature influencing mode choice between transit and car (Fig. S12). Cycle lane share is sometimes positively associated with bike mode choice, most notably in Paris, rest of France, and rest of Germany (Fig. S12, Table S11). In GBDT models of mode choice using pooled data across all cities, the importance of transit accessibility increases compared to the individual city/region models (Fig. S12).

Trip purpose is of high relevance to mode choice for all modes. Leisure trips, especially shorter ones, are more likely to be made by foot (Fig. S6, Fig. S12). Most importantly for car mode choice, companion trips (normally involving escorting children to or from a destination) are consistently substantially more likely to be made by car than other trip types, across all locations (Fig. 6, Table S12). When considering trips that finish at home in addition to trips that start at home, the relevance of shopping trips increases in Berlin and rest of Germany (Fig. S14) – these are more likely to be done by car. Comparing the distribution of trips by purposes and distances, many companion trips below 1 km are made by foot, but above 1 km most companion trips are made by car. German cities are an exception, where other modes (notably biking) remain competitive with car for companion trips up to 4 km (Fig. S7). Commute trips are in some cases more likely to be made by bike, especially in Berlin, Paris, and rest of Germany (Fig. S12). Finally, regarding sex influences, female travelers are more likely to travel by transit than males and are less likely to travel by bike, especially in Madrid and rest of France (Fig S12, Table S11).

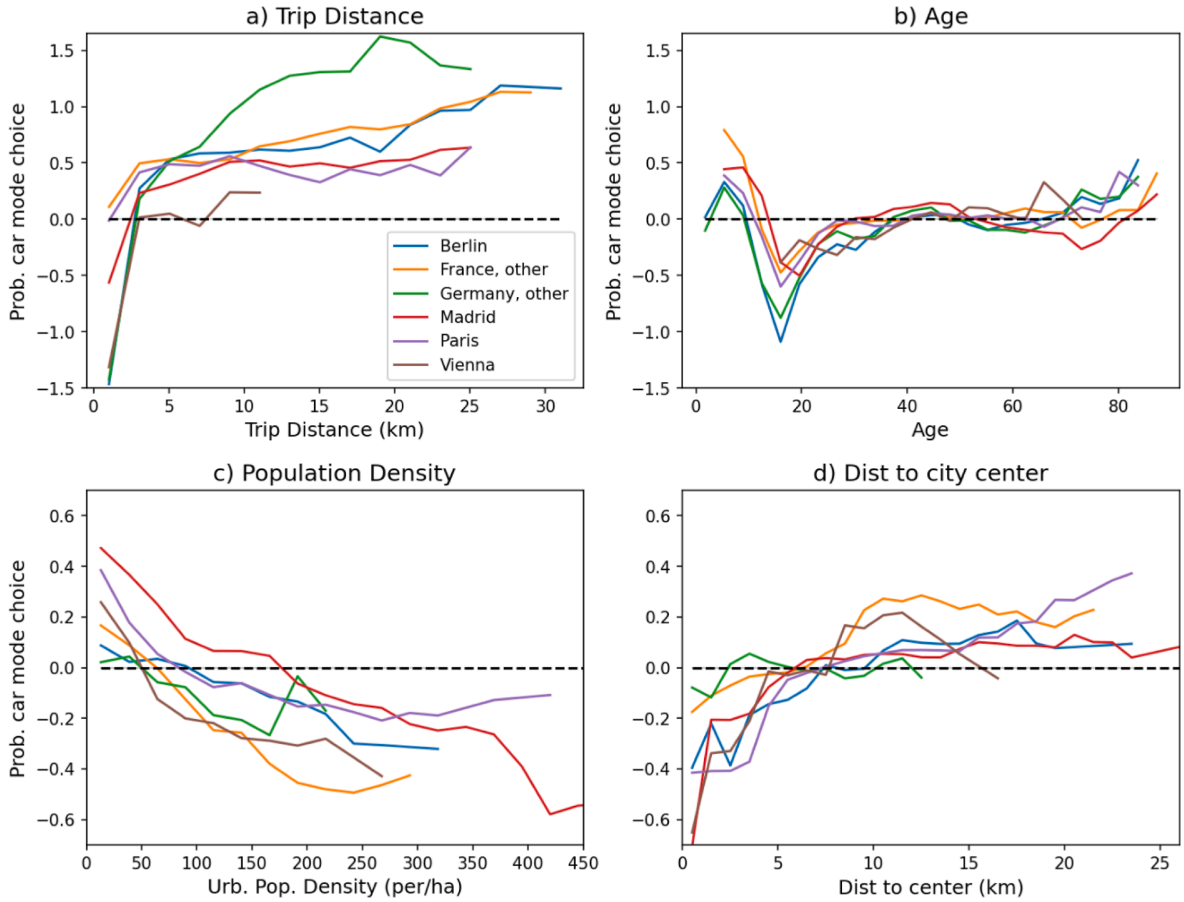

Fig. 7. Average binned SHAP values showing non-linear influences of a) trip distance, b) age, c) population density and d) residential distance to city center on probability of car mode choice in all cities/regions. NB y-axis limits are different between Fig. 7a-b, and 7c-d.

