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ALİ ENES DİNGİL

SOCIO-TECHNICAL FACTORS FOSTERING SUSTAINABILITY IN URBAN TRANSPORTATION: A WORLDWIDE ANALYSIS

DOCTORAL DISSERTATION

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Doctoral dissertation
Technological Sciences, Environmental Engineering (T 004)

2019, Kaunas

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Abbreviations

ACCC	Average cycleway closeness centrality
ADETT	Average daily extra travel time
ANC	Average node connectivity
ARC	Average road connectivity
ARCC	Average road closeness centrality
ATC	Average train connectivity
AWTCC	Average weighted train clustering coefficiency
BIA	BRT accessibility
BRT	Bus rapid transit
CE	Transport-related CO_2 emissions per person per year for commuting purposes
CIA	Cycleway infrastructure accessibility
COL	Collectivism
CSP	Concentrated solar power
DC	Daily average commuting distance to work by private car
DPT	Daily average commuting distance to work by public transport
EU	European Union
EV	Electric vehicle
FCV	Fuel cell vehicle
FEM	Femininity
GDP	Gross domestic product
GHG	Greenhouse gas
HCD	Hofstede's culture dimensions
HEV	Hybrid electric vehicle
HVDC	High-voltage direct current
IA	Infrastructure accessibility
ICE	Internal combustion engine
IND	Individualism
LCA	Life-cycle assessment
LRT	Light rail transit
LTO	Long-term orientation
MAS	Masculinity
MSC	Mode share of private car trips
MSPT	Mode share of public transport trips
OECD	Organisation for Economic Cooperation and Development
OSM	Open Street Map
PHEV	Plug-in hybrid electric vehicle
POD	Power distance
RCRC	Road connectivity over road circuity
RIA	Road infrastructure accessibility
SWP	Share of working population of the total population
TIA	Train infrastructure accessibility

UNC	Uncertainty
US	United States
WCC	Average energy consumption per person km for a private car
WCPT	Average energy consumption per person km for public transport
WT	Transport energy per person per year for commuting purposes

Glossary

Average daily extra travel time	One type of transport performance measurement quantifies the traffic congestion level defined as the extra travel time in a day with respect to the free-floating traffic scenario averaged over all the monitored traffic participants of a distinct urban area.
Distance based network connectivity	The connectivity of a network based on measures of distance.
GDP per capita	A measure of the income level, a city's Gross Domestic Product per person.
Hofstede's culture dimensions	A value-based culture index derived on the grounds of of factor analyses which defines and quantifies the effects of a society's culture on the values and behaviors in a nation.
Infrastructure accessibility	The length of the transport infrastructure per person to quantify the amount of available transport infrastructure.
Network connectivity	A measure of network resilience, the degree of connections in a network.
Network circuity	A measure of network directness, the ratio between the travel distance and the line of sight distance averaged over the network.
Population density	The number of people living in each unit of land area which is employed to justify land use.
Travel mode share	A measurement of user acceptance on a particular type of transportation, the percentage of travelers using the particular transport type.
Transport energy per person per year	A measurement of transport related energy consumption justifies energy efficiency of mobility systems in urban areas.

1. Introduction

The background and the relevance of the research

Worldwide, 55% of the global population is currently living in urban areas, and the present urban population is projected to increase from today's 4 billion people to 6 billion by the year 2050 [1]. Mainly as a result of migration from rural areas, cities are growing in terms of inhabitants and urban area. Thus cities form new residential areas outside and/or further away from the city core. However, the speed of urbanization presents certain challenges, such as meeting the growing demand for transport infrastructure, transport energy consumption and the related costs, air pollution, global warming and congestion. Definitely, one of the recent growing global concerns is global warming. With the mankind facing the global warming, the Paris Agreement was drafted in 2015 with the aim to keep the global average temperature increase below 2 °C with respect to the pre-industrial levels. One year later, in 2016, a record-setting global mean surface temperature (GMST) was measured for the third year in a row [2]. Meanwhile, there is little doubt that the main reason for the global temperature change is anthropogenic, with transportation being one of the major contributors to global warming in terms of human activities. According to the *International Energy Agency* (IEA), the total global energy consumption for transport reached 28% of the total end-use global energy in 2010, of which, urban transportation accounted for approximately 40% [3, 4]. Furthermore, the transport sector in 2009 produced over 6,500 million tonnes of CO_2-equivalent emissions (equal to 22.5% of the total energy-related CO_2 emissions), of which, roughly 75% stem from road-based transportation [5]. Consequently, reducing transport-related energy consumption is one of the main objectives of transport planners with the aim to achieve more sustainable mobility. In addition, with the growing population, one of the major challenges for urban transportation is congestion. According to current estimations, citizens will be spending three times more than presently in traffic jams, which equals 106 hours per year by 2050 [6]. The costs of urban traffic congestion equal 557 million US$ per year in the United States (US) economy, and are estimated to equal £13 billion per year in the United Kingdom's (UK) economy [7, 8]. Furthermore, the forecasted congestion costs will have reached £21 billion per year for the UK by 2030. The social costs of urban mobility in Beijing reached 7.5–15% of the city GDP as a combined impact of congestion, accidents and pollution [9].

Sustainable mobility can be defined as *satisfying the current transport needs without sacrificing the ability of future generations to meet transport systems where social, environmental and economic accessibility can be sustained* [10]. The level of satisfying objectives for these three dimensions represents the degree of sustainable mobility. Urban areas consist of the same components and their interrelations in which individual framing conditions make the difference regarding the characteristics of urban systems [11]. Urban zones take different user privileges and urban characterizations as a result of differences in terms of socio-technical factors: cultural, educational, income level, the nature of demography, technologic, land use and infrastructure. As an example, in the US, people tend to live in low-density, single-family houses and commute by car to work. In Japan by contrast, high-rise residential buildings dominate, and workers commute by public transportation (mostly rail-based) [12]. Local governments and urban transportation planners want to know if the planned transport investments would be sustainable in the long term. Some major challenges highlighted above and the efforts towards enhancing sustainable mobility require integrated and strategic planning due to the fact that urban mobility bounds up with multi-dimensional factors. Local planning is necessary as each urban zone is under different socio-technical conditions. The following questions are presently addressed: *How does the urban mobility system work under differently built environments and how do the system variants interrelate? In turn, which transport strategies would be sustainable and under which conditions?* To answer these questions, each of the socio-technical factors should be examined systematically. In multi-dimensional analysis, a series of indicators and the interaction among them are identified by using logic architectures [10]. The correlations and internal relations between these factors, the question how these factors affect the users and the transport performance, and what all these relations will bring should be identified. In order to achieve this, worldwide analysis and a comparison of urban areas is necessary because it is of paramount importance in order to draft or reassess holistic transport planning. Holistic socio-technical analysis for urban mobility has not yet been traced in literature, and local analysis by itself cannot offer a holistic view of the topic. Examining similarities and differences within urban areas and the worldwide assessment of recent urban mobility strategies helps to understand whichever alternative sustainable system can be successful and under which socio-technical conditions success can be achieved. Also, understanding how cities are shaped by setting the appropriate transport priorities can help to achieve sustainable mobility objectives [13].

Aim of the research

The aim of the research is to establish the role of socio-technical factors in enhancing sustainability of the urban mobility system; an associations scheme will be used to derive which transport strategies can minimize the socio-economic costs and the environmental footprint of the urban transportation system.

Tasks:

1. To provide multi-dimensional information which needs to be collected and processed for worldwide analysis through detecting the identified and missing associations among socio-technical factors and how the urban mobility system works under differently built environments during a systematic literature review.

2. To perform worldwide analysis so that to identify correlations and quantify these relations by calibrating models based on socio-technical factors and transport

performance indicators, such as the travel modal split, congestion and transport energy consumption.

3. To conclude, as a result of the discovered correlations, identified models, interrelations between factors and literature contribution, to identify an association scheme that can derive which transport planning strategies would be sustainable.

Research object and research methodology details

The research object is urban transportation. The research consists of systematic literature review and quantitative statistical analysis. The general approach of the present thesis is to collect, process, correlate and model. Worldwide analysis and comparison of urban areas requires a large and diverse multi-dimensional database. Open data is sourced from regional statistical offices, government sources, municipalities, and established studies. The *Python* software package *OSMnx* was used for the extraction and conversion of each transport infrastructure information for the desired urban locations as well as for performing some infrastructure design-related calculations. An *Excel* database was created as a result of specific transportation data drilling, processing and collection. Also, the *Excel* database was used for the calculation of some urban indicators. Software *IBM SPSS Statistics V25.0* was used for the processing of statistical data.

Scientific novelty and practical value

This is the first systematic transport multivariate analysis using recent directly observable open source data from different urban areas around the world. An integrated and supportive socio-technical scheme was created based on the worldwide analysis and systematic literature review. The results of the present thesis and the developed supportive socio-technical scheme for urban mobility can be used by local governments, urban transportation planners, and policy makers to shape future urban strategies.

Structure and contents of the thesis

The dissertation consists of an introduction, literature review, methodology, six main chapters of analysis, conclusions and a list of references. The second section contains a systematic literature review of social and technical factors and how these factors influence the users and transport performance. The third section explains the employed method and specific transportation data drilling, processing and collection from respected open data sources. The sources, their collection method and the pre-processing steps of all the necessary information are explained. In the fourth section, the following aspects are dealt with reference to the investigated city panel: (i) analysis of cultural dimensions in urban travel patterns, (ii) influence of the higher education level on the urban travel modal choice, (iii) multivariate analysis between socio-economic factors, land-use, transport infrastructure and performance, (iv) multivariate analysis between the transport infrastructure, the infrastructure design and performance, (v) assessment of the yearly individual transport energy and individual CO_2 emissions by means of the quantitative relationship between the population density, transport infrastructure and energy consumption for transport purposes, and (vi) a supportive socio-technical guide for urban mobility. To conclude, the main findings are summarized in the final section.

2. Literature Review

Urban areas are the 'engine' of the innovation, knowledge, economic development and employment; thus urban mobility systems possess vital importance to the economic functioning of cities and the welfare of the population by providing accessibility for work, goods and all social activities [14]. Urban areas serve transport services under two main infrastructure types: road-based systems and rail-based systems. Some cities, such as Tokyo, Berlin and Hong Kong, have adopted rail-based urban mobility while as some others (especially US cities) have adopted road-based urban mobility (car and bus-based systems). Especially cities in Denmark, the Netherlands and some other EU countries have matured their cycling infrastructure since 1970s.

The socio-economic transformation of cities has been booming with the increasing urban sprawl, whereas the expansion of sustainable transport modes has not been happening at the same rate; in turn, the growth of private car ownership peaked [14]. This situation has developed along with the increasing social inequity, socio-economic costs and environmental impacts. Sustainable mobility requires environmental (air pollution and GHGs), social (accessibility, equity) and economic (costs) considerations factored into decisions affecting the mobility system [10]. To take action, the EC published its *Urban Mobility Package* in 2013 where *Sustainable Urban Mobility Plans* (SUMPs) are given the main focus. The concept of SUMPs aims to create alternatives to car use and ownership and provide a shift towards cleaner and more sustainable transport modes through focusing on the people within a zone rather than directly on the transport while interacting urban functions and its surroundings [15]. Sociotechnical factors recognize the interaction between people and technical factors in complex systems which bound up multi-dimensionally. Urban zones take different privileges and characterizations as a result of differences in terms of socio-technical components: cultural, educational, income level, nature of demography, technological, land use and infrastructure. The holistic understanding of urban mobility components is essential for the success of sustainable urban development strategies [11]. In this section, a systematic review is presented to understand how cities are shaped by socio-technical factors and how these factors in turn affect the transport users and transport performance worldwide.

2.1. Social factors

2.1.1. Culture

Culture is a very important indicator which reflects an inherent characteristic of societies. Culture is a common characteristic of a society in which artists and creative thinkers describe reality of their citizens with an "interpretation code" [16]. Reflection of common attitudes, values, beliefs and behaviors can be defined as culture [17]. Culture is accumulated, experienced and rooted in the DNA of a community not only as tangible items, but also as traditions of public life, rituals, food, conviviality, feasts, landmarks and symbols [16]. However, what exactly is meant by 'culture' is still an open question; some works related to the explanation of the phenomenon of culture have been conducted with the science of genetics, shared heritage and social conditioning [17]. A Darwinian analysis of cultural change is proposed by Richard Dawkins (1976) in which 'memes' are analogous to genes [18]. Furthermore, Dawkins described memes as discrete replicators which can be worked on by natural selection. A robust cross-national correlation between the relative frequencies of variants in genes associated to social sensitivity and the relative degree of individualism–collectivism in societies is reviewed [19]. The results show that genetic variation can interact with ecological and social factors to influence psycho-cultural differences.

