

## Exploring a quantitative assessment approach for car dependence: A case study in Munich

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**Abstract:** While discussions are ongoing about the exact meaning of car dependence, its assessment has been primarily qualitative. The few quantitative approaches adopted so far have tended to analyze either high car use and ownership or a lack of public transport accessibility as indicators of car dependence. This study aims to quantitatively evaluate car dependence in Munich after merging these three aspects—car use, ownership, and lack of public transportation—and identify its associated potential spatial predictors. The exploratory approach is applied to traffic zones in the transit service area around Munich, Germany, which includes calculating an indicator for car dependence and its linkage with socio-spatial factors using multiple linear regression. For this purpose, traffic data from 2017 and census data from 2011 are used, which are the most recent available. It was found that car dependence is higher in suburban areas with low local numbers of employees, low land costs, and high average income tax payments. Identifying areas with higher car dependence and associated factors can help decision makers focus on or prioritize these areas in providing better access to alternative transportation and basic opportunities. Future research could focus on application in additional regions, using recent and aligned data, and further combinations with qualitative research.

### Article history:

Received: October 7, 2021  
Received in revised form:  
September 29, 2022  
Accepted: December 26, 2022  
Available online: March 27,  
2023

## 1 Introduction

The concentration of transport on the automobile compared to other modes has led to a number of problems for the global society. Parking or moving cars take up large proportions of land in many places (Litman, 2019). Emissions from automobiles are a significant contributor to climate change and have not been reduced in the last 30 years (European Commission, 2018). People living near busy roads face sometimes severe effects on their health (Frumkin, 2002). Especially now, in light of the COVID-19 crisis, the attractiveness of the private car is expected to increase (Furber et al., 2020).

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<http://dx.doi.org/10.5198/jtl.u.2023.2111>

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The *Journal of Transport and Land Use* is the official journal of the World Society for Transport and Land Use (WSTLUR) and is published and sponsored by the University of Minnesota Center for Transportation Studies. This paper is also published with additional sponsorship from WSTLUR.

However, reducing the influence of the automobile in the transportation sector could bring many benefits, such as saving space, transportation equity and climate mitigation (Newman & Kenworthy, 2015). This is where the concept of car dependence comes into play. It reveals various problems caused by an increased focus on the automobile while also disclosing the benefits of supporting alternative ways of future transport planning, such as public transit, walking, or cycling.

Car dependence has been discussed to a large extent qualitatively and in respect of its consequences. Urry (2004) described that this transport development leads to an extreme spatial separation of different neighborhoods and land uses. This, in turn, obliges the population to use the car, which is associated with congestion, temporal uncertainties, and urban environments that are hazardous to health. Ultimately, he concludes that the population would finally live “encapsulated in a domestic, cocooned, moving capsule.” In line with this, Hickman and Banister (2014) noticed environmental changes due to increased motorization. Frumkin (2002) added direct impacts of car dependency, as well as impacts of land use development leading to serious physical, and also social health problems as a result of urban sprawl.

In order to identify and then mitigate the problem of car dependence on a large scale, a viable method could be first to quantify it. According to the IPCC (2022), it is necessary to act immediately in the transport sector in order to be able to demonstrate decreasing transport emissions by 2025 at the latest. Therefore, this article aims to quantify car dependency in Munich, Germany by combining car ownership and accessibility to basic needs and alternative modes of transportation. In addition, the second objective of this research is to explore spatial factors associated with this indicator of car dependence. These factors may help explain why some areas have more car dependency than others. The approach could be a commencing point for local stakeholders to find solutions to mitigate car dependence. It should not only aim to reduce the presence of cars, but rather to change the current transportation system and thereby travel behavior in a sustainable way (Litman, 2002).

This paper continues with a literature review on the concept of car dependence and previous approaches to assess it. We proceed with a general description of a new approach to assess car dependence quantitatively and identify its potential spatial predictors. The approach is further applied in the service area of the transit system in Munich, Germany. Data was used from the Bavarian State Traffic Model 2017 and census data from 2011, which are the most recent available. Finally, the results of the car dependency in Munich and its spatial predictors are presented and discussed.

## 2 Literature review

The matter of car dependence has been discussed in transportation for decades now. As early as the 1970s, urban planners, as well as sociologists such as Goodman (1972), Lefebvre (1992) and Illich (1974) noted that the automobile and its vast industry were changing transportation patterns in unsustainable ways. While they were thinking mainly about equity and equality issues, later environmentalism was added as a critique (Lucas et al., 2001). Their criticism can be seen as a response to the automotive industry’s discovery that increasing its influence can create dependence on the industry itself (Goodman, 1972). Since then, researchers like Newman and Kenworthy (1989) established the term car or automobile dependence and focused their studies on this particular topic.

After the early criticism of the “vicious circle” (Lefebvre, 1992) of the automobile hardly gained a foothold, many effects on humankind and the environment can be identified nowadays. Consequences for land use include urban sprawl and soil sealing (Frumkin, 2002). Newman and Kenworthy (1999) explored that there are correlations globally between urban density and energy use per capita, which is reinforced by Banister’s (2011) findings that commuting distances increased sharply over the past 50

years. In this respect, Cervero and Kockelman (1997) concluded that, on the part of the built environment, it is above all density, diversity, and design that can be decisive for mode choice. Accordingly, areas in which these three characteristics have strongly adapted to automobile patterns are predestined to remain in this state and can lead to “automobile captivity” (Beimborn et al., 2003). This, in turn, leads to several environmental problems, such as emissions, especially of greenhouse gases, high consumption levels of the finite resource oil, and finally, the resulting climate change (Hickman & Banister, 2014).