5. Discussion

5.1. Interpretation

Considering our first research question, we find that the general shape of relationships between car use and density, and car ownership and income match those from literature (Dargay et al., 2007; Newman & Kenworthy, 1989). Population density is clearly an effective metric for estimating urban car travel at aggregate and disaggregated levels (Fig. 1), but country and other contextual effects are also important. An s-shaped curve succinctly describes growth of car ownership and mode share with income in our data, but the saturation levels of car ownership and particularly mode share at high income differs by city size and country (Fig. 2). The data from Berlin and Paris demonstrate that more moderate levels of car ownership and mode share can exist at higher income levels.

For our second question, we find that distance to city center is consistently the most important feature for predicting average and commute trip distances, and the most important urban form feature for predicting car ownership and mode choice (Fig. 3). This is in keeping with literature (Ding et al., 2018; Stevens, 2017; Tao & Næss, 2022; Wagner et al., 2022). Higher distance to center shows non-linear influences on all modelled outcomes. Commute and average trip distances become substantially lower for residents living less than ~ 10 km from the center of large cities Berlin, Paris, and Madrid, whereas the thresholds are around 7 km for Vienna and 4 km for average trip distances only in rest of France and rest of Germany. Car ownership and mode choice usually becomes much less likely below ~ 5-7 km from the center. For comparison, Tao and Næss show a threshold for reduced car ownership below 10 km, and a rapid decline in car mode choice below 7 km from the center of Stavanger, a small Norwegian city (Tao & Næss, 2022). Distance to subcenter shows greatest relevance in models of average trip distances in Paris and Madrid. Various density measures (population, built-up, street intersection) are of relevance to trip distance models depending on location, while population density, transit accessibility and cycle lane share all have moderate importance in models of car ownership and mode choice.

Average trip distances appear to decline non-linearly when populations are greater than 50 per/ha in Berlin, 80 per/ha in Madrid, and 30 per/ha in Vienna and rest of France. Exceeding a population density of around 30–50 per/ha is sometimes indicated as an important threshold for achieving shorter travel distances (Ding et al., 2018; Li et al., 2019, p. 201; Newman & Kenworthy, 1989). Car ownership and mode choice also decrease beyond population density thresholds which vary by location (Fig. 7c, Fig S11). Identifying the relevant thresholds for non-linear growth in travel distances and car ownership/mode choice can be a valuable tool to guide sustainable city development and planning, but the variation in thresholds between cities shows that the local context is important, and the relevant thresholds may differ for cities outside of our sample.

For our third question, we find that companion trips are highly associated with car mode choice, female travelers are less likely to travel by bike especially in Madrid and rest of France, and travelers older than certain thresholds (varying by location) are less likely to travel by bike. Lower likelihood of female and older travelers to travel by bike has been documented in literature (Wang & Ross, 2018), but the regional differences and nonlinear age effects shown here adds nuance to understanding of influences of demographics on mode choice. Young adults (20–45) in Berlin and Paris have lower likelihood of car ownership, and the same effect is observed in smaller cities, but it is much weaker. Potential explanations include increased access to car sharing (Giesel & Nobis, 2016) and cultural preferences for living car-free (Lee-Gosselin, 2017) in larger cities.

Our results indicate a strong linkage between urban form and mobility outcomes. There is a tight connection between car usage and population density at the aggregate level (Fig. 1 a-b). This relationship is also quite strong comparing car travel and mode share vs population density at local levels within cities (Fig. 1 c-d). Local contexts clearly matter. The exponential decay of car travel with increased density has different shape in different locations, and the combined car use data for seven small and medium German cities are not well summarized by population density (Fig. 1 c-d), possibly due to other differences between these cities. On the relevance of aggregate vs disaggregate analyses, we tend to agree with Ewing et al (2018) that aggregate data are more important for the long-term aspirations of city planning. The disaggregate approach is however more appropriate for planners deciding between development alternatives with different spatial/location characteristics in existing cities. The spatially explicit estimation of urban form influences demonstrated here and elsewhere (Silva et al., 2018; Wagner et al., 2022) can in fact assist urban planners to identify where new developments can lead to the lowest induced emissions from urban mobility (Nachtigall et al., 2023).

If such assessments are to be considered by urban planners, the importance of establishing causality becomes greater. Distance to center often has the strongest effect among urban form features, and it has a plausible casual effect on travel distances given higher concentrations of employment and attractions in city centers. To paraphrase transport rationale findings, lower distance to center can causally influence lower travel distances by enabling travelers to access the most desirable facility with the lowest travel time, cost, and inconvenience (i.e. lowest 'friction of distance') (Næss et al., 2018). In essence, the causal effect is valid if city centers contain a higher density of attractions accessible with less friction of distance, which is usually true. Density measures are also plausible proxies for high concentrations of destinations and attractions, facilitating shorter trip distances and greater feasibility of non-car travel modes. Higher street intersection density enables more efficient routing and shorter travel distances, and is a common metric for walkability (Grasser et al., 2017). The causal influence of density measures through the mechanism of greater co-location of populations and densities/attractions are subject to some caveats. High population densities can occur in residential-only areas with low attraction density and land-use diversity. Similarly, high built-up density can occur in single-use areas such as industrial parks and airports, and in such cases may not coincide with more sustainable mobility outcomes. Finally, all density metrics can be influenced by and correlated with distance to city center.