Two major global analyses based on cross-cultural variation by social scientists are worth mentioning those by: Geert Hofstede [23] and Ronald Inglehart [20]. Hofstede is known for six basic culture dimensions that come to terms with the society's needs in order to organize itself; meanwhile, Inglehart's work is focused on two main dimensions explaining the dynamic change of culture. Hofstede's culture dimensions prevail in the analysis of cross-cultural psychology and international management, while Inglehart's work is generally used in politics and sociology [21]. In this paper, we analyze the role of Hofstede's culture dimensions due to the fact that travel behavior is more related to the human psychology whereas Hofstede's culture consideration is multi-dimensional. Hofstede's researches [22–26] were conducted with reference to a sample of one hundred thousand employees from IBM – a multinational corporation – coming from 50 different countries based on a specific global survey on the value associations. As a result of factor analyses aimed to examine the worldwide survey, Hofstede described six culture dimensions, such as *power distance* (POD), *uncertainty avoidance* (UNC), *individualism versus collectivism* (IND/COL), *masculinity versus femininity* (MAS/FEM), *long-term orientation* (LTO) and *indulgence* (INDG). Hofstede's culture dimensions shed light on the embedded values of diverse cultures. Culture dimensions proposed in Hofstede's works are described as follows. The IND/COL dimension of culture is the degree of interdependence which a society maintains among its members. Hofstede stated the IND/COL dimension to be the fundamental dimension of culture, called as patterns of the "me or we" sense. The fundamental issue addressed by the power distance (POD) dimension in the community culture is a measure of the centralization degree of power where the higher power distance means high inequalities in the community. Cultures with a low POD would not admit inequalities as easily. IND/COL and POD are strongly correlated with each other. Collectivist cultures have a low POD. When the POD is high, a community can emphasize the citizens' status. The fundamental issue addressed by the uncertainty avoidance (UNC) dimension is the level of built-in worry of the community culture. Communities with a high UNC have a high level of anxiety in an uncertainty situation. The MAS/FEM dimension demonstrates the level of competition in the community. A masculine culture would be less concerned with the quality of life. The long-term orientation (LTO) dimension shows the perceived importance of keeping links with one's own past while dealing with the challenges of the present and the future. Lastly, the indulgence dimension (INDG) can be described as the degree of socialization or control over impulses and desires in a society.

The national culture, as a subset of culture, while having been increasingly explored over the recent decades, was defined by Hofstede as "the collective programming of the mind that distinguishes the members of one national group from another" [27]. Different cultural conditions lead to different choice evaluations because of the varying 'value associations' [17]. Paulssen *et al*. [28] analyzed the role of Schwartz theory of human values on their travel mode choices. The results showed that the hierarchical value-based model of cognition brings a better understanding on how to increase public transport patronage for urban planners and policy-makers. One study tested Hofstede's culture dimensions (HCD) in order to explain travel behavior differences on the perceptions of and the feelings about the security as well as how the actual experience affects people's patronage of public transport [29]. The results demonstrated that HCD can be used to explain travel behavior differences based on the ethnicity background. Another research using Hofstede's cross-cultural indices power differential and individualism in 14 cities from different nations investigated whether qualitative cultural differences influenced individual or group choices to procure and use hybrid and electric cars [27]. A recent research [30] examined the role of culture in the mode choice for various migrant groups within Auckland. The results showed that the national culture was a strong motivator regarding how public transport is perceived differently by different national groups within a city.

2.1.2. Education level

The education level can be called as an acquired characteristic of societies. Education is imparting, acquisition and construction of knowledge (e.g., *know-what*, *know-why*) including facts, representations, meanings and values as structured information about the world [31]. Education and learning are decisive factors shaping the society and its spatial forms in dynamic collective ways. Educating citizens is presented as one of the hopeful paths towards providing sustainable development in the United Nations final report: *UN Decade of Education for Sustainable Development* [32]. The report shows that teaching and learning such issues as the climate change, disaster risk reduction, biodiversity, poverty reduction, and sustainable consumption can increase the awareness level in a society and, in turn, influence personal choices. A higher education level is an important proxy used in literature to assess the awareness level of societies with the current issues in a macroscopic way. Analysis was conducted in order to investigate the relationship between the public attitudes and the education level with a large cross-national database of the *International Social Survey Program* (ISSP) [33]. The obtained results indicate that the level of education is well-correlated with environmental concerns, even when other socio-demographic characteristics are controlled for. Also, a report by OECD [34] showed that an increase in the average education level improves the overall care for health in a society.

A research conducted within the *Dutch National Travel Survey* database demonstrated that the education level is positively correlated with the public transport mode choice for leisure trips [35]. Another study investigated how some characteristics in a society affect the travel mode choice in the Netherlands [36]. The results demonstrated that highly educated commuters show the highest propensity to travel by public transport (train) rather than by car. Car-sharing is one of the key strategies aiming at reducing car usage. A study analyzed the relationship between the membership potential of car-sharing programs and the socio demographic factors in Quebec City [37]. The obtained results indicated that car sharing was attractive only for specific segments of the population, such as highly educated people. Similar findings were observed in another study: individuals with a higher education level have a greater propensity to use car-sharing services [38]. A cross-sectional study in six cities was conducted in order to investigate social environment factors and individual attitudes regarding bicycle ownership and use [39]. The results showed that a higher education level has a positive effect on the regular usage of bicycles.

2.1.3. Income level

The income level is an important proxy shaping personal choices. A discrete choice modeling approach was employed including 112 medium-sized cities in Europe [40]. The results demonstrated that the share of the car mode increases with the car ownership and GDP per capita. Similar results were received during comparative analysis of travel behaviors in the urban areas of the US [41], and a meta-analysis was conducted in the United Kingdom [42]. Also, a negative relationship between the public transport usage and the income level was demonstrated for the United Kingdom [42], urban areas in the US [41], and the Sao Paulo metropolitan area [43]. However, this negative relationship was not found for 112 medium-sized cities in Europe [40]. Some results demonstrated that the public transport share decreases with the car ownership for US cities [44] and for Hong Kong [45]. Oppositely, a positive relationship between the car usage and the car ownership was demonstrated in a number of cities [42, 46, 47].

2.1.4. Nature of demography

The nature of demography is a complex structure referring to such factors as the distribution of gender, age, household composition, marital status and other variables in societies. These factors model the attitude towards physical conditions, housing, the value of time and responsibilities. Such attitudes as spending time with the life partner, taking care of the household members, different value orientation between men and women, willingness to lead a more comfortable life while ageing show differences in the priority and choice path but are hard to analyze in a consistent way. Many studies investigated the above listed factors. In a number of studies, the obtained results showed that women use less car with respect to men [35, 48, 49], and that married people tend to use the car more frequently than single people do [35, 50]. Furthermore, travelling with young children encourages travel by car [50–52]. Also, car usage increases with age [53], while the trip frequency and distance are reduced [54, 55].

2.2. Technical factors

2.2.1. Land use

Such population density measures as ‘sprawl’ or ‘dense’ are used to define the land use conditions in literature [56–58]. The shortened travel distance and duration of the trip within the city and the increased accessibility to the public transit services were reported for the cities with a higher population density [59, 60]. Many studies demonstrated that cities with a higher population density tend to use public transport or active modes more [35, 36, 47, 61, 62]. Furthermore, the private vehicle is less preferred in denser zones [47, 63]. Also, residents of mixed-use designed cities with a high population density tend to drive much less than others [35, 64]. There are only two cases of empirical evidence in literature [65, 66] which demonstrate a particular relationship between the transport energy consumption and the population density. Newman and Kenworthy [65] conducted early bivariate analyses in 1988 demonstrating a robust relationship between the population density and the transport-related fuel consumption for 32 cities worldwide. Their main result was disproportionately high transport energy consumption per person in cities with low population densities. Also Brownstone and Golob [66] estimated a joint model of residential density, vehicle use, and fuel consumption based on the California subsample of the 2001 *U.S. National Household Travel Survey*. Their main result demonstrated that a decrease in the density of 1,000 housing units per one square mile implies an increase of 1,200 miles driven per year and 65 more gallons of fuel used per household.

2.2.2. Infrastructure

The three following sub-sections provide comparative evaluation of different infrastructure systems (private vehicles, public transit and non-motorized mobility) with worldwide comparison.

2.2.2.1 Private vehicle

The results for the European Union (EU) for 2014 showed that cars are still the most common mode of daily transport (accounting for 54%), followed by public transport (19%), walking (14%), bicycle (8%) and others [67]. As far as the daily travel mode share in the US is concerned, the share of the private vehicle mode is over 85%, followed by 5.2% public transportation in 2015 [68]. There were approximately 258 million passenger cars circulating on the roads of the EU-28 in 2016, i.e., on average 506 passenger cars per 1,000 inhabitants [69]. In comparison, the US cities have 1.8 cars per household [70]. A strong correlation between the road infrastructure expansion and the vehicle ownership growth were determined for 50 countries and 35 cities [71]. A positive relationship between highway expansions and car usage was shown between 1982 and 2009 in the US [72]. A negative correlation between the transit ridership and the highway extension was found for the Montreal region, Canada [73]. A positive relationship was demonstrated between the car usage and the car ownership in a number of studies [46, 61, 74]. The integrated effects of ring roads and highways in Chinese cities caused 25% of central inhabitants to move to the surrounding zones [75]. The empirical estimates by Baum [76] show further that each highway expansion within an urban centre of the US metropolises causes an average 18% drop of inhabitants in the city centre. Analysis in Wisconsin State, US, during 1980–1990 demonstrated that highway expansions caused a population increase in the suburban areas thus booming the urban sprawl [77]. Similar results were shown for analyses in California between 1980 and 1994 [78].

The EU spends annually €1,044 billion on private transportation, of which, the operation of personal transport equipment accounts for €523 billion, purchase of personal transport equipment accounts for €291 billion, and purchased transport services account for €230 billion [79]. The estimated annual budget of the average EU household for transportation is approximately €2,000. There are important societal and economic costs of road transportation. In 2015, approximately 26,000 people died on EU-28 roads, and a further 1.4 million people were injured (135,000 of whom were injured seriously) [80]. However, it was estimated that the number of road accident fatalities in the EU decreased by 40% between 2006 and 2015 as a result of improvements in the road safety [81]. It was reported that the external costs of road accidents in the EU, including Norway and Switzerland, accounted for 225 billion Euro and were estimated at 1.7% of GDP in 2008 [82]. The accident costs of passenger cars were €157 billion per year, which makes up the largest share (70%) of the total accident costs. The social costs of road crashes in high-income countries are about 2.7% of GDP and 2.2% of GDP in low- and middle-income countries worldwide [83].

The US is the leading country in terms of the release of transport-related CO_2 emissions in the world; 1,618 million tCO_2-eq emissions (equal to 31% of the total energy-related CO_2 emissions of the US, of which, 87% is related to road-based transportation), of which approximately 25% is global transport related CO_2 emissions [5]. China is following with 503 million tCO_2-eq emissions (72% from road-based transportation), of which, approximately 7% is related to the total energy-related CO_2 emissions. Overall, the external costs (excluding congestion) of transport in the EU, including Norway and Switzerland, were calculated to be more than 500 billion, i.e., 4% of the total GDP in 2008 [82]. In addition, the annual congestion cost of road transport amounts to between €146 and 243 billion ('congestion cost' is the monetary equivalent value of the time spent in traffic jams), which is approximately 2% of GDP. The figure below (Fig. 2.1) sums up the results of the report in which the total external cost of passengers cars with reference to year 2008 is presented.

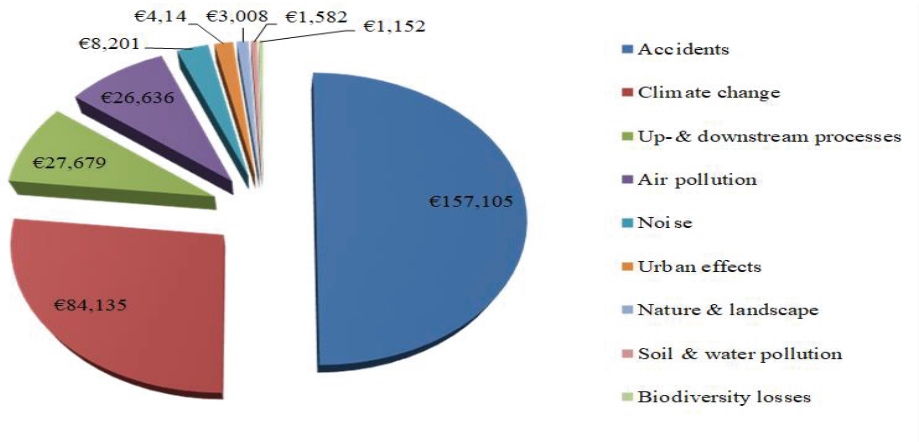

Figure 2.1 Total external costs of passenger cars in EU, 2008.