The described development is also reflected in the health sector, where consequences of increased air, noise, and light emissions, accidents, and a lack of exercise are added to the list of problems (Frumkin, 2002). Even equity (Kenyon et al., 2002), micro- and macroeconomics (Litman & Laube, 2002), and cultural development (Mögele & Rau, 2020) are affected by the widespread use of cars. As an example, Mögele and Rau (2020) noted that “transport policy and planning in Germany (and elsewhere) have largely ignored the cultural dimensions of mobility.” At the same time, failing to recognize that the country has already become a “car state,” makes it difficult to promote other modes of transport as parts of mobility.

It is recognized that there are many often adverse effects of excessive automobile use that cannot be remedied by technologies such as automated, connected, or electronic vehicles alone.

## 2.1 Definition of car dependence

Different definitions of car dependence have been used in the sciences. Lucas and Jones (2009) noted that the term is often used to describe a variety of different issues related to automobile use and dependence. The main characteristics are high levels of car use and ownership, car-oriented land use patterns, and limited travel alternatives (Litman & Laube, 2002; Newman & Kenworthy, 1999; Victoria Transport Policy Institute, 2019; Wiersma et al., 2015).

Zhang (2006) described car dependence as the likelihood that driving is the only element in a traveler’s possible choice of transport modes after forming the choice set of transport modes and the mode choice decision. Mattioli et al. (2020) presented it as the process by which car use has become “a key satisfier of human needs, largely displacing less carbon-intensive alternatives.” Mattioli (2013) also defined it as a “dynamic, unrelenting and self-reinforcing macro-social process with systemic properties, (...) that strongly resists any deliberate attempt to induce change, despite increasing awareness of its negative externalities.” He adds that it “tends to progressively widen the gap between the benefits of the automobile system for car users and the situation of non-car users.” Goodwin (1995) also acknowledged that it is more a process than a state operating on the individual and social level. Litman and Laube (2002) saw negative economic, social, and environmental impacts as a part of this process. Both Litman and Laube (2002) and the Victoria Transport Policy Institute (2019) saw a balanced, multi-modal transport system opposed to the described phenomena.

For this article, car dependence is defined as a transport development focused on the car as the main mode of transport to access basic opportunities (Newman & Kenworthy, 1999). It manifests itself in the form of an accessibility gap between cars and other modes of transportation, as well as reduced accessibility to opportunities without a car (Zhang, 2006).

In addition to the definition, the categorization of car dependence has also been addressed. Lucas (2009) described three perspectives: car users and their degree of connection to the car, type of activities and the need for a car for these activities, and finally, the typology and accessibility with or without a car in different regions. In alignment with Lucas, others referred to these as micro, meso, and macro levels of car dependence (Mattioli et al., 2016).

Further classification into subjective and objective dependence was described by von Behren et al. (2018). The subjective grading occurs through a “combination of the ‘affinity’ (...) and ‘perceived need’

of car use (...),” while the objectiveness can be seen in every individual’s travel behavior and the question if “everyday life without a car is difficult or easily feasible” (ibid.). Following these classifications, this study tests a method for analyzing objective car dependence at the macro level.

## 2.2 Assessment of car dependence

The definition and nature of the concept of car dependence vary widely, so do existing assessment methods. Previous research has often focused on subjective assessment methods. Dupuy (1999) used data from France on car use and car ownership to measure positive sectoral effects of the automobile sector for drivers in terms of accessibility to services. Zhang (2006) calculated the probability that the car is the only element in the choice of transportation as the degree of car dependence, for which he used data from a transportation survey. Zhao (2011) developed a subjective measure of car dependence based on personal perceptions of a surveyed user group. In this way, subjective car dependence, actual travel behavior, and the intention to change it could be compared. Actual car use was found to explain about 50 percent of the variation in subjective car dependence.

The focus of Mattioli et al. (2016) was on meso-level car dependence. They tried to find out why cars are irreplaceable and for which activities. Mobility intensity and the probability that the activity is associated with car use were calculated for 55 activities. It was found that especially accompanying children, shopping, and transporting goods can be classified as car-dependent. von Behren et al. (2018) surveyed groups of people in Berlin, San Francisco, and Shanghai on their travel behavior, psychological factors, and technology awareness. They then calculated objective and subjective car dependence. Zhang et al. (2020) analyzed a household travel survey of 1280 respondents in Beijing, China to explore the influence of transit access on household car ownership using a machine learning approach.