Bike lanes and transit accessibility have clear causal mechanisms for mode choice. However, they are often highly correlated with other urban form features making it difficult to assess their independent effect on mode choice (c.f. SI Section 5). Transport rationale literature report convenience/comfort, frustration aversion and time saving as three prominent considerations for mode choice (Næss et al., 2018). The convenience element can explain why active travel is only common for shorter trip distances. Mode choice for longer trips would rest on whether it is quicker, more convenient, and less frustrating (considering road traffic, transit reliability and punctuality, etc.) to travel by car or public transit. The speed and quality of urban road and transit networks are directly influenced by urban and national infrastructure planners through long-term infrastructure investment priorities.

5.2. Policy implications

Three main policy recommendations arise from our findings. The first is to concentrate future residential developments and population growth close to city centers. This has the greatest potential to reduce travel distances, car ownership, and car mode shares. In our city sample, living within approximately 5 km of the city center corresponds to lower car ownership and mode choice in all cities, and trip distances are substantially lower for residents living within 10 km of the center of large cities, and around 4 km of the center of small and medium cities. Determining the corresponding thresholds for other cities outside of our sample will benefit from local data, but our values or others from literature (see literature review) can serve as useful starting points for similar cities. Affordability of housing is a crucial consideration when advocating for development close to city centers, where housing prices are typically higher (Cao, 2015; Wolday et al., 2018), presenting a major barrier to compact central development (Cao & Hickman, 2018). An important part of the local context if pursuing compact urban developments will be the local land and housing availability, land-use policies, and strategies for affordable housing provision.

A second recommendation is to implement measures which reduce car and increase transit mode choice for longer trips. Two actionable strategies to reduce car mode choice for long trips are to increase transit accessibility (frequency and coverage) in existing population centers which are not well served by transit, and to ensure that any population growth which doesn't take place near city centers happens in areas close to existing or planned transit hubs with population densities approaching or exceeding 50 per/ha. Increasing transit frequency may be achievable in a relatively short timeframe, but increasing coverage is a longer-term effort. Increasing the costs of private car use will likely be necessary to substantially reduce car use (Axsen et al., 2020; Ingvardson & Nielsen, 2018), e.g. through increased prices for fuel, parking, or congestion charges. These instruments can be initially unpopular and have undesirable equity implications, as lower income residents can be more car dependent and have lower access to sustainable modes (Mattioli, 2021; Wagner et al., 2022). However, some 'push' factors in combination with 'pull' factors seem unavoidable in order to substantially replace car use with more sustainable alternatives (Axsen et al., 2020; Liotta et al., 2023; Xiao et al., 2022).

A final recommendation is to develop targeted solutions for encouraging active travel and improving transit accessibility for disproportionately car dependent population subgroups and trip types. Companion trips are much more likely to be done by car, especially for trips over 1 km (Fig. 6, Fig. S7, Fig. S12). Lower costs and increased network connectivity to facilitate trip chaining can increase transit use for companion trips (Hensher & Reyes, 2000). Shared mobility, including ride-sourcing and car sharing, could displace private car use for some family trips, although further research is required into shared mobility engagement of households with children (Amirnazmiafshar & Diana, 2022). To increase bike mode share for less engaged groups, previous research has identified dedicated biking infrastructure and increased safety perceptions as two priorities (AitBihiOuali & Klingen, 2022; Graystone et al., 2022). Our results show that higher cycle lanes shares are often associated with increased bike mode choice (Table S11, Fig. S12). The success of additional biking infrastructure in increasing bike mode shares has been demonstrated in cities in Europe (Kraus & Koch, 2021; Lanzendorf & Busch-Geertsema, 2014) and New York (AitBihiOuali & Klingen, 2022). Access to cargo bikes and electric bikes can increase biking mode choice for trips with small children (Bjørnarå et al., 2019; Riggs, 2016), and electric bikes can be competitive against cars and transit for longer trips. Cargo and electric bikes are not affordable options for lower income households, and attempts to increase the uptake of these novel technologies must consider this constraint. The promise of increased access to sustainable mobility modes extends beyond individual trips. Ubiquitous availability of sustainable modes can reduce the necessity of car ownership and perhaps weaken the association between household size and car ownership (Fig. S11), facilitating larger reductions in car use. As the substantial country effects indicate, local culture and other omitted variables can be important to mobility practices. Efforts to increase sustainable mobility will benefit from information and promotion campaigns appropriate to local contexts to complement improved infrastructure investments for alternative modes (Buehler et al., 2017).