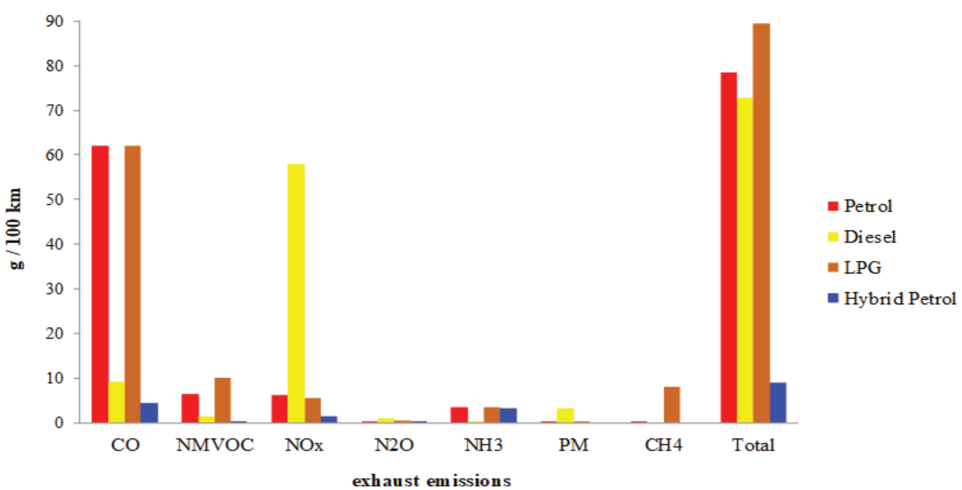

Figure 2.2 Comparison of exhaust emissions by different passenger cars, 2016.

The total passenger car external costs amount to €314,310 million in EU-27, excluding Malta and Cyprus, but including Norway and Switzerland. The main cause of external costs is the road accidents, which is followed by climate change and air pollution. The emission factors of cars (CO, NMVOC, NOx, N_2O, NH_3, PM2.5) were calculated by considering the fuel types of different vehicle categories and their emission standards [84] summed up in Fig. 2.2. Hybrid vehicles emit the lowest amount of emissions; 8.99 g/100 km. LPG cars are the most polluting car type with a total amount of 89.49 g/100 km emissions followed by petrol cars. Diesel cars are the major NOx contributor.

2.2.2.2 Public transit

Nelson *et al*. [85] found that Washington public transit systems reduce the total congestion by two person-minutes per transit passenger mile carried during peak times. It was measured that the average daily delay time increased by 47% during the non-working period of the public transit services of Los Angeles after a sudden strike of public transit workers [86]. Transit-oriented communities drive 10–30% fewer miles than automobile-oriented communities do, and use alternative modes 2–10 times more frequently [87].

There were significant rail infrastructure investments undertaken in the UK in the recent decades. As a result, the ridership on regional and urban rail services in London grew by more than a third in the last ten years; the growth was even more relevant in some cities, such as Huddersfield (by 91%), Wolverhampton (by 96%), Coventry (by 143%), Leeds by (71%), and Sheffield (by 96%) [8]. A sharp rise in the car ownership in cities with low railway intensity and, on the other hand, a relatively slow rise of car ownership in the cities with high railway intensity was highlighted for six Asian megacities located in China, Japan and Thailand [88]. The US cities with rail lines experienced heavy declines in car usage in comparison with cities without any rail infrastructure between 2000 and 2009 [89]. A study showed modal shift outcomes of the light rail transit (LRT) infrastructure build-up: 17–37% of former car drivers shifted their mode towards LRT in Nantes, 21% for the Blue Line LRT in San Diego, and 22% for the Super-tram LRT in Sheffield [90]. Similar mode shifts from car to rail systems are also highlighted in other works, such as a 19% mode shift to rail for Croydon Tramway [91], an 8–14% mode shift for Copenhagen Metro, and an 11% modal shift on average for 14 LRT systems in Europe [92]. In a worldwide comparison, it was found that a 10% increase in the subway network size causes an approximate increase of 6% in subway ridership [93]. The rail-bus infrastructure replacement resulted in a significant increase of transit ridership from 95% to 350% in the major corridors of Los Angeles [94]. Temporal and spatial analyses between 1992–2008 for the initial light rail service in Denver indicated that three light rail corridors in operation succeeded in lowering the level of traffic on highways within the rail transit influence zone comparing with the highways outside the influence zone [95]. The average travel time reductions of 21% resulted in an increased ridership of 15–20% for the Los Angeles metro system, with up to 33% for some corridors [96]. It was found that LRT investments alleviated the road traffic congestion growth in some US cities after systems had started to operate, such as from 4.5% annual growth to 2.2% in Sacramento and from 2.8% to 1.5% in Baltimore [97].

The urban rail transit has many advantages compared to road-based urban mobility. These advantages in comparison to the conventional bus systems lead to a considerable number of passenger capacity with a higher speed travel, a guaranteed travel time for passengers with the spatial isolation feature of the system, and lower transport-related emissions [98]. Furthermore, the accident rate is very low compared with the road-based systems. The net financial returns of the urban rail transit in Hong Kong equal approximately to $2.33 billion from 1980 to 2005 [99]. The results of another study demonstrated that the urban rail transit of Beijing could reduce 1,036,733 tons of hydrocarbons (HC), 85,827 tons of CO, and 326,295 tons of NOx, which leads to over 8.56 billion Yuan savings every year [100]. Analysis based on an eight-year database of 43 cities showed that particulate matter dropped by 4% in a 10-km radius disk surrounding the city centre following subway system investments [101]. Rail transit-based cities, such as Hong Kong, Tokyo and Berlin, with high public transport (89%, 68%, and 61%, respectively) as well as non-motorized mode shares seem to be very successful in terms of the reduction of CO_2 emissions comparing with other cities [102]. CO_2 emissions as kg per capita per year are respectively 378 kg, 818 kg and 774 kg for these cities. Furthermore, the road-dependent cities, such as Houston and Montreal, with low public transport and non-motorized mode shares (26% and 5%, respectively) exhibit 5,690 kg and 1,930 kg CO_2 emissions in terms of kg per capita per year. European railways reduced 14% of CO_2 emissions per passenger-kilometres from 1990 to 2011 [103]. Chen and Whalley [104] estimated that there was a reduction of approximately 5–15% for CO and NO after subway investment in Taipei. In several studies, a positive impact of the rail network expansion was demonstrated regarding an increase in the population density near urban rail stations or tracks, thereby strengthening the compactness of urban areas [105–107]. A survey-based study was conducted to show the differences of transit users between rail-based and bus-based public transportation for Switzerland and Germany transit users [108]. The preference for rail-based services (75% for trams and 63% for regional trains) compared to bus services under equal service conditions was demonstrated. Some studies demonstrated the effects of urban rail investments on property values, such as an increase in property values in the vicinity of rail stops, e.g., the DART system in Dallas with an increase of 10–25% [109], or the metro system in Phoenix with an increase of 25% [110]. The annual transportation cost savings (based on congestion, accidents, infrastructure-related factors and parking) are $112 billion as a combination of the US cities with well-established rail transit systems [111]. One study compared the noise impacts of light rail vehicles, conventional articulated diesel buses, and dual-propulsion (electric motor/diesel engine) articulated buses at 15 m (50 ft) and 56 km/h [112]. The results showed that diesel buses are noisier; light rail vehicles are slightly quieter, and electric buses are significantly the quietest. Estimations from Austroads showed that the urban traffic noise costs had averages at $1.81 for cars, $1.67 for buses and $1.55 for train travel per 1,000 passenger-kilometres [113].

Table 2.1 Lifecycle assessment of energy, GHG and air pollution for all modes.

Lifecycle Assessment	Energy Consumption (MJ/PMT)	Greenhouse Gas Emissions (gCO_2e/PMT)	CO (mg/PMT)	SO2 (mg/PMT)	NOX (mg/PMT)	VOC (mg/PMT)	PM10 (mg/PMT)
Buses-peak (diesel)	0.8 (0.59)	79 (61)	0.26 (0.15)	130 (18)	530 (500)	82 (17)	51 (20)
Cars (gasoline Sedan)	4.6 (3)	360 (230)	12 (12)	480 (72)	1,000 (640)	1,300 (770)	780 (81)
Jeeps (gasoline SUV)	6.3 (4.5)	430 (280)	13 (12)	470 (16)	1,000 (590)	1,300 (760)	720 (73)
Trucks (gasoline)	7.8 (5.7)	500 (330)	16 (15)	530 (18)	1,400 (910)	1,600 (950)	850 (87)
Buses off-peak (diesel)	6.4 (4.7)	630 (490)	2.1 (1.2)	1,000 (150)	4,300 (4,000)	660 (140)	400 (160)
BART (heavy rail elevated and subway system)	2.2 (1.1)	150 (84)	520 (43)	740 (450)	290 (32)	200 (9.6)	130 (4.9)
Caltrain (commuter rail line)	2.2 (1.1)	160 (74)	420 (83)	310 (11)	1,600 (1400)	200 (59)	170 (38)
Muni (light rail system)	3 (1.2)	200 (90)	670 (46)	970 (480)	290 (35)	150 (10)	53 (5.2)
Greenline (light rail system)	2.3 (0.87)	220 (120)	720 (140)	1,200 (730)	410 (160)	130 (9.3)	65 (7.4)
CAHSR (high-speed rail system)	1.6 (0.43)	130 (32)	770 (16)	490 (170)	360 (12)	250 (3.7)	62 (1.8)

Vincent *et al*. [114] stated that the Brisbane Southeast BRT system reduced the overall travel times by up to 70%. The Metrobus BRT system in Mexico City was reported to have resulted in travel time savings of 40% [115]. Metrobus in Istanbul with a thorough implementation of BRT elements, including an almost fully segregated infrastructure, ensured travel time reductions of 65% [116]. The BRT infrastructure build-up increased the ridership by 10% one year after the opening and resulted in a decrease in the bus public transportation in Seoul [117]. Similarly, BRT expansion resulted in a 125% BRT ridership increase in Dublin [118], whereas, in Istanbul, Metrobus increased its ridership by 150% [112]. The BRT infrastructure build-up resulted in a 40% mode shift from car passengers to O-Bahn BRT in Adelaide [119]. Similar car–BRT modal shifts were demonstrated in other cities: 25% for Curitiba BRT [120], 29% for Nantes BRT [121], and 19% for Kent BRT [122].

Carrigan *et al*. [123] demonstrated the economic benefits of the BRT systems for TransMilenio in Bogota (Phases 1&2), Metrobus in Istanbul (Phases 1&4), Rea Vaya in Johannesburg (Phase 1A), and Metrobus in Mexico City (Line 3). The economic contribution of the travel time savings of BRT systems is calculated for some cities to be $1,830 million for the Bogota City economy, $6,369 million for Istanbul, $331 million for Johannesburg, and $142 million for Mexico City. Furthermore, for the same period, the benefits from carbon emission reductions were estimated as $239 million for Bogota, $152 million for Istanbul, $18 million for Johannesburg, and $10 million for Mexico City. It was found that the BRT infrastructure development was lower in price up to 4–20 times in comparison with LRT, and 10–100 times in comparison with metro systems [124]. The BRT system resulted in a 5–10% increase of property values near BRT stops in Seoul [117], as well as in a 16% increase for properties near the East Busway system in Pittsburgh [125]. It was also found that BRT was a more cost-efficient and effective mode comparing with LRT when the lines carried less than 1,600 passengers per hour [126]. BRT systems tend to increase unit costs, and the traffic signal priority of the system becomes ineffective for short headways above 2,000 passengers per hour, in which case, LRT systems are more cost-efficient and effective. Both BRT and LRT are cheaper than the regular buses in terms of operation costs for passenger-kilometres.

Speed is one of the main factors determining the mode choices for passengers. Vuchic [127] surveyed the average operating speeds of the urban transit modes around the world. The highest speed is that of the rail-based modes, e.g., 37 mph for commuter rail, 26 mph for heavy rail, and 20 mph for light rail, followed by the road-based modes with 19 mph for BRT and 14 mph for the conventional buses. Chester and Horvath [128] made a life-cycle energy and environmental inventory of passenger transportation in the US for such modes as cars, jeeps, trucks, buses, light rail, heavy rail, passenger trains and plane types. The criteria for the rail-based life-cycle energy and the environmental inventory are available in this paper. A summary of the life cycle energy, GHG and air pollution inventories for all the modes is provided in Table 2.1 (values in parentheses are for one operation cycle).