As with qualitative methods, quantitative methods developed for assessing objectively car dependence have numerous examples in literature. MacKenzie (2009) developed a scorecard used to calculate car dependence by analyzing 34 transport-related factors. These were divided into four categories: sustainable accessibility of opportunities, pedestrian and bicycle infrastructure, reliability of the public transportation network, and public transportation pricing structure. Car dependence levels were then compiled based on the average scores of the regions studied in England. Motte-Baumvol et al. (2010) investigated the travel behavior in the Paris metropolitan region by using mobility data from a transport survey and dividing the population into car owners and non-car owners on the one hand and into four levels of car dependence on the other. Wiersma et al. (2015) analyzed access to daily amenities and jobs in the Netherlands. Using predefined thresholds and the national mobility balance, they identified where citizens never need a car, occasionally need one, or need a car daily. The latter were then considered car dependent. Four spatial characteristics were identified as indications of car dependence: population density, settlement size, transportation infrastructure, and mono- or polycentricity. Finally, Siedentop (2013) developed an indicator approach for the German test region of Stuttgart that analyses objective evidence of the need for a private car due to a lack of mobility alternatives.

Referring to the chosen car dependence definition, the above-mentioned quantitative approaches analyze either high car usage and ownership or low accessibility by public transport. To complement both concepts, the approach of this article merges both car ownership and public transport accessibility, as well as the accessibility to points of interest (e.g., food, health, education, etc.). Regression techniques may help to explore a study area in more detail and to identify predictors associated with quantitative car dependence in the traffic zones. These predictors can help to identify areas that should be considered to avoid or mitigate car dependency. As part of the pragmatic and explorative approach, results are finally to be compared to other methods analyzing car dependence.

### 2.3 Potential spatial factors associated with car dependence

Local mobility structures are usually understood by looking at external factors. Deffner et al. (2006), for example, found the main influencing factors to be planning, historical development, socio-economic situation, lifestyles, communication, and political decisions of the city. Wulfhorst (2003) described long- and short-term mobility changes as the interplay of land use, accessibility, transportation demand, supply, and activities. Therefore, secondly, it is relevant to see which spatial factors are associated with car dependence.

Multiple Linear Regression (MLR) can “directly accommodate multiple predictors” (James et al., 2013) to predict responses to events, which has been used in transportation sciences (e.g., Duran-Rodas et al., 2019). To the best of our knowledge, previous studies have not considered a similar analysis concerning car dependence in particular.

Simple linear regression is an “approach for predicting a quantitative response  $Y$  on the basis of a single predictor variable  $X$ ” that approximates a linear relationship between those two variables (James et al., 2013). MLR is an extension of this method by the number of predictors. So far, MLRs have been used in transport sciences to capture characteristics that can explain mobility behavior or developments. For example, Duran-Rodas et al. (2019) used a MLR to elaborate spatial characteristics that influence the ridership of shared vehicles. However, there is no known application in car dependence research yet. Still, it can be assumed that the method can be beneficial. MLR can help explore the study area in more detail and identify predictors associated with quantitative car dependence in the traffic zones.

For this purpose, preselected spatial factors from the literature, whose data were openly available, were collected and analyzed (Table 1).

- The share of accidents involving cyclists or pedestrians has been chosen as a potential predictor, as Lucas and Jones (2009) and Frumkin (2002) found that pedestrians and cyclists make up a high proportion of road accident victims. For the European Union, this represented almost 40 percent of all road accidents in 2016 (European Commission, 2018).
- The factors representing the number of employees in the region and the balance of commuters were chosen as a result of Cervero and Kockelman’s (1997) research. They found that mode choice for work commuters is different from non-work commuters. The choice is supported by a sub-result of the survey by Villeneuve and Kaufmann (2020), according to which respondents confirmed preferences of car drivers in the labor market and at the political level.
- Income tax expenses have been investigated, as Jeekel (2014) identified a spatial mismatch between living and working places for poorer and less educated households, noting that “many poorer households have cars, but their mobility comes at a price; a great part of their household income goes to car mobility.” Lucas and Jones (2009) also found that non-motorized households are predominantly found in lower-income groups.
- Land purchase values, and the distance to the nearest town center can be considered due to the factors mentioned above. Both are primarily related to issues of urban sprawl, built environment, and financial equity issues (Lucas & Jones, 2009).
- Both, MacKenzie (2009) and W. Zhang et al. (2020) included the distance to the nearest public transit stop in their car dependency analyses with the result that this is quite relevant for users in the study area.
- The availability of parking spaces was identified as an influencing factor by von Behren et al. (2018). They describe it as a “pain point for car use” and add that its absence can indirectly lead to independence from the automobile. However, this factor could not be considered in this paper due to lack of data availability.
- Finally, population, building, or job density have often been recognized as relevant comparators, such as by MacKenzie (2009) or Wiersma et al. (2015).

**Table 1.** Spatial factors associated with car dependence

Spatial Factor	A	B	C	D	E	F	G	H
Share of accidents involving cyclists/pedestrians	✓							
Land purchase value		✓						
Commuter's balance			✓					
Income tax						✓	✓	
Number of employees	✓	✓		✓	✓			
Distance to next Town Centre						✓		
Public Transport Stop Distance	✓				✓			
Parking Situation								✓
Population / Job Density	✓			✓				

A: MacKenzie (2009), B: Duran-Rodas et al. (2019), C: Sohn and Yun (2009), D: Wiersma et al. (2015), E: Zhang et al. (2020), F: Lucas and Jones (2009), G: Motte-Baumvol et al. (2010), H: von Behren et al. (2018)

### 3 Methodology

Based on previous research on measuring car dependence, our exploratory approach is presented based on the estimation of a car dependence factor (CDF). It is intended to meet the following requirements: 1) the characteristics for auto-oriented development shall be considered, and 2) the results should be visualized in as much detail as possible.