6. Conclusion

In this paper we assess the influence of urban form on mobility behaviors in 19 European cities, using urban mobility surveys enriched with descriptions of local urban form features. The main contribution of this paper to the literature is the illustration of similarities and differences of urban form and mobility linkages at aggregate and disaggregate levels for an understudied set of cities and countries. We find that exponential decay models are effective at summarizing relationships between car travel and urban area population density at both aggregate and disaggregate levels. Substantial country differences in car ownership and use are observed for small and medium cities – French cities have much higher reported household car ownership, daily car travel, and car mode share than German cities. Further, higher shares of biking is seen in German cities (mode share of 9–14 % of distance travelled), while mode shares are much lower (0–2 %) in French cities, Madrid, and Vienna. Transit mode shares are highest in the largest cities: Paris, Madrid, Berlin and Vienna (mode share 39–50 %) and range from 10 to 27 % in the small and medium sized French and German cities.

Several key results common to the cities and regions deserve attention. Non-linear influences of distance to center on car ownership are observed, with large increases of car ownership probability for households living more than approximately 5 km from the center across all cities. Distance to center is the most important influence on trip distances, and non-linear thresholds for commute and average trip distances are seen at around 10 km from the center in Berlin, Paris and Madrid, and around 4 km from the center for average trip distances in small/medium French and German cities. Population density thresholds of 30–50 per/ha are also identified below which car ownership becomes much more likely (Berlin, Paris, rest of France), and commute/average trip distances longer (Berlin, Vienna, rest of France). These thresholds may differ for cities outside of our sample, but the commonalities among cities and city groups studied here are notable, and the thresholds can serve as useful benchmarks for similar cities until local values are established.

Our study draws attention to the importance of mobility in small and mid-sized cities, which are less studied than large cities (Ao & Næss, 2023), yet hold over half of Europe's urban population (Clark et al., 2018) and have higher car dependency. Several of the cities in our analysis are projected to grow rapidly in the coming decades (Fontana, 2023). Restricting future urban development to certain distance to center and density thresholds appears the surest way to reduce mobility-related energy use and emissions as cities grow. Conversely, excessively strict, or poorly identified designation of areas for future development can encourage longer trip distances if the designated areas are not close to employment locations (Schwanen et al., 2004). The spatially explicit demonstration of urban form influences on sustainable mobility outcomes can be vital in enabling urban and transport planners to identify low emission areas for new development at high spatial resolution. A comprehensive approach to identifying areas for sustainable urban development would also consider the embodied and future energy emissions from new or refurbished buildings. This is an exciting area which will be prioritized in future research.

7. Code availability statement

Code developed for this study is freely available upon in the project repository at https://github.com/peterberr/sufficcs_mobility.

CRediT authorship contribution statement

Peter Berrill: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Florian Nachtigall:** Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation. **Aneeque Javaid:** Writing – original draft. **Nikola Milojevic-Dupont:** Writing – original draft, Software, Methodology, Formal analysis. **Felix Wagner:** Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Felix Creutzig:** Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization.

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.

Data availability

Mobility surveys are confidential (with exception of Madrid) but can be freely requested for research purposes from the responsible authorities. Urban form features are generally calculated using open source data and are available at https://github.com/peterberr/sufficcs_mobility/tree/main/outputs.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101027476 (SUFFICCS project) and grant agreement No 101056810 (CircEUlar project). The authors thank Andrea Broaddus for feedback on an earlier version of this article.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2024.104087.

References

ADISP. (2022). *Réseau Quetelet*. https://commande.progedo.fr/fr/utilisateur/connexion.

AitBihiOuali, L., Klingen, J., 2022. Inclusive roads in NYC: Gender differences in responses to cycling infrastructure. Cities 127, 103719. https://doi.org/10.1016/j.cities.2022.103719.

Amirnazmiafshar, E., Diana, M., 2022. A review of the socio-demographic characteristics affecting the demand for different car-sharing operational schemes. Transport. Res. Interdiscipl. Perspect. 14, 100616 https://doi.org/10.1016/j.trip.2022.100616.

Ao, Y., Næss, P., 2023. Travel behavior in smaller urban and rural areas. Transp. Res. Part D: Transp. Environ. 115, 103608 https://doi.org/10.1016/j.trd.2023.103608.

Axsen, J., Plötz, P., Wolinetz, M., 2020. Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. Nat. Clim. Chang. 10 (9), 809–818. https://doi.org/10.1038/s41558-020-0877-y.

Bjørnarå, H.B., Berntsen, S., te Velde, S.J., Fyhri, A., Deforche, B., Andersen, L.B., Bere, E., 2019. From cars to bikes – The effect of an intervention providing access to different bike types: A randomized controlled trial. PLoS One 14 (7), e0219304. https://doi.org/10.1371/journal.pone.0219304.

Buehler, R., Pucher, J., Gerike, R., Götschi, T., 2017. Reducing car dependence in the heart of Europe: Lessons from Germany, Austria, and Switzerland. Transp. Rev. 37 (1), 4–28. https://doi.org/10.1080/01441647.2016.1177799.

Cao, X., 2014. Residential self-selection in the relationships between the built environment and travel behavior: Introduction to the special issue. J. Transp. Land Use 7 (3), 1–3. https://doi.org/10.5198/jtlu.v7i3.726.