The obtained results show that public transportation is energy efficient compared to the auto-based models, but the efficiency of the public transport depends on the load factor as seen by the lifecycle assessment of the conventional bus. The system is the least efficient during off-peak times within all the modes, while it is the most efficient mode for the peak times. The performance of the public transport in New York City, San Francisco, and Chicago is taken into account in this study, too, and these cities have around 60–80% private car mode share for commuting. However, if the high public transport mode shares of such cities as Tokyo, Hong Kong and Berlin were analysed, the results would be more significant in terms of the efficiency of the system, since the load factor is a very important parameter for public transportation. Chester *et al*. [129] investigated new bus rapid transit and light rail lines in Los Angeles and assessed the near-term and long-term life-cycle impact. The obtained results demonstrated that ensuring the mode shifts of 20–30% of transit riders from automobiles would result in passenger transportation greenhouse gas reductions for the city, and the larger is the shift, the quicker is the payback. A case study about integrated transportation and land-use life-cycle assessment framework on the Phoenix light rail system demonstrated that marginal benefits from the reduced automobile use and potential household behavior changes exceeded the marginal costs of a new rail service [130]. A comparison of the life cycle emissions of BRT – TransMilenio – with the other modes in Bogota was conducted with the well-to-wheels approach on the OpenLCA software [131]. The results demonstrated that BRT produced the lowest emissions of CO_2-eq, CO, NOx, and the lowest emissions of PM2.5 were achieved by an electric BRT and buses powered by natural gas.

2.2.2.3 Non-motorized mobility

With the growing concerns over traffic congestion and pollution from motorized vehicles, a research focused on the cycling infrastructure indicated a positive correlation between the bicycle usage and the bicycle infrastructure expansion in 43 US cities as based on the data from *Bureau of the Census* [132] and in 13 European cities [133]. Estimations for the US cities demonstrated that completing the sidewalk network of cities reduced automobile travel by 5% (from 22.0 to 20.9 vehicle miles) and increased non-motorized travel by 16% (from 0.6 to 0.7 miles per day) [134, 135]. Cycling increases the public transit accessibility of the Dutch cities where cycling is used by 10% as the egress mode [136]. Significant modal shifts from car to cycling have been stated for Denmark, the Netherlands and some other EU regions since the 1970s [137]. Dutch cities are among the most cycling places in the world: it was reported that Dutch residents make more than one-quarter of all trips (37% for leisure times, 24% for commuting to work, 20% for education purposes, 13% for shopping and 6% for others) by bicycle [138]. It was stated that the Netherlands (2015) had a 35,000 km total length cycle path, and approximately 1,000 km distance is cycled per person a year (on average, 2.9 km daily distance) [139]. The Netherlands have a growing population of 17 million people, and all of them together own 22.5 million bicycles; as a result, on average, the Dutch own 1.3 bicycles *per capita* [140]. Amsterdam and Utrecht are leading in terms of bike usage in the country: 57% and 60% of daily trips, respectively, are made by bicycle [141, 142]. For example, Utrecht has the biggest bicycle-parking garage (for 12,500 bikes) in the world [141]. These cycling investments in the Netherlands came up with socio-economic and environmental benefits. Health benefits of cycling, such as a reduction of travel accidents, save 19 billion euro per year in the Netherlands, which is equal to 3% of the Dutch gross domestic product. Economic assessments of cycling were reported for the Netherlands, and cycling was stated to be the cheapest mode of transport with annual costs ranging between 175–300 EUR (compared to cars: €2,500–8,500) [138, 143]. Besides, the annual infrastructure cost per traveler kilometre is €0.03 for bicycles, €0.10 for cars, €0.14 for buses, and €0.18 for trains. Another point is space control; a bike takes only one-eighth in the space of a parked car, and much more than 50% of the public space is used for car parking [143].

Denmark is another country with a widely adopted cycling culture where cycling accounts for 17% of all trips and, specifically, 85% of trips shorter than 5 km [144]. Cycling trips are made for the following reasons: 34% for leisure activities, 12% for going to work, 17% for educational purposes, and 17% for other purposes [145]. The cycling infrastructure in Denmark is very well established with more than 12,000 km of separated bike paths and bike lanes in cities and in the countryside [145]. Furthermore, the door-to-door strategy and bike-train-bike journeys are promoted in order to combine cycling with the public transport. Therefore, people have opportunities to bring bicycles onto trains [146]. As a result, approximately 27% of rail passengers cycle from their home to a train station, while 8% cycle from a train station to their final destination [147]. According to the report from the Capital Region of Denmark [148], the cycling residents save 30 million DKK of overall costs of noise pollution and 27 million DKK of overall costs of air pollution per year. Furthermore, cycling does not produce GHG emissions comparing with other modes which emit 115,000 tonnes of CO_2 emissions per year (cars emit 101,000 t, buses emit 8,000 t, and trains emit 6,000 t) [145]. Studies showed that the cycling safety is greater in cities with higher levels of cycling, and that injury rates fall as the levels of cycling increase [149, 150]. For example, the cycling fatality rate in the US is five times higher than in Denmark and the Netherlands [151]. In Copenhagen, cyclists provide more revenue for shops in the city centre than cars, and estimations show that cyclists can provide €111 billion of economic profits every year in the EU cities [152].

Also, a large increase in the sales of e-bikes has been observed, especially in Asia and Europe during the recent years due to megapolis residents considering their advantages of competitive travel speeds compared to the local public transport under conditions of rush-hour driving. This advantage of e-bikes increases the potential mode-shift by car users and, in turn, alleviates the environmental impacts thus improving the public health [153]. A study investigated the factors affecting the e-bike share in Shanghai; the results highlighted that, compared to the conventional bike share usage, the e-bike share is less sensitive to the trip distance and weather conditions [154].

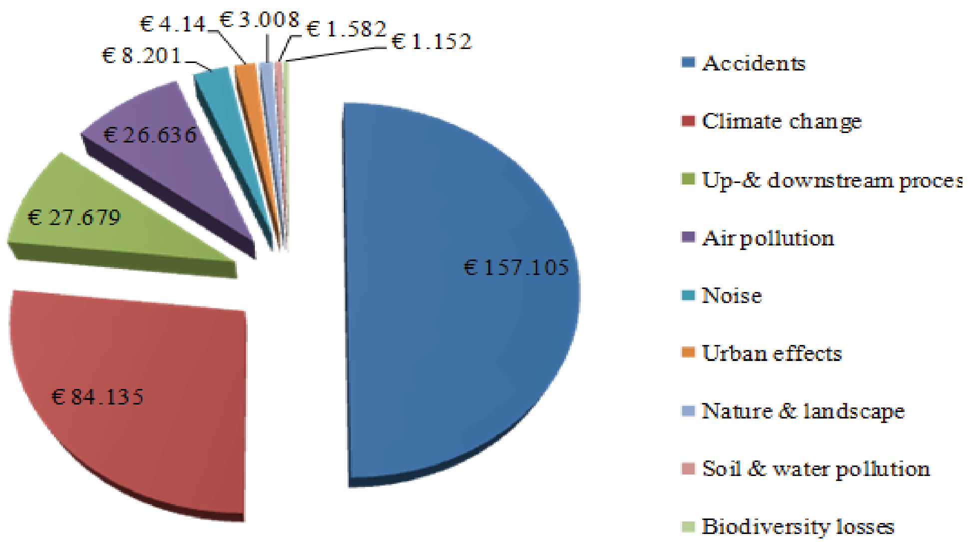

Figure 2.3 Economic benefits of cycling in the EU-28, 2016.

Studies showed that a well-developed cycling infrastructure has a strong beneficial effect on the property value along traffic-calmed roads. The traffic volume and residential property values were modeled in the city of the Hague (the Netherlands), and the results demonstrated that, by decreasing the traffic volume by 50%, the housing prices increased by 1.4% on average [155]. An increase in the model share of cycling by 1% would increase the turnover of local retailers by 0.2%, or €87.6 million per year, in Austria [156]. A positive effect of the cycling infrastructure on employment was demonstrated by the findings of the *European Cyclists Federation* [157]. Their estimations suggest that there are 654,909 full-time jobs under the bike sector in the EU-28. The employment effect of the cycling infrastructure is 1.28 times higher than the general transport infrastructure. A rise in the modal share of walking and cycling modes increased the gross domestic product (GDP) of German cities by 1.11% [158]. The travel mode shift from short distance car trips to cycling in the US has a potential of $3.5 billion savings that can even grow to $6–17 billion in the future with the increasing preference towards cycling and walking [159]. The overall amount that would be saved on gasoline expenditure is in the range of $10 to $35 billion annually. CO_2 emissions were estimated for a car ride and a bus ride to be 271 g and 101 g per kilometre, respectively. The results of shifting one's main daily travel mode (car or bus) to cycling (~10 km) can help to avoid emitting 715 and 266 kg of CO_2 emissions per year, respectively [160]. The biking scheme in Barcelona avoided 960 t of CO_2 emissions of the city compared to the situation before the system was applied [161]. Over 90,000 inhabitants used the system during the six initial months of operation. A systematic classification of benefits of cycling was reported [152]. The results show that the overall economic benefits of EU cycling were €513 billion in 2016. The distribution of the overall benefits is presented in Fig. 2.3.

A complete life cycle assessment (LCA) was conducted in order to compare the modes of transportation including walking, cycling, and e-cycling to contribute to Chester & Horvath's previous work (2008) [162]. The results show that the life cycle energy usage of the modes is 102 KJ/PMT (for walking), 319 KJ/PMT (for biking) and 356 KJ/PMT (for e-biking). Besides, 33 kg GGE/PMT is calculated as the life cycle GHG emissions of non-motorized modes. That makes biking and walking the most energy efficient and environmentally friendly modes. Furthermore, electric bicycles emit 90% fewer pollutants per passenger mile traveled comparing with a bus operating off peak and use less than 10% of the energy required for a sedan car.

2.2.3. Infrastructure design

Transportation networks are complex dynamic systems which have been compared with the neural networks of the brain where neural cells distribute information by exchanging chemical transmitters between synapses [163]. Urban transportation networks are the distributors of cities for energy, materials and people to specific zones of the city, in the same way as a cardiovascular network distributes energy and materials to cells in an organism [164]. The term 'complexity' for transport networks results in rich behaviors arising from systems connections, interactions with subsets and the dynamic processes (vehicles or people) acting on a network structure (pattern & configuration) [165]. In recent years, understanding the structure and dynamics of urban transport networks has been improved through analyses of network topology measures by using the mathematical tools of graph theory [166]. The configuration of networks helps to detect the travel behaviors of inhabitants [167, 168], to evaluate transportation performance [163, 164], and to understand how cities are organized [163, 171]. Complex network analysis allows important feedback for urban modeling. It is also an effective evaluation tool since providing feedback to the system is important for correcting, improving or upgrading urban models before executive plans have been drafted [172]. Dynamic system variables, such as population and traffic volume, account for the state of the system as it changes over time [165]. On the other hand, one can evaluate cities through co-evolution, where humans shape their city and are shaped by the city, thus making topological measures an important proxy. Various concepts of the graph theory are used to describe the network features. The topology of a network can be described as the arrangement (centrality, clustering) and connectivity of a network [173]. Geometric variations of their structure, such as shape, density and circuity, become more visible when complexity is analyzed at a more macroscopic level.

Various indicators are identified in literature as a measure of network patterns. The quality of a transport system can be evaluated based on the intensity of connections between road segments through connectivity measures [174]. There are several indicators to evaluate the connectivity pattern of the networks, such as *Alpha Index*, *Beta Index*, *Gamma Index* and *Eta Index* [175]. The average node connectivity is a useful network proxy defined as the average over all the pairs of vertices of the maximum number of internally disjoint edges connecting a pair of vertices [175, 176]. It is a measure of network resilience: in the networks with low average connectivity, the network circulation is forced through low-permeability choke points, which increases the risk of traffic jams and network disruptions [165]. Another important indicator is the average circuity of a network (or its directness) which is the ratio of the shortest distance on the network over the Euclidean distance averaged over all the origin-destination pairs in the network [167, 168, 177]. The degree centrality is a local measure which offers a hierarchical view of the city where closeness centrality is mainly radial with a strong side effect. The average degree of centrality is described as an average connection of each road segment to all the segments in a network [178]. The average closeness centrality is the average distance of the shortest paths between any node and all other reachable nodes of the network [178]. This captures the notion of the accessibility of places in a city. The average clustering coefficient is a measure of the network structure of nodes defined as the average number of triangles between nodes in a network. The clustering coefficient is a measure of direct accessibility [172].