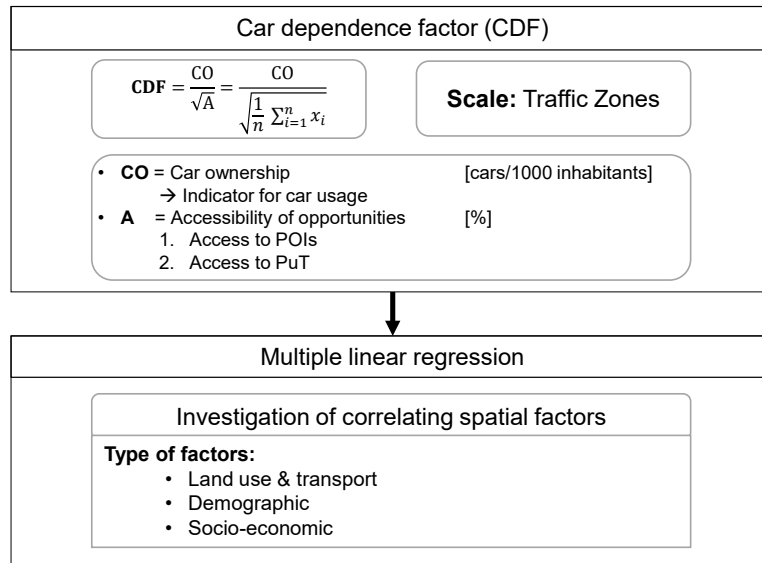
Altogether, the approach consists of two parts: the calculation of CDF for every transport zone, and the multiple linear regression to explore spatial factors associated with CDF. The novel approach is a combined method based on a literature review on car dependence on the one hand and a statistical method common in sciences and transportation on the other. The entire procedure is shown systematically in Figure 1.

#### 3.1 Car dependence factor (CDF)

After initial considerations, we used a formula for calculating the degree of car dependence for traffic zones based on the extent of car usage and the accessibility to basic needs for people without car access. Mathematically, we defined CDF as the rate of car ownership per unit of residents and the square root of the average accessibility to basic opportunities per analysis zone (Equation 1).

$$CDF = \frac{CO}{\sqrt{A}} \quad (1)$$

$$A = \frac{1}{n} \sum_{i=1}^n x_i \quad (2)$$



**Figure 1.** Approach to assess car dependence quantitatively and identify associated spatial factors

### Car ownership (CO)

In equation (1), “CO” stands for car ownership, which is an indicator for higher car usage (Kitamura, 1989), lower transit usage (Paulley et al., 2006), and lower utility cycling (Goodman & Aldred, 2018), as it is generally the case in European countries (European Commission, 2018). Car ownership refers to the degree of motorization, which is the average number of passenger cars per thousand inhabitants. It is often documented by official institutions and publicly available. Here, the value is used as a proxy for automobile use, which is more challenging to record and often not publicly available at the required resolution.

### Average Accessibility to opportunities (A)

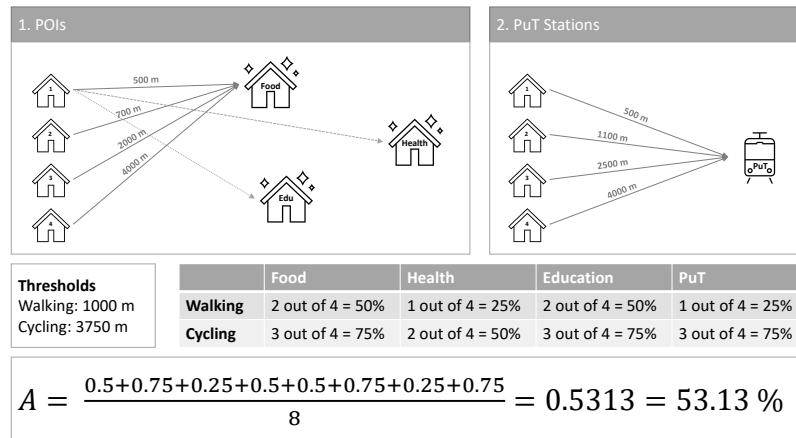
“A” can be described as an indicator at a “zone” level of access by walking or cycling to basic needs (including public transport infrastructure) instead of using the car. In equation (1), “A” is estimated as the average percentage of buildings within a zone of analysis, which have access to two types of basic services: 1) “Basic” Points of interest (e.g., food, health, education), and 2) Public transport stations.

The percentages of access to the two components mentioned above were averaged in the denominator for each zone. This indicator can be used to understand the level of access to POIs and alternative transportation as a whole, and it also allows for comparison between zones.

Figure 2 shows a graphical representation of the calculation of “A.” While four arbitrary starting points are set in the figure, all buildings located in the study area were chosen as starting points in the application. Whether or not a building block has access to a basic opportunity is defined by whether a location within the study area is further than a cycling or walking threshold distance to perform an activity comfortably or not. The proportion of all buildings in each zone below this threshold is included in the accessibility of opportunities.