Cao, X., 2015. Residential Preference and Choice of Movers in Light Rail Neighborhoods in Minneapolis Minnesota. Transport. Res. Record 2494 (1), 1–10. https://doi.org/10.3141/2494-01.

Cao, M., Hickman, R., 2018. Car dependence and housing affordability: An emerging social deprivation issue in London? Urban Stud. 55 (10), 2088–2105. https://doi.org/10.1177/0042098017712682.

Cao, Z., Zhou, J., Li, M., Huang, J., Dou, D., 2023. Urbanites' mental health undermined by air pollution. Nat. Sustainability 6 (4), 4. https://doi.org/10.1038/s41893-022-01032-1.

Charreire, H., Roda, C., Feuillet, T., Piombini, A., Bardos, H., Rutter, H., Compernolle, S., Mackenbach, J.D., Lakerveld, J., Oppert, J.M., 2021. Walking, cycling, and public transport for commuting and non-commuting travels across 5 European urban regions: Modal choice correlates and motivations. J. Transp. Geogr. 96, 103196 https://doi.org/10.1016/j.jtrangeo.2021.103196.

Chatman, D.G., 2014. Estimating the effect of land use and transportation planning on travel patterns: Three problems in controlling for residential self-selection. J. Transp. Land Use 7 (3), 47–56. https://doi.org/10.5198/jtlu.v7i3.729.

Chen, T., Guestrin, C., 2016. XGBoost: A Scalable Tree Boosting System. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 785–794. https://doi.org/10.1145/2939672.2939785.

Christidis, P., Navajas Cawood, E., Fiorello, D., 2022. Challenges for urban transport policy after the Covid-19 pandemic: Main findings from a survey in 20 European cities. Transp. Policy 129, 105–116. https://doi.org/10.1016/j.tranpol.2022.10.007.

Clark, G., Moonen, Ti., & Nunley, J. (2018). *Europe and its Urban Development, 1970 to 2020*. European Investment Bank. https://www.eib.org/en/essays/the-story-of-your-city.

Consorcio Regional de Transportes de Madrid. (2019). *Encuesta de Movilidad de la Comunidad de Madrid—Documento Síntesis*. https://www.crtm.es/media/712934/edm18_sintesis.pdf.

Creutzig, F., Jochem, P., Edelenbosch, O.Y., Mattauch, L., van Vuuren, D.P., McCollum, D., Minx, J., 2015. Transport: A roadblock to climate change mitigation? Science 350 (6263), 911–912. https://doi.org/10.1126/science.aac8033.

Creutzig, F., Agoston, P., Minx, J.C., Canadell, J.G., Andrew, R.M., Quéré, C.L., Peters, G.P., Sharifi, A., Yamagata, Y., Dhakal, S., 2016. Urban infrastructure choices structure climate solutions. Nat. Clim. Chang. 6 (12), 1054–1056. https://doi.org/10.1038/nclimate3169.

Dargay, J., Gately, D., Sommer, M., 2007. Vehicle Ownership and Income Growth, Worldwide: 1960–2030. Energy J. 28 (4), 143–170.

Ding, C., Cao, X., Liu, C., 2019. How does the station-area built environment influence Metrorail ridership? Using gradient boosting decision trees to identify non-linear thresholds. J. Transp. Geogr. 77 https://doi.org/10.1016/j.jtrangeo.2019.04.011.

Ding, C., Cao, X., Næss, P., 2018. Applying gradient boosting decision trees to examine non-linear effects of the built environment on driving distance in Oslo. Transportation Research Part A: Policy and Practice 110, 107–117. https://doi.org/10.1016/jC.tra.2018.02.009.

Ding, C., Liu, T., Cao, X., Tian, L., 2022. Illustrating nonlinear effects of built environment attributes on housing renters' transit commuting. Transp. Res. Part D: Transp. Environ. 112, 103503 https://doi.org/10.1016/j.trd.2022.103503.

Engebretsen, Ø., Næss, P., Strand, A., 2018. Residential location, workplace location and car driving in four Norwegian cities. Eur. Plan. Stud. 26 (10), 2036–2057. https://doi.org/10.1080/09654313.2018.1505830.

European Environment Agency. (2022, May 31). National emissions reported to the UNFCCC and to the EU Greenhouse Gas Monitoring Mechanism [Data]. https://www.eea.europa.eu/data-and-maps/data/national-emissions-reported-to-the-unfccc-and-to-the-eu-greenhouse-gas-monitoring-mechanism-18.

Ewing, R., Cervero, R., 2010. Travel and the Built Environment: A Meta-Analysis. J. Am. Plann. Assoc. 76 (3), 265–294. https://doi.org/10.1080/01944361003766766.

Ewing, R., Tian, G., Goates, J., Zhang, M., Greenwald, M.J., Joyce, A., Kircher, J., Greene, W., 2015. Varying influences of the built environment on household travel in 15 diverse regions of the United States. Urban Stud. 52 (13), 2330–2348. https://doi.org/10.1177/0042098014560991.