Some studies analyzed the relationship between the network configuration and travel behaviors. The differences of the average network centrality among subzones of cities affect the inhabitant life and behaviors through various spatial factors [171]. Eighteen cities across the world were analyzed through multiple centrality assessment by primal geographic network graphs (degree, closeness, betweenness, straightness and information), and 1-square-mile network comparisons were conducted [170]. The obtained results demonstrated that a set of different centrality indices allows capturing the skeleton of most central routes. They are determined by the city structure and subzones which appear to affect the spatial cognition and the collective dynamical behavior. Furthermore, hierarchical clustering analysis or the correlation between different centrality measures is able to characterize the classes of cities. It was demonstrated that clustering measures are important for rail networks: an average increase in triangle connections of a rail network can reduce transit circuity [172], [179]. Public transit networks are more circuitous than roads, which suggests that the shortest route is much longer than the line of sight. This is one of the reasons behind the preference of the private automobile over public transit [168]. The increase in the average circuity of public transit networks can drop the transit ridership and thus cause a mode shift towards road mobility. Network circuity is also used to explain the residential place choice of employers for commuting in US metropolitan cities [167].

A few works investigated the role of the network configuration in transportation performance. A positive correlation was demonstrated between the delay time and the average circuity of networks, and a negative correlation was shown between the average circuity and the 'treeness' (disconnectivity) of the networks for 48 cities in the United States [164]. Another paper compared the road transportation performance of the 50 largest metropolitan areas in the United States by comparing the hierarchy, connectivity and directness (circuity) of their road networks [169]. The results showed that a 1% increase in the network connectivity reduces the commuting time by 0.1%, a 1% increase in road accessibility reduces the average metropolitan commute times by 90 seconds, and a 1% increase in the 'treeness' reduces the auto mode share by 0.061%. The circuity of the network is an important measure of the transportation efficiency, and it is determined by the transport network configuration, transport planning, and the underlying terrain [166]. The circuity of transit networks was examined for 36 metropolitan areas (excluding the fringes and low accessibility zones) in the United States through maps generated by the *OpenStreetMap* System (OSM) [168]. The results showed that transit circuity exponentially declines as the travel time increases thus helping to understand the mode choices. Furthermore, the average circuity of transit networks is greater than the average road circuity in the cities, which demonstrates how public transit network systems expanded. Networks can be well-connected, but can be still poor in terms of directness. Therefore, connectivity and directness can be coupled effectively without impeding each other [180], and, in combination, they are important measures for road traffic. Centralization extremes of networks may reflect different travel behaviors according to the differences between small and large cities, and how the road infrastructure and traffic might change as cities are growing [164]. Study [181] demonstrated several scenarios aiming at reducing travel times, and it found that the necessary transfers could be provided by optimizing the closeness and the degree of centrality in cities. The obtained results showed that the closeness centrality is an important proxy to detect the overall accessibility of the system.

2.2.4. Technology and policies

Technological improvements play the key role in socio-technical transformations. There were significant improvements in terms of electrification and fuel efficiency in the recent years. Up to 49% of transport-related carbon emissions should be reduced by energy efficiency and technological improvements until 2030 [182]. Furthermore, nowadays, e-vehicles as a combination of renewable energy integration and energy efficiency emit around 200–300 gCO_2/kWh, with the predictions being zero with further technological improvements [183]. The energy conversion rate of electric vehicles (EVs) is 60% higher than that of internal combustion engines (ICEs), and 50% higher than that of hydrogen cars [184]. In addition, hybrid vehicles (HEVs) are 35% more fuel efficient compared to ICE vehicles [185]. Vehicle fuel efficiencies of car types (HEV, EV, FCV-fuel cell hydrogen vehicle) were compared, and projections have been made for 2020 and 2030 [186]. The results show that baseline gasoline ICE vehicles with conventional drive trains can achieve a 50% increase in fuel efficiency with advanced technologies continuously improved up to 2050. Compared to BEVs, hydrogen vehicles that are able to travel more than 160 km are superior in terms of mass, volume, cost, initial greenhouse gas reductions, refueling time, well-to-wheels energy efficiency and life cycle costs [187].

There have been 50% improvements observed in vehicle fuel economy (MJ/km) in the recent years [188]. Comparing with more than 20 years ago, Americans have started to use 26% heavier vehicles with 107% more powerful engines, whereas the average fuel efficiency increased by more than 60%. The EU aims to increase vehicle fuel efficiency at 6% during their life cycle [189]. The electrification of bus systems delivered 37% of fuel economy [190]. Analysis shows that e-buses have the lowest noise pollution among the related types, while diesel buses are the noisiest. A shift from diesel to electricity for Bogota TransMilenio BRT buses would reduce CO_2-eq emissions by 86% and PM2.5 emissions by 88% [131].

A complete LCA of different vehicle types was conducted [191]. The obtained results show that BEV has the lowest lifetime GHG emissions, followed by HEVs. As expected, for all types, when vehicles get larger, they generally have higher emissions. For the average EU electricity mix (a combination of renewable and non-renewable energy supplies), BEVs have less than a half of the life cycle emissions than ICE vehicles, and also feature lower operational costs for BEVs [193]. Due to the mass production of e-vehicle batteries recently, the price per kWh is expected to fall to 65% of the present level over the next years. Fig. 2.4 demonstrates BEV and PHEV sales shares of the leading countries shifting to e-vehicles and e-car registration within 2010–2016 according to the *International Energy Agency* [194]. As the European Union has recently invested in the e-charging infrastructure for electric cars, such as a shift toward public options & away from home, the share of home charging will decline approximately to 75% until 2020 and to about 40% by 2030 in comparison with the date of the research [192]. Furthermore, in China, public e-charging will dominate in the nearest future; it is expected to be 55% to 60% in 2020 and approximately 80% by 2030. The UK government is shifting towards e-mobility infrastructures. *Highway England* has come up with an innovative road infrastructure system that can recharge electric vehicles as they drive [193]. 83% of the entire network will be within 20 miles from a charger by the summer of 2019, and the re-charging road infrastructure system will be completed within such a distance by 2020. The *SolaRoad* (2014) project built another innovative infrastructure in the cycle culture town Krommenie in the Netherlands, with energy harvesting cycleways to travelers [194]. The results of the six initial months showed that the path pulled more than 150,000 riders, and, more basically, delivered more than 3,000 kilowatt-hours, which is enough to power a house for a year. Recently, the SolaRoad project has created 9,800 kilowatt-hours of energy. As electrification is trending up, the most important part is the integration of renewable sources into energy production. Renewable sources are without operational emissions and have the lowest indirect life cycle emissions. The estimated/indirect emissions are 10–25 gCO_2e kWh for wind and hydro energy, 30–100 gCO_2e/kWh for solar photovoltaic energy, 10–130 gCO_2e/kWh for nuclear energy, and 600–1200 gCO_2e/kWh for fossil fuel [183]. The idea of renewable combination is essentially of a high-voltage direct current (HVDC) electricity grid that connects all the major natural energy sources (solar, wind, hydro, bio and geo). According to the *Desertec* (2018) project, a combination of renewable sources in Europe, northern Africa and the Middle East, particularly with the integration of concentrated solar power (CPS) in deserts, can provide clean energy for 90% of the world's population [195].

The global smartphone ownership is a median of 72% across the developed countries, and the internet usage is a median of 87% in 2018 [197]. That renders intelligent transport applications into an important tool so that to help optimize urban mobility systems. A lack of synchronization between the modes induces differences between the theoretically quickest trip and the 'time-respecting' path; on average, in the UK, 23% of the travel time is lost in connections for trips with more than one mode [198]. The potential travel time reduction of BRT systems would be increased up to 69% by integration with intelligent transportation systems [199]. Intelligent transport services have important potential to contribute to GHG emissions reduction goals of the EU [196]. The function of some services and their benefits are evaluated in some studies [201–204]. The results are summarized in Table 2.2.

ICT is increasingly improving urban transport systems by enabling efficient and effective use of travel information and vehicle use, as well as improving the network management. A new distributed algorithm for controling traffic signals ensuring global optimality leads to the maximum network throughput proposed as an alternative to the other light timing systems as SCATS (founded in Sydney, used in 25 countries) and SCOOT (founded in the UK and used in a few countries) [205]. A combination of modal shifts and optimal trip routing with successful limitation and pricing polices reduces car trips in cities [206]. Some policies aim to reduce the growth of vehicle fuel consumption by limiting the vehicle use or vehicle ownership. The limitation of vehicle ownership in Shanghai and the limitation of vehicle use in Beijing resulted in some differences between the cities, such as the number of passengers per vehicle, GDP per capita and vehicle type structure. As a result of the policy effectiveness analysis of different policies, it is expected that the fuel consumption in Shanghai in 2020 will be reduced by 59.4% and in Beijing by 5.7%, which shows that the limitation of vehicle ownership is more viable in terms of reducing the fuel consumption [207].

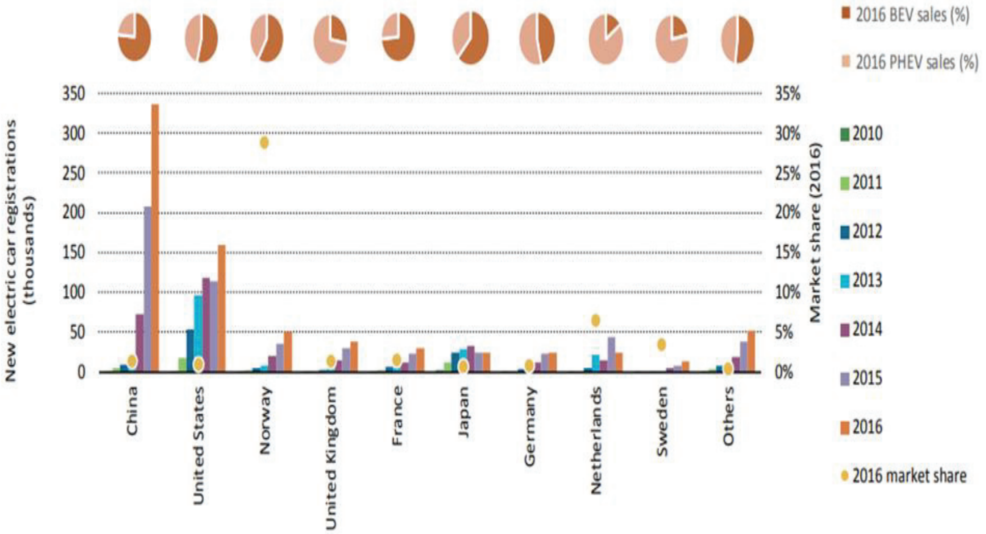

Figure 2.4 Electric car sales, market share, and BEV and PHEV sales shares in selected countries, 2010–2016 (International Energy Agency, 2017).

A number of policies aiming at stressing such points as the reduction of carbon emissions and congestion can contribute to a modal shift towards public transport. For example, London's congestion charge is an exceptionally conspicuous case of such a strategy [208]. Congestion charging resulted in the overall reduction of 11% in vehicle kilometres in London between 2002 and 2012. The urban traffic was improved with a 10% reduction of levels comparing the years 2013 and 2003; there was a 28% decline in car crashes, and the net revenues were calculated to be €123 million for 2007 [204]. A congestion charging policy applied in Stockholm reduced approximately 20% of the traffic volume and GHGs emissions [209]. Bus priority applications brought some benefits to cities, such as 52% reduction of the average public transport waiting times at the traffic lights in Toulouse, an increase in the frequency of service from 10 min to 7.5 min in the same capacity and up to 4% punctuality of the system in Malmo [204]. In addition, there was a reduction in emissions, such as 33.3% of PM, 20% of NOx, 26% of CO, 4.1% of CO_2 in Tallinn. A recent study reviewed shared mobility systems. It demonstrated that car sharing strategies concentrate on convincing transport users to adopt more conscious and sustainable behavior through referring the studies which demonstrate how shared systems mitigated traffic congestion and air pollution by dropping the number of vehicles in circulation in urban areas as well as by eliminating the need for parking spaces [210]. Furthermore, bike/e-bike-sharing systems are a more convenient connection to public transport while providing travel time reduction within city centres and improving bodily health. The city of Copenhagen implemented mixed-use regulations around public transport connections, station proximity, and parking management policies [211]. As a result of the successful implementation of a combination of policies, the passing times within modes are quite low, the PT accessibility is high, and the GHG emission was reduced. The potential of the city is to build approximately 1.3 million square metres of commercial space within 600 metres of a station that corresponds to approximately 33,000 jobs for the plan period of 2015–2027. This plan will reduce a total of 95,000 tonnes of carbon emissions (i.e., the annual reduction of carbon emissions by approximately 0.7%) during the entire period compared with the scenario without station proximity.

Table 2.2 Functions and benefits of intelligent transport services.