Regarding the thresholds, a maximum travel time of 15 minutes was assumed for both pedestrians and cyclists. Using the average speeds of three to five kilometers per hour for pedestrians and 15 kilome-

ters per hour for cyclists described in Pajares et al, (2021), the limit for walking was set at one kilometer for pedestrians and 3.75 kilometers for cyclists. These distances are consistent with Daniels and Mulley (2013) and the European Commission (2020). Daniels and Mulley note that the average walking distance from home to public transport is less than one kilometer. The European Commission cites an average traveling distance for cyclists of three kilometers in European countries.



**Figure 2.** Exemplary graphic representation of A, only food was considered as POI

In this approach, we did not weigh the different components considering them as basic opportunities at the same level. Additionally, indicator “A” was square rooted in order to relativize particularly extreme values. Ultimately, car ownership CO per square-rooted access to opportunities “A” for each transport zone forms the CDF, representing the degree of car dependence. In this way, the equation primarily indicates the degree of car ownership, divided by a potential lack of access to basic facilities with means of transport other than the private car.

### 3.2 Identifying spatial factors associated with car dependence

After selecting the factors, the MLR between CDF and these factors could be calculated. It was chosen to apply Spearman correlation tests (Spearman, 1904), which is more reliable when not all values would be normally distributed and outliers had to be expected (Hauke & Kossowski, 2011). After identifying the correlations among the chosen factors and following a conservative approach, factors were selected when the correlation to the CDF was greater than 0.3. Furthermore, a threshold spearman correlation of 0.7 was set to eliminate redundant variables and avoid multicollinearity (Duran-Rodas et al., 2019). In the end, factors with a p-value of less than 0.05 could be assumed to be associated with CDF (Berkson, 1942). In addition, the highest possible coefficient of determination R<sup>2</sup> was aimed for.

### 3.3 Study area

The study area is Munich transport and tariff association MVV. This area includes nine counties, covering 5711 km<sup>2</sup> with almost three million inhabitants in 176 municipalities (MVV, 2020). Figure 3 depicts the study area and its location.

The study area includes the second-largest airport in Germany (Landeshauptstadt München, 2020b); industry, with six of Germany’s 30 largest and highest-turnover listed companies in the Munich area (Landeshauptstadt München, 2020a); and education, with three state universities and more than ten other higher education institutions (StMWK, 2020).

This results in a highly mobile region with nearly 1.7 million passenger vehicles registered in the



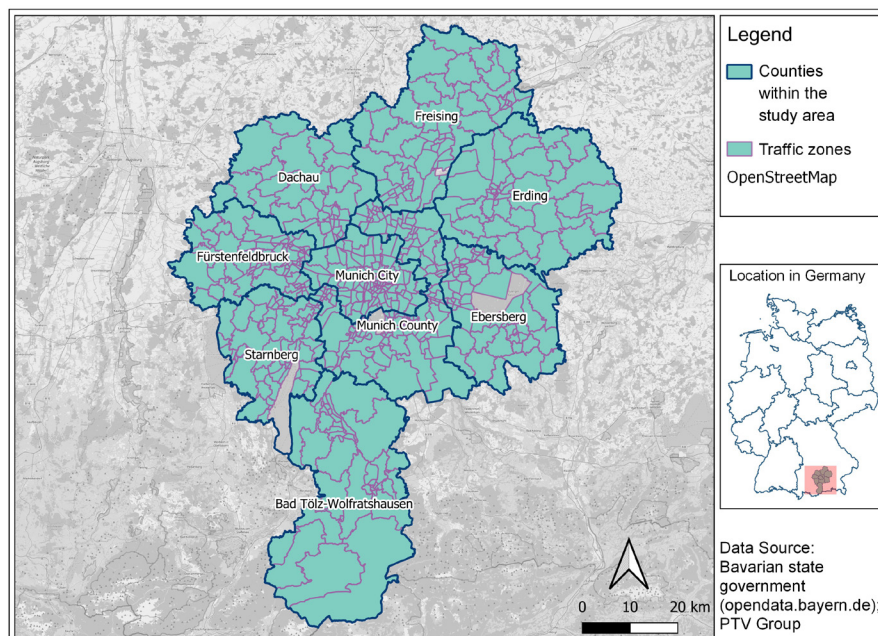
area (MVV, 2020). The public transport company MVV offers 388 lines served by underground and suburban trains, streetcars, and buses. The most used modes of transport<sup>1</sup> are motorized individual transport with a share of 46 percent of all trips made and public transport with a share of 18 percent (Follmer & Belz, 2018). Moreover, 21 percent of trips are made on foot and 15 percent by bicycle.

### 3.4 Data collection and processing

For this paper's application, the "CO" values were taken from the State Transport Model 2017 for Bavaria of the PTV Group. It is described in Pillat (2017) and collects a set of traffic data for Bavaria that is divided into individual traffic zones (Figure 3).

To calculate the "A" values, data was first collected covering all building blocks and points of interest (POIs) in the study area from OpenStreetMap (OSM)<sup>2</sup>. The following locations were considered for the three categories: Health included the tags "doctor" and "hospital," Food included "supermarket" and "greengrocer," and Education included "kindergarten" and "schools."<sup>3</sup> For the distances to public transport, all train, bus, and streetcar stations were taken directly from the Munich Transport and Tariff Association (MVV).<sup>4</sup> To calculate the distances between all buildings in the study area and the selected POIs, a distance matrix was created using QGIS. The resulting crow flight distances were multiplied by 1.3 to estimate the more realistic path distance (Reneland, 2001).