Ewing, R., Hamidi, S., Tian, G., Proffitt, D., Tonin, S., Fregolent, L., 2018. Testing Newman and Kenworthy's Theory of Density and Automobile Dependence. J. Plan. Educ. Res. 38 (2), 167–182. https://doi.org/10.1177/0739456X16688767.

Fontana, G., 2023. March 29). Projecting Europe's Metro Population Growth from 2021–2100. Visual Capitalist. https://www.visualcapitalist.com/cp/projecting-europes-metro-population-growth-2021-2100/.

Giesel, F., Nobis, C., 2016. The Impact of Carsharing on Car Ownership in German Cities. Transp. Res. Procedia 19, 215–224. https://doi.org/10.1016/j.trpro.2016.12.082.

Grasser, G., van Dyck, D., Titze, S., Stronegger, W.J., 2017. A European perspective on GIS-based walkability and active modes of transport. Eur. J. Pub. Health 27 (1), 145–151. https://doi.org/10.1093/eurpub/ckw118.

Graystone, M., Mitra, R., Hess, P.M., 2022. Gendered perceptions of cycling safety and on-street bicycle infrastructure: Bridging the gap. Transp. Res. Part D: Transp. Environ. 105, 103237 https://doi.org/10.1016/j.trd.2022.103237.

Hagenauer, J., Helbich, M., 2017. A comparative study of machine learning classifiers for modeling travel mode choice. Expert Syst. Appl. 78, 273–282. https://doi.org/10.1016/j.eswa.2017.01.057.

Hensher, D.A., Reyes, A.J., 2000. Trip chaining as a barrier to the propensity to use public transport. Transportation 27 (4), 341–361. https://doi.org/10.1023/A:1005246916731.

Hillel, T., Bierlaire, M., Elshafie, M.Z.E.B., Jin, Y., 2021. A systematic review of machine learning classification methodologies for modelling passenger mode choice. Journal of Choice Modelling 38, 100221. https://doi.org/10.1016/j.jocm.2020.100221.

Holz-Rau, C., Scheiner, J., Sicks, K., 2014. Travel Distances in Daily Travel and Long-Distance Travel: What Role is Played by Urban Form? Environment and Planning a: Economy and Space 46 (2), 488–507. https://doi.org/10.1068/a4640.

Hubrich, S., Ließke, F., Wittwer, R., Wittig, S., Gerike, R., 2019. Methodenbericht zum Forschungsprojekt Mobilität in Städten – SrV 2018. TU Dresdem. https://tu-dresden.de/bu/verkehr/ivs/srv/ressourcen/dateien/SrV2018_Methodenbericht.pdf?lang=en.

Ingvardson, J.B., Nielsen, O.A., 2018. How urban density, network topology and socio-economy influence public transport ridership: Empirical evidence from 48 European metropolitan areas. J. Transp. Geogr. 72, 50–63. https://doi.org/10.1016/j.jtrangeo.2018.07.002.

Javaid, A., Creutzig, F., Bamberg, S., 2020. Determinants of low-carbon transport mode adoption: Systematic review of reviews. Environ. Res. Lett. 15 (10), 103002 https://doi.org/10.1088/1748-9326/aba032.

Kim, E.-J., 2021. Analysis of Travel Mode Choice in Seoul Using an Interpretable Machine Learning Approach. J. Adv. Transp. 2021, 1–13. https://doi.org/10.1155/2021/6685004.

Kraus, S., Koch, N., 2021. Provisional COVID-19 infrastructure induces large, rapid increases in cycling. Proceedings of the National Academy of Sciences 118 (15), e2024399118. https://doi.org/10.1073/pnas.2024399118.

Lanzendorf, M., Busch-Geertsema, A., 2014. The cycling boom in large German cities—Empirical evidence for successful cycling campaigns. Transp. Policy 36, 26–33. https://doi.org/10.1016/j.tranpol.2014.07.003.

Lee-Gosselin, M.E.H., 2017. Beyond "Peak Car": A reflection on the evolution of public sentiment about the role of cars in cities. IATSS Research 40 (2), 85–87. https://doi.org/10.1016/j.iatssr.2016.05.004.

Li, W., Bao, L., Wang, L., Li, Y., Mai, X., 2019. Comparative evaluation of global low-carbon urban transport. Technol. Forecast. Soc. Chang. 143, 14–26. https://doi.org/10.1016/j.techfore.2019.02.008.

Liotta, C., Viguié, V., Creutzig, F., 2023. Environmental and welfare gains via urban transport policy portfolios across 120 cities. Nat. Sustainability 6 (9), 9. https://doi.org/10.1038/s41893-023-01138-0.

Liu, J., Wang, B., Xiao, L., 2021. Non-linear associations between built environment and active travel for working and shopping: An extreme gradient boosting approach. J. Transp. Geogr. 92, 103034 https://doi.org/10.1016/j.jtrangeo.2021.103034.

Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., Lee, S.-I., 2020. From local explanations to global understanding with explainable AI for trees. *Nature*. Machine Intelligence 2 (1), 1. https://doi.org/10.1038/s42256-019-0138-9.