Application	Function	Benefits
Zipcar – London	Car-sharing service	Reduced car travel costs and miles by 42% per year.
Zimride – USA	Ride-share service	Saves over £50 million in vehicle operating costs, such as fossil energy, insurance and maintenance.
Sfpark – San Francisco	Parking service	Reduced congestion, 30% drop in GHG emissions.
Suica smartcard – Tokyo	Multi-modal smart ticketing	Integrated payment across modes, time saving.
SignalGuru – Cambridge and Singapore	Green Light Optimal Speed Advisory	20.3% saving on fuel consumption.
*Moovit, Citymapper *TI system in *Monza/IT*	Real-time journey planner	-Modal-shift to PT and time savings -4.1% modal-shift to PT.
Velib, Bicing	Bike-sharing	Reducing excessive demand on single mode for last mile connections.
*TSC – in Aalborg (Denmark) *Across EU	Adaptive traffic signal control system	-Travel time decreased by 8.5% per trip (for peak times), and fuel consumption decreased by 2.5%. -Improvement 5–20% in the travel mean speed.

2.3. Literature review conclusions

Social factors, such as culture, educational level, income level, and the nature of demography have been reviewed above. Their influence on the transport user patterns has been assessed. Culture is an interpretation code of societies which may explain common preferences in a certain location. Prediction of alternative transport systems which could be adopted in a city can help urban transport planners and policy makers to adjust the urban environment in a more sustainable manner. However, social value associations and the impact of culture on travel behavior are denoted by a gap in literature that complicates the understanding of the connection between transportation and culture. At the moment, to the best of the knowledge of the author of the presesnt thesis, no research papers have been found to analyze the role of culture in urban travel patterns in a holistic way. Culture is an inherited characteristic of societies and a basement of user privileges. Some policy and urban transport strategy comparisons can be drawn by answering the question: *which alternative transport systems can be sustained under which cultural conditions?* In the next section, culture will be analyzed globally, and the influence of culture on transportation will be modeled. The education level can be referred to as an acquired characteristic of societies. Personal choices are changeable by educating citizens in societies. Education is a decisive factor that can shape societies dynamically in a collective way, and a higher education level is an important proxy to assess the awareness level of societies with the current issues. Meanwhile, there is also lack of holistic analysis comparing education and transportation in literature. *Linking education and travel patterns can inspire future urban policies and strategies.* In the next section, the effect of the educational level on the travel mode choices will be analysed globally to stress out the importance of education. The income level is an important proxy assessed in a number of works. Literature showed that societies with a higher income tend to own more cars and to drive more. The income level will be used in the next section under different analyses as a variant so that to understand the influence of the economic level on the user behavior and to detect the extent to which it impacts the infrastructure development at a global level. The nature of demography presents a complex structure: distribution of gender, age, household composition, marital status and other variables in societies. Literature demonstrated that the differences of users' physical conditions, housing and time value, as well as some obligations due to responsibilities change people's habits. Such factors as ageing, marriage, or having children, encourage users to use cars more frequently. The distribution of demography is an important criterion before drafting new strategies.

Such technical factors as infrastructure, land use, network design, technology and policies have been reviewed above. Their influence on the user profile and transport performance with interaction between these factors was demonstrated at a worldwide level of detail. Technology and policies act as the system optimization tools intended to sustain urban mobility. In this context, infrastructure and land use are two major interconnected technical factors. It is outlined in literature that cities with high population density provide high accessibility to the public transport transit and active modes; meanwhile, people drive much less than in other regions; also, the public transit mode share of these cities is higher. Usage of public transit and non-motorized systems can increase with the concentration of activities and proximity in cities by mitigating land segregation; in addition, this reduces transport-related energy consumption and costs. The relationship between the transport infrastructure expansion and population growth, spatial expansion and land-use change has been highlighted in many works. A tight relationship between transport and urban development has been shown as well. Also, the relationship among the infrastructure, land use and travel mode choice has been demonstrated empirically in a number of studies referred to above. It is clearly outlined in literature that cities growing with an urban rail system and revitalization of urban fabric synchronously increased their economic growth and reduced car dependence [213]. Besides, cities with large and well established rail systems have significantly higher transit ridership per capita, lower average vehicle ownership per capita and annual mileage, less traffic congestion, lower traffic death rates, lower consumer expenditures on transportation, and higher transit service cost recovery than otherwise comparable cities with less or no rail transit service [111]. A consequence of these effects is a further increase in the transport infrastructure demand which is often referred to as the 'induced demand' [205]. Traffic congestion and car excess led bus-dependent public transport systems to slow down; the efficiency of urban public transport is decreasing and causing frequent traffic accidents that are threatening people's safety and health [94]. Therefore, such currently existing bus-dependent road-based systems could neither meet the growing demand of the residents' travel, nor the demand of the city's economic development. Rail modes demonstrate the best performance through the modal shift and ridership. However, the BRT infrastructure looks more competitive than the rail modes with advantages of lower infrastructure costs and cost-benefit efficiency below 1,600 passengers per hour. Furthermore, the BRT infrastructure provides more significant travel time savings than the rail modes, but there is not enough evidence in literature showing that this system alleviates urban traffic. Especially, rail systems have been shown to achieve de-congesting effects in the literature. The BRT infrastructure is generally adopted by South American cities where lower economic conditions compared to the EU & the US are manifested. Cycling is highlighted above as an alternative to short car trips with advantages of contribution to physical and mental health, traffic alleviation, noise and exhaust emission reduction and affordable costs. Well-established alternative mobility systems save travel time; the modal shift from the private car to other means of transport in turn alleviates road congestion; thus, these are the positive effects on economic efficiency and environmental quality in cities. Also, increasing alternative transportation options to car mobility promotes social equity in urban areas.

One of the objectives of the present analysis is to shed more light on the relations between the transport-socio-economic indicators and the transport performance indicators. The used data is thought to be comparable across all the selected cities thus allowing absolute global evaluation of the transport performance indicator. With respect to previous studies, the number of comparable cities is larger, and the data is more recent. *Solid transport policies are addressed by answering the question: under which conditions can railways and superior bicycle infrastructure be used more thus reducing the congestion levels?* Also, multivariate analysis connecting the land use and infrastructure is missing in literature. There are only two instances of empirical evidence in literature [65, 66] which demonstrate a particular relation between transport energy consumption and population density. The cited works are *early publications, and only bivariate perspectives* have been considered, which attracted some criticism. *There is a need to update transport energy consumption of cities and to understand how it relates not only to the population density but also to the transport infrastructure*. The main focus of the analysis will be to establish a quantitative relation among the population density, transport infrastructure and transport energy consumption. In the following section, the gap is filled with the connecting infrastructure and land use exploration in order to systematically investigate their internal relationship and how these factors affect the users and transport performance.

Transport systems are complex systems; thus the functional properties of a transportation network can affect the user patterns in turn changing the network performance. Understanding the topology of transportation networks is important in order to upgrade the transport network design and to improve the transportation performance. Literature showed that the network design exerts influence on user preferences as less circuitous transport networks are preferred. Also, an increase of connectivity in the road network can alleviate traffic congestion. However, *neglecting the effects of alternative transportation networks* (railway and cycleway) is one of the limitations affecting the creation of general models through network analysis [170]. Also, focusing just on *local analyses* (within cities from the same country) would not demonstrate the global effect of the network design. In the next section, *the influence of the network configuration of different layers* (road, railway and cycleway) on the road congestion will be analyzed worldwide by merging infrastructure accessibility and network configuration.

3. Methodology

Worldwide analysis and comparison of urban areas is of paramount importance in order to draft or reassess a supportive and integrated socio-technical scheme. This is the first systematic multivariate transport indicator analysis using recent observable open source data from different urban areas around the world. Around 200 cities which are distributed over 55 countries are examined under different analysis patterns in the next section with the database presented in this section. The first chapter of the next section contains analysis of the effect of culture dimensions in the urban travel patterns in the investigated cities. This chapter attempts to investigate the role of Hofstede's culture dimensions (HCD) in urban travel patterns in 87 urban areas and 41 countries. The relationship between HCD and some urban travel patterns, such as mode choices (individual transportation versus public transportation), car ownership and infrastructure accessibility (road infrastructure per capita) is demonstrated. Additionally, the relationship between culture and some demographic indicators (the population density and GDP per capita) which are closely associated with the travel choices are checked. The second chapter presents the analysis of the influence of the higher education level on the urban travel mode choice in the investigated cities. The objective of the chapter analyses is to evaluate the influence of the higher education level on the urban travel mode choices for 45 urban areas from 29 countries. The relationship between the higher education level and the urban travel mode choices is demonstrated. Also, a higher education level is controlled with the population density and GDP per capita, which *does* significantly influence the travel behaviors. The third chapter contains the multivariate analysis of the relations within socio-economics, land use, transport infrastructure and transport performance of cities. This chapter attempts to determine important transport and socio-economic indicators from 151 urban areas and 51 countries based on comparable, directly observable open-source data such as the *OpenStreetMap* (OSM) and the *TomTom* database. The indicator *road kilometres per person*, sometimes cited as the *infrastructure accessibility*, is calculated by processing the OSM data. Information on the congestion levels was taken from the *TomTom* database and the socio-economic data from various publicly accessible databases. Relations between the indicators are identified through correlations, and regression models are calibrated while quantifying the relation between the transport infrastructure and performance indicators. Three sub-categories of cities with different population sizes (small cities, large cities and metropolises) are defined and studied individually. In addition, qualitative analysis is performed by putting five different indicators into relation. The fourth chapter contains the multivariate analysis on the relations within transport infrastructure, infrastructure design and transport performance of cities. This chapter attempts to determine the important network indicators, such as connectivity, centrality and clustering measures for different network types (road, rail and bike) from 86 urban areas and 32 countries based on comparable and directly observable open-source data such as the *OpenStreetMap* (OSM) and the *TomTom* congestion database. Relations between the indicators are identified through correlations, and regression models are calibrated while quantifying the relations of the infrastructure accessibility and network indicators with delay times. The indicator *average road connectivity over average road circuity* (RCRC) has not been studied before in literature, which is proposed in this section. Lastly, in the fifth chapter, estimates and analyses of the transport energy per person per year and transport-related CO_2 emissions per person per year with a large and diverse sample set are based on comparable, directly observable open-source data of 57 cities distributed over 33 countries. The main focus of this section is to establish quantitative relation among the land use, transport infrastructure and transport energy consumption.

The general approach of the present thesis is to collect, process, correlate and model the publicly available and comparable data from a large number of cities around the world offered by different analyses. In this section, the sources, the collection method, and the pre-processing steps of all the necessary information are explained. The worldwide analysis and comparison of urban areas requires a large and diverse multi-dimensional database. This research involves two years of labor with specific transportation data drilling, processing and collection from respected open data sources. Open data is sourced from regional statistical offices, government sources, municipalities, and respected studies. Around 200 cities which are distributed over 55 countries are examined under different strategies in Section 4 with the database being presented in this section. The present worldwide transport analysis requires socio-information of the population, the working population, the annual growth rate (% increase in population), the income level (GDP per capita), the car ownership (cars per 1000 inhabitants), the higher education level (% post-secondary attainment), and the culture dimensions (POD, UNC, IND/COL, MAS/FEM, LTO). On top of that, the analysis requires technical information of the population density (spatial area in sq. km), the land area (sq. km), each infrastructure accessibility (infrastructure length per inhabitants), design parameters for each infrastructure (network circuity, network connectivity, network centrality, network clustering coefficient). User preferences are assessed through the collected transport mode usage (% share). Also, in order to assess the transport performance, specific data is used for the analysis as the transport mode usage (% share), congestion level (extra travel time per day with respect to the free-floating traffic scenario), traveled commuter distances by modes (km), specific energy consumption for different transport modes. The present annual transport energy consumption is calculated with the information of the population, working population and land area, the traveled commuter distances, the travel mode share and specific energy consumption for different transport modes in Section 4.5.

Python software package *OSMnx* was used for the extraction and conversion of the infrastructure information for the desired urban locations as well as for performing some infrastructure design related calculations. *Python* is a high-level multi-purpose programming language with dynamic semantics. *Python* as an object-oriented programming language which covers high-level built-in data structures with dynamic features of typing and binding. *Python* features many modules and packages that can be defined as a code library which includes functions, classes and variables in the desired fields. The main idea is to exploit the *OSMnx* which is a *Python* module in order to create a transport graph. The main features of *OSMnx* are network extraction/clean-up/simplification and node clustering, OSM to JSON extraction and conversion, and node elevation determination via *Google API*. The *OSMNx* package converts OSM data to a *Networkx DiGraph* object, and the *Networkx* converter generates a raw net from the *Networkx DiGraph*. This graph represents the transport network with edges, nodes and some attributes. *OSMNx* also produces a JSON file containing all the OSM attributes of ways and nodes of the converted area.