For the execution of the MLR, different sources were compiled. Accident statistics could be obtained from the "Accident Atlas" of the German federal and state statistical offices (Statistische Ämter des Bundes und der Länder, 2020b). Information on land sales values, income tax, commuting, and number of employees was obtained from the most recent publicly available census surveys conducted in 2011 (Statistische Ämter des Bundes und der Länder, 2020a). Density values of population and jobs were also obtained from the 2017 Bavarian State Transport Model (Pillat, 2017).



**Figure 3.** Location and traffic zones of the study area

<sup>1</sup> In the present study, motorized individual transport includes car use, but also (small) motorcycles and commercial vehicles. The study also distinguishes between drivers (34 percent) and passengers (12 percent), which is not done here for simplicity reasons.

<sup>2</sup> All OSM data was obtained in late October 2020 via the platform "Geofabrik" (Available online: <https://download.geofabrik.de/>)

<sup>3</sup> The tag "schools" contains all primary and secondary schools. Universities were not included initially, as this approach targeted the most basic needs.

<sup>4</sup> Available online: <https://www.mvv-muenchen.de/fahrplanauskunft/fuer-entwickler/opendata/index.html>

## 4 Results

In the two-staged approach to assessing car dependence quantitatively in the public transport region of Munich, the CDF was calculated first. A high CDF represents a high degree of car dependence and vice versa. Accordingly, regions with high levels of motorization tend to be more car dependent. The lack of access to opportunities can then further increase the CDF through low scores of “A.” Table 2 provides basic statistics of the three values. The MLR subsequently conducted led to information on spatial factors that can be associated with the given value of car dependence.

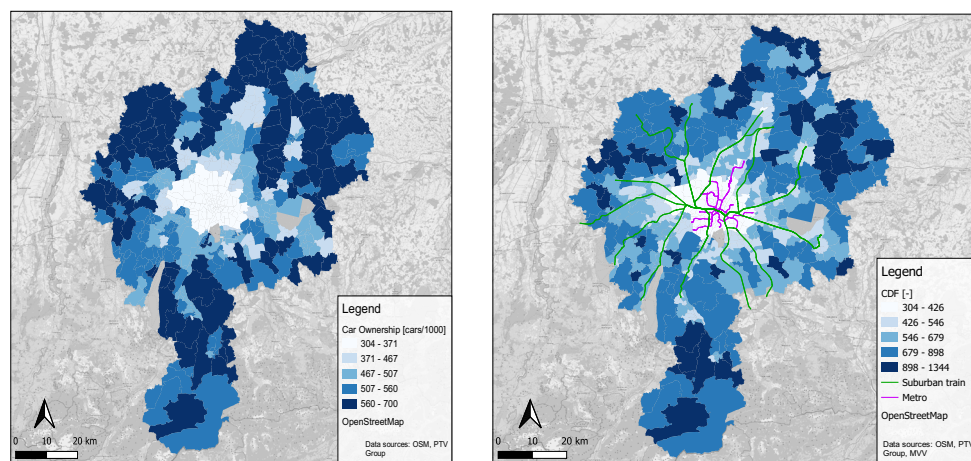
**Table 2.** Descriptive statistics of CDF and the MLR

Variable	Min.	St. Dev.	Q1	Mean	Q3	Max.
CDF	303.7	179.3	475.3	574.0	642.4	1344.4
Car ownership [Cars/1000 inh.]	303.6	77.1	449.3	482.4	525.0	700.1
Accessibility of opportunities	0.47	0.13	0.80	0.88	0.98	1.00
Share of accidents involving cyclists/pedestrians	0.00	0.30	0.17	0.43	0.65	1
Land purchase value [€/ha]	263.60	753.50	660.60	1263.50	1703.00	2638.20
Commuter's balance (p. pers.)	0.00	0.30	0.04	0.21	0.27	1.96
Income tax [€/pers.]	0.00	3.40	5.07	6.95	7.86	27.87
Number of employees (p. pers.)	0.00	0.40	0.28	0.51	0.67	2.52
Distance to next Town Centre [m]	41	3,057	1,328	3,515	4,876	20,664
Public Transport Stations [/ha]	0.00	0.10	0.01	0.04	0.06	1.83
Population density [/ha]	0.01	39.4	2.41	27.39	37.71	312.34
Job density [/ha]	0.00	56.6	1.14	21.97	17.94	690.76

Looking at the spatial distribution of the CDF in Figure 4, it appears the CDF is higher in rural areas than in urban areas. This is reflected in the study area by lower values in the center, increasing outwards. The areas with a minimal degree of CDF are the state capital Munich and isolated zones outside the city, such as parts of Garching, Erding, and Freising in the North of Munich.<sup>5</sup>

Maximum values were reached in zones far from the center of the study area. These are predominantly outside the catchment area of the suburban train (S-Bahn). In general, proximity to the S-Bahn network seems to be a good indicator of a rather low car dependence (Figure 4). A direct, but obvious correlation can be seen between CDF scores and car ownership. Areas with a higher number of cars often have higher car dependence. However, areas with high car ownership that are close to the city or near the commuter rail network have relatively low CDF scores.