Mattioli, G., 2021. Chapter Four - Transport poverty and car dependence: A European perspective. In: Pereira, R.H.M., Boisjoly, G. (Eds.), Advances in Transport Policy and Planning, Vol. 8. Academic Press, pp. 101–133. https://doi.org/10.1016/bs.atpp.2021.06.004.

Mertens, L., Compernolle, S., Deforche, B., Mackenbach, J.D., Lakerveld, J., Brug, J., Roda, C., Feuillet, T., Oppert, J.-M., Glonti, K., Rutter, H., Bardos, H., De Bourdeaudhuij, I., Van Dyck, D., 2017. Built environmental correlates of cycling for transport across Europe. Health Place 44, 35–42. https://doi.org/10.1016/j.healthplace.2017.01.007.

Minx, J.C., Lamb, W.F., Andrew, R.M., Canadell, J.G., Crippa, M., Döbbeling, N., Forster, P.M., Guizzardi, D., Olivier, J., Peters, G.P., Pongratz, J., Reisinger, A., Rigby, M., Saunois, M., Smith, S.J., Solazzo, E., Tian, H., 2021. A comprehensive and synthetic dataset for global, regional, and national greenhouse gas emissions by sector 1970–2018 with an extension to 2019. Earth Syst. Sci. Data 13 (11), 5213–5252. https://doi.org/10.5194/essd-13-5213-2021.

Nachtigall, F., Wagner, F., Berrill, P., & Creutzig, F. (2023). The built environment and induced transport CO2 emissions: A double machine learning approach to account for residential self-selection (arXiv:2312.06616). arXiv. 10.48550/arXiv.2312.06616.

Naess, P., 2014. Tempest in a teapot: The exaggerated problem of transport-related residential self-selection as a source of error in empirical studies. J. Transp. Land Use 7 (3), 57–79. https://doi.org/10.5198/jtlu.v7i3.491.

Næss, P., 2022. Meta-Analyses of Built Environment Effects on Travel: No New Platinum Standard. J. Plan. Educ. Res. 42 (2), 199–205. https://doi.org/10.1177/0739456X19856425.

Næss, P., Peters, S., Stefansdottir, H., Strand, A., 2018. Causality, not just correlation: Residential location, transport rationales and travel behavior across metropolitan contexts. J. Transp. Geogr. 69, 181–195. https://doi.org/10.1016/j.jtrangeo.2018.04.003.

Næss, P., Strand, A., Wolday, F., Stefansdottir, H., 2019. Residential location, commuting and non-work travel in two urban areas of different size and with different center structures. Prog. Plan. 128, 1–36. https://doi.org/10.1016/j.progress.2017.10.002.

Newman, P.W.G., Kenworthy, J.R., 1989. Gasoline Consumption and Cities: A Comparison of U.S. Cities with a Global Survey. J. Am. Plann. Assoc. 55 (1), 24–37. https://doi.org/10.1080/01944368908975398.

Pucher, J., Renne, J.L., 2005. Rural mobility and mode choice: Evidence from the 2001 National Household Travel Survey. Transportation 32 (2), 165–186. https://doi.org/10.1007/s11116-004-5508-3.

Riggs, W., 2016. Cargo bikes as a growth area for bicycle vs. auto trips: Exploring the potential for mode substitution behavior. Transport. Res. F: Traffic Psychol. Behav. 43, 48–55. https://doi.org/10.1016/j.trf.2016.09.017.

Sabouri, S., Tian, G., Ewing, R., Park, K., Greene, W., 2021. The built environment and vehicle ownership modeling: Evidence from 32 diverse regions in the U.S. J. Transp. Geogr. 93, 103073 https://doi.org/10.1016/j.jtrangeo.2021.103073.

Schwanen, T., Dijst, M., Dieleman, F.M., 2004. Policies for Urban Form and their Impact on Travel: The Netherlands Experience. Urban Stud. 41 (3), 579–603. https://doi.org/10.1080/0042098042000178690.

Seabold, S., & Perktold, J. (2010). *Statsmodels: Econometric and Statistical Modeling with Python*. 92–96. 10.25080/Majora-92bf1922-011.

Silva, M., Leal, V., Oliveira, V., Horta, I.M., 2018. A scenario-based approach for assessing the energy performance of urban development pathways. Sustain. Cities Soc. 40, 372–382. https://doi.org/10.1016/j.scs.2018.01.028.

Sporkmann, J., Liu, Y., Spinler, S., 2023. Carbon emissions from European land transportation: A comprehensive analysis. Transp. Res. Part D: Transp. Environ. 121, 103851 https://doi.org/10.1016/j.trd.2023.103851.

Srinivasan, S., Ferreira, J., 2002. Travel behavior at the household level: Understanding linkages with residential choice. Transp. Res. Part D: Transp. Environ. 7 (3), 225–242. https://doi.org/10.1016/S1361-9209(01)00021-9.

Stevens, M.R., 2017. Does Compact Development Make People Drive Less? J. Am. Plann. Assoc. 83 (1), 7–18. https://doi.org/10.1080/01944363.2016.1240044.