An *Excel* database was created as a result of specific transportation data drilling, processing and collection. Also, the *Excel* database was used for the calculation of some urban indicators. Software *IBM SPSS Statistics V25.0* was used for the processing of statistical data to analyze and to model relationships within different factors. As the database was originally numeric, which shows normal distribution, the Pearson correlation was chosen to be used for correlation analysis, while the 95% confidence level over 0.2 correlation was taken into account. To understand the associations deeper, some statistical methods were used, and regression modeling was attempted. The statistical approaches used in the analysis section has its mathematical glossary part presented after the list of references.

The *IBM SPSS* is advanced statistical software including a vast library of machine-learning algorithms. The software provides deep digging into big databases with multi-dimensional tools for data analysts. The programme enables users to draw conclusions and make predictions with the appropriate modules. *SPSS Statistics* contains more than 20 different modules. Some of these modules are *SPSS Regression*, *SPSS Advanced Statistics*, *SPSS Data Preparation*, *SPSS Forecasting*, etc. The correlation and regression analysis was performed with the software *IBM SPSS Statistics*.

3.1. Social data

The data of at least two consecutive population censuses were extracted from City population [214]. Population estimations are used in cases when the local census data was not available. To calculate the annual population growth rate, we subtracted the past consecutive population census value from the current population census, then divided it by the past population census, and multiplied by 100 to express it as a percentage value. The commuting age population is justified by OECD as the population interval between 15–64 years of age [215]. The share of the 15–64 year old population of a prominent majority of cities was collected from the city population, and the commuting population was calculated for each city. In those cases when the commuting population data was available for the ages 18–64, the commuting population was calculated by adding the country population percentage from 15 to 19 of age, as collected from *Statista* [216], to the given commuting population percentages.

The recent data of GDP per capita for each urban area was sourced from the *Organization for Economic Cooperation and Development* (OECD) database [217]. All the GDP values are expressed in American Dollars, with the average value of the years 2010–2014. The missing OECD data was completed [218–223]. Errors may occur by mixing the GDP data from the OECD database with the data from other sources. This error type concerns predominantly smaller cities. The actual car ownership data for cities was collected from the regional statistical offices and government sources [224–229] and was expressed as the car ownership per 1000 inhabitants. For US cities, the car ownership data was sourced as the car ownership per household from [230] and converted to the car ownership per 1000 inhabitants while using the average household inhabitants database [221].

The higher education level (EDU) data was used as post-secondary attainment among 24–64 years old inhabitants for the cities and collected from the sources [225, 225, 231–233] for cities. All the data is expressed as the percentage of post-secondary attainment among 24–64 years old inhabitants in cities. The quality of education is not considered in the analysis as it may cause errors. The value of five different culture dimensions (IND/COL, POD, UNC, MAS/FEM, LTO, INDG) of the researched countries based on Hofstede's cultural dimensions theory is sourced from hofstede-insights.com [234] for 41 countries. HCD is scored on a scale of 0–100. Meanwhile, cities from the same countries showed similar travel patterns; the average value of variants is taken with summing the city data from the same countries. All the countries represent an average indicator value of their cities in terms of the availability of the data.

3.2. Technical data

The administrative spatial area information of urban areas was extracted from the city population database [214]. The population density is calculated as the population per spatial area in sq. km by using the population and spatial area data. Uncertainties in the determination and comparison of population densities are due to the fact that the boundary definitions of urban areas are not unified.

Table 3.2 Lists of all the network indicator acronyms.

Average road circuity:	*ARC*
Average train circuity:	*ATC*
Gamma Connectivity:	*Γ*
Beta Connectivity:	*B*
Alpha Connectivity:	*A*
Eta Connectivity:	*H*
Average Node Connectivity:	*ANC*
Average road connectivity over average road circuity:	*RCRC*
Average road closeness centrality:	*ARCC*
Average weighted train clustering coefficient:	*AWTCC*
Average cycleway closeness centrality:	*ACCC*
Road infrastructure m per 10 inhabitants:	*RIA*
Train infrastructure m per 10 inhabitants:	*TIA*
Cycle infrastructure m per 10 inhabitants:	*CIA*

This research will use the length of the transport infrastructure per person in order to quantify the amount of the available transport infrastructure. This term is known as 'infrastructure accessibility' [235]. The infrastructure accessibility (IA) is expressed as the infrastructure length per inhabitant (in meter infrastructure per 10 inhabitants). The network infrastructure length is determined for each infrastructure type of a city from the OSM database by using the *OSMNx* software package [236]. OSM is a crowd sourced, unified and publicly available map of the world. The OSM infrastructure data looks trustworthy for many cities, although it still needs some improvements regarding micro-level details. The OSM data quality seems sufficient for macro-level analyses [237]. OSM consists of three basic components: nodes, ways and relations [238]. Each component has various characterizing attributes called *tags*, for instance, the way tags can be used to identify the type of infrastructure such as railway=monorail or highway=primary.

The *Python* software package *OSMnx* extracts and converts the OSM network data of the desired location into a directed transport graph (which is a graph object of the *Python networkX* package) and performs some topological corrections as well as node clustering simplification. The links of the graph retain the tag information of the ways. Clearly, it is possible to generate sub-graphs for each transport infrastructure (ordinary roads, cycleway and rail). *OSMnx* does provide options to generate and analyze each of the sub-graphs.

Table 3.1 *OSMnx* output for Amsterdam City.

Road Network Length in kilometres	Passenger Rail Track Length in kilometres	Passenger Rail Track Length in kilometres	Tram Length in kilometres	Separated Cycleway Length in kilometres	Cycleway[as part of road] Length in kilometres
1746.120	249.808	48.879	199.821	553.401	20.585

The area of the retrieved transport graph can be specified by providing the polygon surrounding the area or through the name of the city. In the latter case, the administrative boundaries of the desired city are retrieved from *OpenStreetMaps Nominatim* database. In most cases, the official boundaries were available on *Nominatim*, and only in rare cases, manual boundaries had to be defined. The statistics module of the *OSMnx* was used to determine the length of each subgraph, e.g., the road length, the rail length, and the cycleway length. Roads, cycleways, sidewalks and busways links are represented in OSM by means of the highway tag of the way element. There are different network options (drive, bike, service, etc.) in *OSMnx* to filter the desired network types. The option 'drive' was used to extract the total drivable roads of each city. In OSM, the railways are represented by the railway tag of the *way* element. The *OSMnx* package uses these OSM tags to extract a network graph for a specific infrastructure type. In particular, railway components have several associated tags: railway=subway, railway=tram, railway=rail (the latter is for passenger train tracks). In some cities, especially in the US, commuter trains, such as light rail systems, are declared with the OSM tag: light_rail. Some examples may be listed: the RTD system in Denver (141 km), the DART system in Dallas (150 km), the MAX Light Rail in Portland (97km), the Valley Light Rail in Phoenix-Mesa (42 km), METRORail in Houston (38 km), etc. All the related tags were included in the filter to extract the entire rail network of each city area. Cycleways are represented in two OSM features: separate cycleways are indicated with the highway tag (highway=cycleway), and on-road bicycle lanes are specified with the tag (cycleway=*). *OSMnx* converts the road, rail and bicycle infrastructure into networkx graph after performing topological correction. The *networkx* graph is the universal graph manipulation package for the *Python* software. Finally, the infrastructure accessibility IA was determined for all the infrastructure types by using the population data. The BRT infrastructure length is sourced from www.brtdata.org [239], and BIA is determined in mm per 10 inhabitants. Errors of the infrastructure data are due to the incomplete OSM network or wrongly specified road attributes by volunteer contributors. As an example of the output from *OSMnx*, the results for Amsterdam City are shown in Table 3.1.

The *Python* software package *OSMnx* was also used to calculate some of the design parameters for each infrastructure. The node and edge numbers of the networks in cities are calculated with the *OSMnx stat* module. The average node degree of cities is calculated by *OSMnx* and other connectivity measures (alpha, beta, gamma and eta indexes) as formulated in study [175] with the node and edge values provided by *OSMnx*. The average closeness centrality for roads, railways and cycleways (ARCC, ATCC, ACCC) and the average weighted railway clustering coefficient (AWRCC) are also calculated by *OSMnx*. A list of all the network indicator acronyms is presented in Table 3.2 above.

3.3. Performance data

One of the performance indicators used for this study is the congestion level in terms of the average daily extra travel time (ADETT) which is the extra travel time per day with respect to the free-floating traffic scenario averaged over all the monitored traffic participants of a distinct urban area. Comparable data on the congestion level is retrievable through the *TomTom* database [240]. *TomTom* is used by more than 6 million connected GPS devices, and traffic is monitored by many million GSM probes and millions of government-owned road sensors [241]. As *TomTom*'s methodology is sufficiently accurate and unified all over the world, it is a suitable data source for the present study. However, errors may occur due to several reasons: the *TomTom* data is not produced by a representative selection of the population; the special distribution may be non-homogeneous; finally, the coverage may differ from city to city and may also differ from the urban boundaries found in Section 3.2.

The commuting mode choice for the cities was collected for a variety of different sources. The data for the private car mode share and the public transport mode share in percentage values was extracted from sources [224–226, 231, 242–246] for cities between 2008 and 2016. The modal split data is extracted as the last national mobility survey from regional open sources, such as *Eurostat* for European cities, *American Fact Finder* for American cities, *Development Bank of Latin America* for Latin America cities, as well as some national statistic sources, such as *Statistics Canada*, *Australian Bureau of Statistics*, *New Zealand Stats*, etc. The data stemming from different years can lead to compatibility problems. However, this specific data is not available for the same years for such a large and diverse sample of cities. On the other hand, the travel behavior is not likely to change in short term periods as transformations of the urban form and infrastructure takes a long time. For this reason, it is assumed that the mobility data can be collected within an 8-year time period, without running into severe compatibility problems. The commuted distance of the majority of cities for the car and public transport

(PT) was collected from the *World Bank* database [247]. This database covers 144 data items for 93 cities in 42 countries. The data items were collected from secondary sources and can be broadly classified into such categories as demographics, travel demand, the supply of urban transport infrastructure, energy, traffic safety, air quality, and macroeconomic data. Some of the cities where the PT commute distance was missing was completed from the *Moovit commute distance* database [248]. For some European cities, the commuted distance for private cars was completed from the *Eurostat* database [225]. For the City of Amsterdam, the country average from the *Statistics Netherlands* report [249] was used as the commuted distances. For Copenhagen, the commuted distances were extracted from the *Cycling Embassy* statistical report [250]. For Canadian and US cities, the commuted distance for private cars was extracted from the *Canadian Governmental Database* and the *Brookings Institute Report* [229, 251] as the Euclidian distance. In order to calculate the effective travel distance, the Euclidian distance was multiplied by the circuity of 1.417, which is the ratio between the travel distance and the line of sight distance averaged over US cities [252]. The use of common circuity for all cities works as an approximation which neglects the particular topology of the cities' street network. The specific energy usage of private cars and public transport in MJ per passenger km were drawn from the *World Bank* database for each city to calculate transport related energy consumption [247]. For several cities from Latin America and Eastern Europe, the specific energies were missing, in which case, the region averages from Kenworthy's study [253] were used. It needs to be emphasized that this type of hypothesis and simplifications is necessary if any specific data is missing, otherwise, the sample size would be sensibly reduced. Also, in order to calculate the environmental impact, the transport related kg CO_2e per kWh as the country average value was extracted from the *International Energy Administration* [254] and was converted into MJ for each city.

4. Analysis and Results of Sociotechnical Factors Affecting Urban Mobility

In this section, various analyses are performed, and their results are discussed.

4.1. Analysis and results of culture dimensions in urban travel patterns

This section describes the analysis of culture dimensions pertaining to travel patterns in the investigated cities. In the first step, correlations between culture dimensions and mobility indicators were checked against the collected data. Thereafter, the travel patterns were modeled based on culture indicators. The worldwide distribution of the sample cities can be seen below in Fig 4.1.