<sup>5</sup> These three cities are part of the Munich metropolitan region but are themselves quite prosperous. Garching and Freising are university locations (TUM (2020)) and both Erding and Freising benefit from Munich Airport (Landeshauptstadt München (2020b)), which is located in between both.



**Figure 4.** Car ownership and car dependence in the study area

In beforehand of the MLR, a spearman correlation analysis was conducted. The results show that almost all factors exceed the selected minimum correlation threshold  $r_s$  (Table 3). The factor determining the proportional personal income tax is just below the minimum value, but it has been considered, nevertheless. For the final selection of factors, only those were favored for which no collinearity was expected. At the same time, the factors were selected to achieve the highest possible regression values in the MLR.

**Table 3.** Spearman correlation results

Coefficients	$r_s$
Percentage of accidents involving cyclists/pedestrians [%]	-0.42
Land purchase value [€/ha]	-0.58
Commuter's balance (p. pers.)	0.50
Income tax [€/pers.]	-0.23
Number of employees (p. pers.)	-0.52
Distance to next Town center [m]	0.49
Public Transport Stations [/ha]	-0.58
Population density [/ha]	-0.77
Job density [/ha]	-0.79

Based on the factors finally considered for the MLR (Table 4), the following trends can be observed: Areas are more likely to be car dependent if they have low employment, low-income tax revenues, low land acquisition values, low percentages of accidents involving pedestrians or bicyclists, a greater distance to the next larger town, and a high difference in outbound and inbound commuters. The coefficient of determination,  $R^2$ , shows that these six factors explain about 64 percent of the variation in the CDF.

**Table 4.** Transformed feature selection and regression results. Note: \*\*\*  $p < 0.001$ 

Coefficients	Beta	Std. Error	Pr(> t )
Intercept	-6.42E-16	1.50E+01	***
Percentage of accidents involving cyclists/pedestrians [%]	-0.123	1.53E+01	***
Land purchase value [€/ha]	-0.368	8.27E-03	***
Commuter's balance (p. pers.)	0.278	2.75E+01	***
Income tax [€/pers.]	0.140	1.36E+00	***
Number of employees (p. pers.)	-0.295	2.29E+01	***
Distance to next Town center [m]	0.394	1.59E-03	***

*Residual standard error*      108.2 on 654 degrees of freedom  
*Multiple R<sup>2</sup>*                      0.639  
*Adjusted R<sup>2</sup>*                      0.635

## 5 Discussion

The spatial visualization of the study area shows that rural areas in the region of Munich have higher car dependence values due to high car ownership and poor opportunities without car access. Some of the urban zones also have high values of car ownership. However, due to the availability of public transportation and proximity to chosen POIs for basic needs, they have lower CDF values. That is the case in Erding, for example. These results are consistent with Frumkin (2002), Urry (2004), and Wiersma et al. (2015) and their explanations on car dependence and spatial separation. There is a uniform pattern that rural regions are more car-dependent than urban regions.

The CDF alone can be used to guide regional transportation and urban planning. In addition, the regression provides information on spatial factors that have been addressed in the literature on spatial development and car dependence. The adverse effects of distance to major cities on the CDF, which were just identified in the spatial visualization, could be confirmed by the linear regression factor "Distance to next town" (Newman & Kenworthy, 2015).

A typical scenario can be identified from the three parameters, employees, income tax, and the commuter's balance. Places where few jobs are offered and generally less income tax is paid show a higher car dependency. This effect goes in line with Urry's (2004) description of car dependence, where the separation of home and work in sprawling areas can only be accommodated by increased car travel.

The regression factor of land sales values shows that structurally weaker regions tend to be more dependent on the car. Conversely, this would mean that land is more expensive if people in the area are less dependent on the automobile. Dargay (2001) has found a correlation between increasing wealth and car ownership. Thus, wealthy people can afford an expensive property that is unlikely to be affected by car dependence. However, it is these same people who then contribute to car dependency by buying more cars. Further research can be conducted to examine the significance of different property types, from flats to detached houses.

The regression factor, which describes the proportion of accidents involving cyclists and pedestrians, can be interpreted in different ways. It shows that areas with a low proportion of accidents involving pedestrians or cyclists have a high car dependence. Conversely, this would mean that decreasing car dependence could bear a higher number of accidents involving cyclists and pedestrians. This result

contradicts Lucas and Jones (2009), who mentioned that car dependence mainly affects pedestrians and cyclists in terms of casualties. However, it would be useful to investigate the absolute proportion of active road users in regions with a high CDF. It is possible that in very car-dependent areas, the number of pedestrians and cyclists is very low, reducing the possibility of accidents. In addition, the severity of accidents in car-dependent regions must be considered. Overall, no causality relationships can be assumed between these factors. With these results, we would like to point out that potential externalities of car dependence should be considered not only at the local level, but also at the regional level.

Some recommendations can be derived from the results just described. For rural areas with high car dependency, better transportation options need to be created. In places where the accessibility to opportunities is good but car ownership is still high, more incentives need to be created to drive less or even buy fewer cars. Here, car users and their level of attachment to the vehicle need to be addressed.