Stevenson, M., Thompson, J., de Sá, T.H., Ewing, R., Mohan, D., McClure, R., Roberts, I., Tiwari, G., Giles-Corti, B., Sun, X., Wallace, M., Woodcock, J., 2016. Land use, transport, and population health: Estimating the health benefits of compact cities. Lancet 388 (10062), 2925–2935. https://doi.org/10.1016/S0140-6736(16)30067-8.

Tao, X., Fu, Z., Comber, A.J., 2019. An Analysis of Modes of Commuting in Urban and Rural Areas. Appl. Spat. Anal. Policy 12 (4), 831–845. https://doi.org/10.1007/s12061-018-9271-9.

Tao, T., Næss, P., 2022. Exploring nonlinear built environment effects on driving with a mixed-methods approach. Transp. Res. Part D: Transp. Environ. 111, 103443 https://doi.org/10.1016/j.trd.2022.103443.

Tennøy, A., Knapskog, M., Wolday, F., 2022. Walking distances to public transport in smaller and larger Norwegian cities. Transp. Res. Part D: Transp. Environ. 103, 103169 https://doi.org/10.1016/j.trd.2022.103169.

Tomschy, R., Herry, M., Sammer, G., Klemenschitz, R., Riegler, S., Follmer, R., Gruschwitz, D., Josef, F., Gensasz, S., Kirnbauer, R., & Spiegel, T. (2016). *Österreich unterwegs 2013/2014. Ergebnisbericht zur österreichweiten Mobilitätserhebung „Österreich unterwegs 2013/2014"*. Bundesministerium für Verkehr, Innovation und Technologie. https://www.bmk.gv.at/dam/jcr:fbe20298-a4cf-46d9-bbee-01ad771a7fda/oeu_2013-2014_Ergebnisbericht.pdf.

Ton, D., Bekhor, S., Cats, O., Duives, D.C., Hoogendoorn-Lanser, S., Hoogendoorn, S.P., 2020. The experienced mode choice set and its determinants: Commuting trips in the Netherlands. Transp. Res. A Policy Pract. 132, 744–758. https://doi.org/10.1016/j.tra.2019.12.027.

Tsoi, K.H., Loo, B.P.Y., Banister, D., 2021. "Mind the (Policy-Implementation) Gap": Transport decarbonisation policies and performances of leading global economies (1990–2018). Glob. Environ. Chang. 68, 102250 https://doi.org/10.1016/j.gloenvcha.2021.102250.

Verbavatz, V., Barthelemy, M., 2019. Critical factors for mitigating car traffic in cities. PLoS One 14 (7), e0219559. https://doi.org/10.1371/journal.pone.0219559.

Wagner, F., Nachtigall, F., Franken, L., Milojevic-Dupont, N., Pereira, R. H. M., Koch, N., Runge, J., Gonzalez, M., & Creutzig, F. (2023). *A Causal Discovery Approach To Learn How Urban Form Shapes Sustainable Mobility Across Continents* (arXiv:2308.16599). arXiv. 10.48550/arXiv.2308.16599.

Wagner, F., Milojevic-Dupont, N., Franken, L., Zekar, A., Thies, B., Koch, N., Creutzig, F., 2022. Using explainable machine learning to understand how urban form shapes sustainable mobility. Transp. Res. Part D: Transp. Environ. 111, 103442 https://doi.org/10.1016/j.trd.2022.103442.

Wang, F., Ross, C.L., 2018. Machine Learning Travel Mode Choices: Comparing the Performance of an Extreme Gradient Boosting Model with a Multinomial Logit Model. Transport. Res. Rec. J. Transport. Res. Board 2672 (47), 35–45. https://doi.org/10.1177/0361198118773556.

Wolday, F., Cao, J., Næss, P., 2018. Examining factors that keep residents with high transit preference away from transit-rich zones and associated behavior outcomes. J. Transp. Geogr. 66, 224–234. https://doi.org/10.1016/j.jtrangeo.2017.12.009.

Wu, X., Tao, T., Cao, J., Fan, Y., Ramaswami, A., 2019. Examining threshold effects of built environment elements on travel-related carbon-dioxide emissions. Transp. Res. Part D: Transp. Environ. 75, 1–12. https://doi.org/10.1016/j.trd.2019.08.018.

Xiao, C., van Sluijs, E., Ogilvie, D., Patterson, R., Panter, J., 2022. Shifting towards healthier transport: Carrots or sticks? Systematic review and meta-analysis of population-level interventions. The Lancet Planetary Health 6 (11), e858–e869. https://doi.org/10.1016/S2542-5196(22)00220-0.

Yang, W., 2023. The nonlinear effects of multi-scale built environments on CO2 emissions from commuting. Transp. Res. Part D: Transp. Environ. 118, 103736 https://doi.org/10.1016/j.trd.2023.103736.

Zhang, W., Zhao, Y., Cao, X., Lu, D., Chai, Y., 2020. Nonlinear effect of accessibility on car ownership in Beijing: Pedestrian-scale neighborhood planning. Transportation Research Part D: Transport and Environment 86, 102445. https://doi.org/10.1016/j.trd.2020.102445.