Since car dependence is also, to a large extent, an equity issue, this must also be addressed. There is an equity gap between regions that are car dependent and those that are not in the study area. Car dependent areas are primarily rural and tend to be structurally weaker as measured by jobs, income tax, and commuting. In addition, land prices tend to be high in areas that are not car dependent. As a result, not everyone can afford to live in a car-independent area. People with lower incomes must move to more remote areas where they are more likely to need a car for daily activities, which in turn would cause financial problems. Reducing car dependence is therefore desirable in terms of equity.

The results mentioned so far are also interesting in light of the ongoing COVID-19 crisis. In the wake of the global pandemic and the lockdown, demand for transport initially fell massively. Afterward, the trend toward private vehicles, such as cars and bicycles, was particularly noticeable (Lozzi et al., 2020). The latter is unlikely to enjoy year-round popularity everywhere. A series of surveys by Furcher et al. (2020) found that about one-third of respondents came to appreciate the value of the automobile in a new way. Thus, to avoid perpetuating the role of the automobile and its unsustainable consequences, the problem must be actively addressed as soon as possible.

While a negative relationship between car dependence and urban development is not a novel conclusion, it still approves the introduced method to quantify it. The method has its limitations both in application and interpretation. With car ownership as the numerator of the CDF, a specific value was chosen that can provide information about car use, but not necessarily. Therefore, in further research, it would be important to classify which zones achieve a high value for car dependence, whether due to high car ownership, less access to activities, both, or even neither attribute. This becomes particularly relevant if the car dependency study is followed by measures to improve the actual situation. Especially to be able to use the CDF more easily in the future and to analyze regional car dependence, embedding it in a visualization environment, such as the accessibility tool GOAT (Pajares et al., 2021) might be useful.

Regarding the accessibility of opportunities factor, it should be noted that while the availability of public transport was considered, the hours of operation and the frequency of the means of transport were not. Thus, in regions with a transit stop, but the mode of transportation is offered very infrequently, CDF scores may be relatively low despite poor accessibility. In addition, only the three categories of health, education, and food were considered as POIs. Furthermore, it must be noted that the distance calculations were performed using only crow fly distances. Although a proven factor supplemented this, it still does not represent actual travel distances.

Another possible problem for the transferability of the method could be the availability of data for the model. An attempt was made to select data and factors that are officially confirmed and publicly available, but this is not guaranteed everywhere. In addition, different data sources were combined in the application, which can always lead to inconsistencies. In any case, careful data maintenance is helpful

and necessary.

To link the car dependence values with spatial comparison factors using a MLR, various data sources were used. These differ in terms of spatial and temporal expression and detail. Especially with regard to the temporal difference of the traffic data from 2017 and the census data from 2011, limitations have to be acknowledged in order to present a comparison under real conditions. Nevertheless, the study results are relevant given that it is an exploratory approach whose focus is mainly on the methodology.

Finally, it is worth mentioning that the Spearman correlation and the MLR should not be “over-interpreted,” meaning that even if their results seem promising, they cannot be taken as evidence but as indications (Hauke & Kossowski, 2011). Thus, the comparative factors elaborated in the MLR alone do not serve to determine the car dependence of a region.

## 6 Conclusions

This article summarized previous approaches to assess car dependence. The core part was exploring quantitatively car dependence in the public transport network area of the region around Munich in Germany.

The main findings of the application were that car dependence was mainly found in rural areas, which are far from larger cities and the Munich suburban train network and have high car ownership. Other factors associated with increasing car dependence were a low number of resident workers, low tax revenue, a high difference between out- and in-commuters, low land prices, and a low proportion of cyclists and pedestrians involved in traffic accidents.

Given the environmental and social impacts of car dependence, strategies to provide alternatives to car use should be developed proactively and at an early stage. Using the described approach to quantitatively assess car dependence, pertinent patterns can be identified and discussed directly with decision makers and urban planners.

Local decision makers can use the results of the application in several ways. The CDF can be used to discuss whether the car is perceived as the only sensible means of transport in an area. Existing public transportation structures can be expanded, or their use encouraged. Factors considered in the MLR can also be looked at locally, such as the labor market or income tax revenue. While these values are not expected to change rapidly, it can give an idea on the role car dependence might play in the future.

The overall process may serve to reduce car dependence: regions with already low CDF values will know how to proceed to avoid upcoming dependence. In contrast, regions with higher values will know that action should be taken. Modern solutions such as on-demand mobility or carpooling may be considered especially concerning higher car dependence in more rural regions and places with little public transport. Furthermore, the integration of land use and transportation with strategies such as densification, transit-oriented development, and growth should be invoked.

As components of the CDF equation, additional research can be conducted on car ownership and accessibility to opportunities without driving. Since car ownership is not the same as car use, this variable could be used directly in further applications. Regarding the accessibility to opportunities, hours of operation and frequency of public transportation could be included in the calculation. Further research should be conducted by weighting the access to the different types of opportunities. To enforce more realistic estimations, it will be useful to perform the distance calculations using the actual road network and to explore non-linear regressions for linking spatial factors with car dependence. Finally, this approach requires further testing with additional study areas to evaluate its transferability. Depending on local geographic data and social contexts as well as data availability, different spatial factors can be assessed as predictors of car dependence in other areas. Local decision makers should also be consulted in this process to determine and improve its usability for future and

sustainable transport and land development.

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