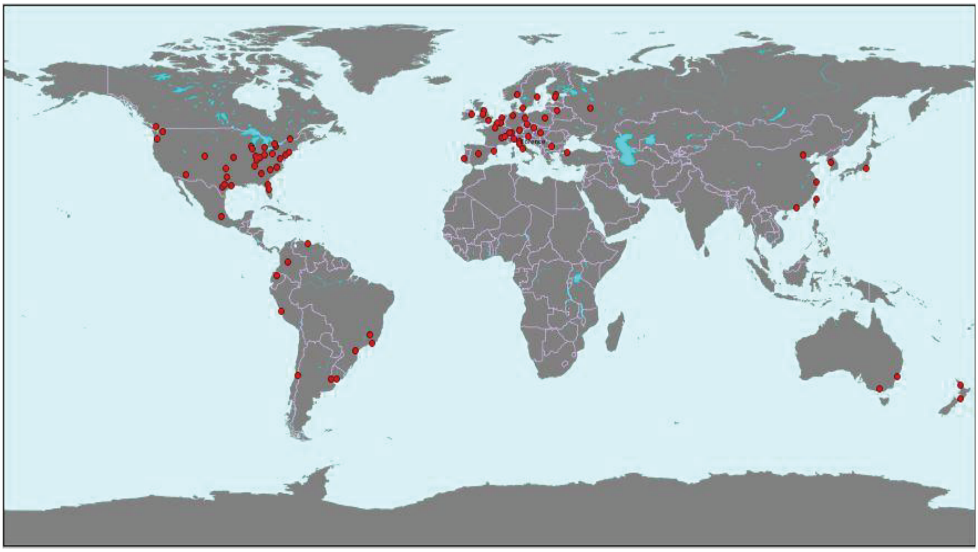

Figure 4.1 Distribution of the analyzed cities

4.1.1. Correlations

Table 4.1 Pearson correlation coefficient between culture dimensions and urban indicators.

	Car Ownership	**Drive %**	Public Transport %	**Road Accessibility**	Population Density	**GDP per capita**
Individualism	0.65	0.62	-0.63	0.45	-0.35	0.67
Power Distance	-0.35	-0.47	0.59	-0.33		-0.50
Masculinity			0.32			
Uncertainty avoidance		-0.33	0.56			-0.32

The Pearson correlation coefficient calculated by *IBM SPSS* between different indicators together is shown in Table 4.1 and Table 4.2. As seen from Table 4.1, some cultural dimensions exert high influence on the urban travel patterns. Correlations suggest that culture can be a valuable tool to understand why societies shape, use and interact with their environment in different patterns. There is a strong positive relationship between individualism and GDP per capita and a negative relationship between the population density and individualism at a moderate level. It can be hypothesized that individualist communities have a higher income and prefer to live in sprawling cities at moderate levels. There is also a positive moderate relationship between individualism and the road network accessibility, which suggests that individualistic societies build more roads. Evidently, car ownership is higher in individualistic communities with a strong correlation (Pearson correlation coefficient = 0.65). Also, strong correlation between individualism and the urban travel mode choices was demonstrated for the driving mode (0.62), and the for public transit usage (-0.63). These findings suggest that individualistic societies prefer driving, while collective places tend to use more public transport services.

Such countries as the US, Australia, Canada, Italy, New Zealand, and the UK exhibit the highest individualism, while they also have the highest car mode share percentage. Such countries as South Korea, Hong Kong, China, Thailand, Peru, Colombia and Brazil demonstrate the highest collectivism, yet they also have the highest public transport usage. However, it can be noticed that there are some incompatible countries, such as the Netherlands and Denmark, that also have high individualism but where driving and public transport mode shares are low compared to other countries. However, these countries have the highest bike usage among all the countries. Cycling can be called as an environmentally friendly individual travel mode that may explain why it is adopted in these nations as the main mode choice. Also, Hungary has high individualism, yet at the same time it has a high public transport mode share. We note that the uncertainty dimension is highly correlated with the public transport usage (0.56); Hungary has one of the highest uncertainty indices with the value of 82 among all the countries. As expected, the power distance negatively correlated with GDP at significant levels. Inequalities in the society may result in the decreasing overall welfare and thus affect people's choices. Also, the power distance negatively correlated with car ownership, driving and road accessibility, and positively correlated with the public transport usage at a high level. We note that the power distance and individualism are negatively correlated here at a very high level with the value of -0.70 as stated in Hofstede's works; thus we take into account the fundamental culture dimension, IND/COL for statistical models in the next section. LTO and indulgence dimensions did not show any significant correlation with any indicators.

Table 4.2 Pearson correlation coefficient between travel mode choices and urban indicators.

	Car Ownership	**Road Accessibility**	Population Density	**GDP per capita**
Drive %	0.69	0.89	-0.63	0.53
Public Transport %	-0.58	-0.83	0.60	-0.46

Table 4.2 demonstrates the correlations between some transport associated indicators and the urban travel mode choices. As expected, there is a high positive correlation between GDP per capita and the drive mode share, while a negative correlation is seen between the public transportation usage and GDP per capita.

There is a strong correlation between the drive mode share and the individual transport needs (car ownership and road accessibility). Oppositely, a strong negative correlation between the public transport mode share and the individual transport needs is seen. Also, a strong correlation between the mode choices and the urban population density is demonstrated. These results suggest that communities not only shape their cities but also in turn are shaped by them. Presumably, the national culture could be the reason behind it.

4.1.2. Statistical models

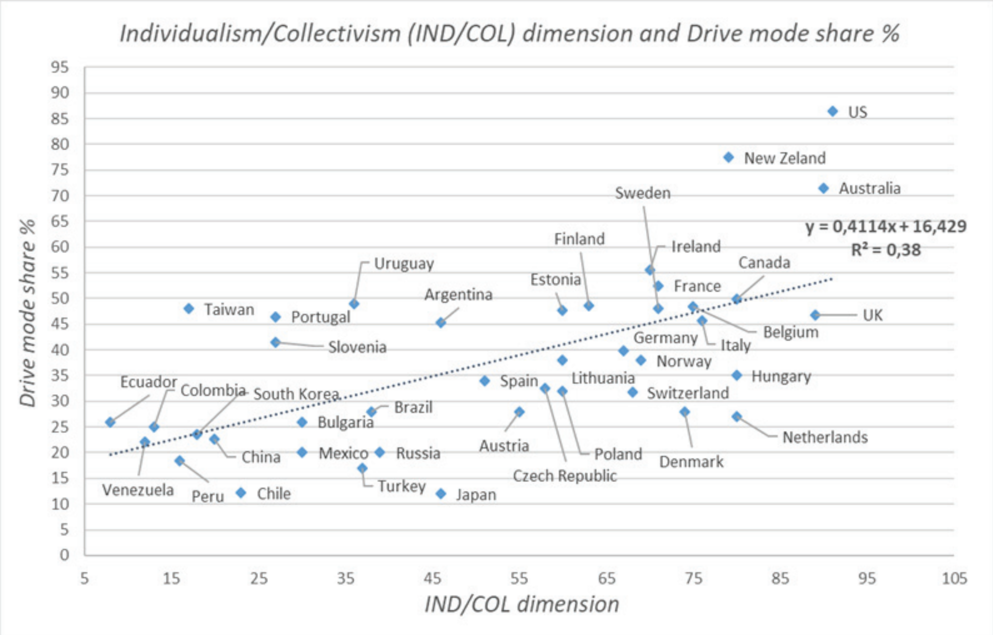

Figure 4.2 Drive mode share over individualism/collectivism (IND/COL) dimension.

As IND/COL dimension and individualistic transport indicators are well correlated, some statistical models were calibrated with the entire set of samples. The best fit between the drive mode share and the IND/COL dimension of all the samples was achieved with a linear function of the shape:

$$\text{Drive mode share }\% = \mathrm{c} + \mathrm{d\ IND} \tag{1}$$

The best fit between the car ownership and IND/COL & between RIA and IND/COL of all the samples was achieved with an exponential function of the shape:

$$\mathrm{RIA} = \mathrm{a}\exp(\mathrm{b\ IND}) \tag{2}$$

$$\text{Car ownership} = \mathrm{a}\exp(\mathrm{b\ IND}) \tag{3}$$

However, the fitting errors with a linear model are only slightly superior. Also, the IND/COL dimension and the public transport share were negatively well correlated, and the public transport share was considerably correlated with the uncertainty dimension and moderately correlated with the masculinity as different from individual travel patterns. The best fit between the public transport mode share and IND/COL of all the samples was achieved with a linear function of the shape:

$$\text{Public transport mode share } \% = \mathrm{c} + \mathrm{d}\ \mathrm{IND} \tag{4}$$

These models were plotted together with the data points in Figs. 4.2–4.5, where regression analyses indicated a good fit.

To better explain the public transport choice in societies, a further model was built with the entire set of samples, which includes individualism, uncertainty and masculinity that do have a significant effect on the public transport usage:

$$\text{Public transport mode share } \% = \mathrm{c} + \mathrm{d}\ \mathrm{IND} + \mathrm{e}\ \mathrm{MAS} + \mathrm{f}\ \mathrm{UNC} \tag{5}$$

Coefficients *d*, *e and f* quantify the effects on public transport usage due to an increase/decrease in independent variables. Further tables (4.3–4.7) demonstrate quantifications as the results of t-tests for linear regression models.

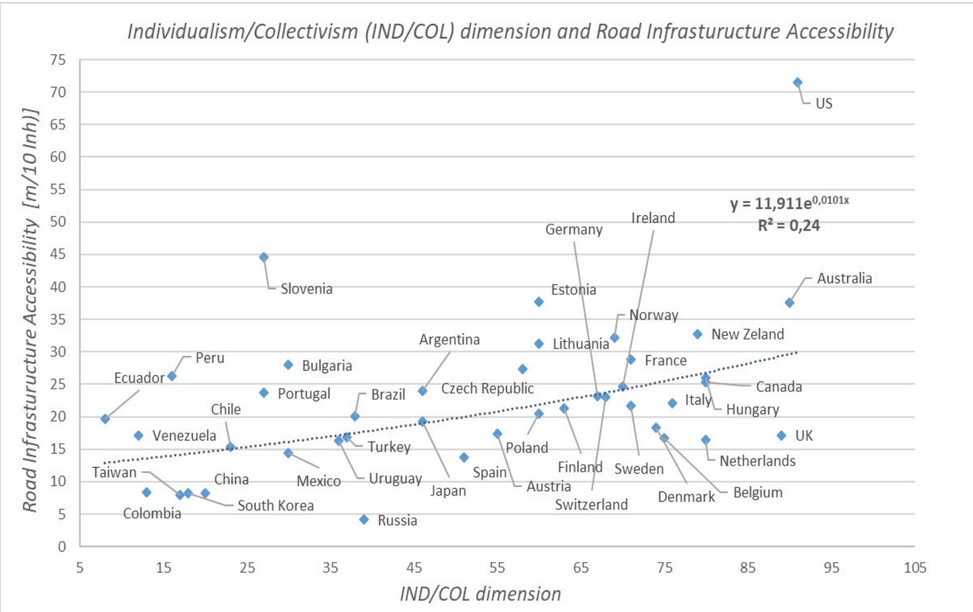

Figure 4.3 Road network accessibility over the individualism/collectivism (IND/COL) dimension.

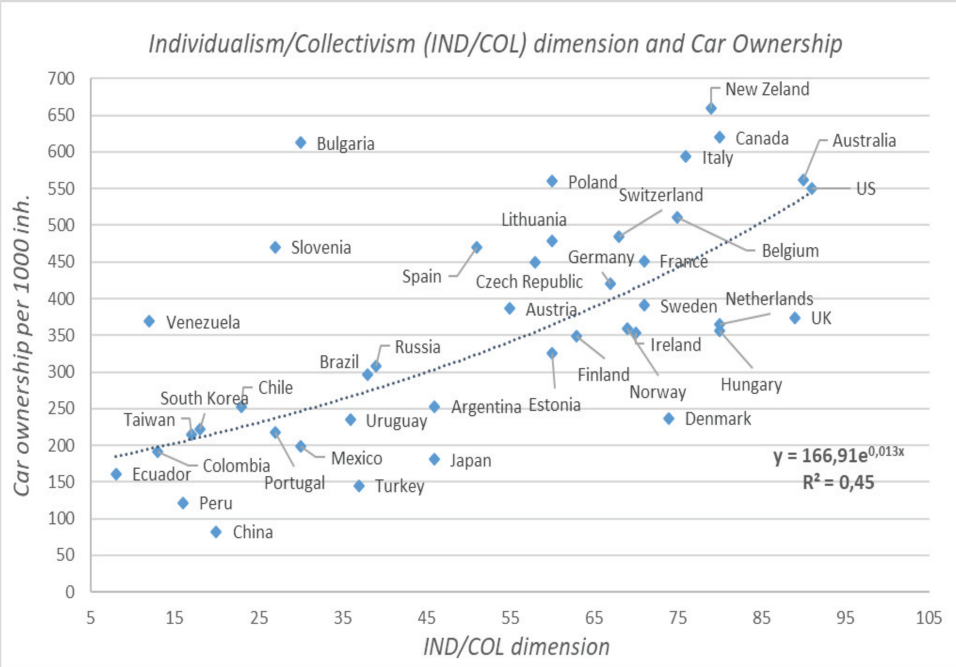

Figure 4.4 Car ownership over the individualism/collectivism (IND/COL) dimension.

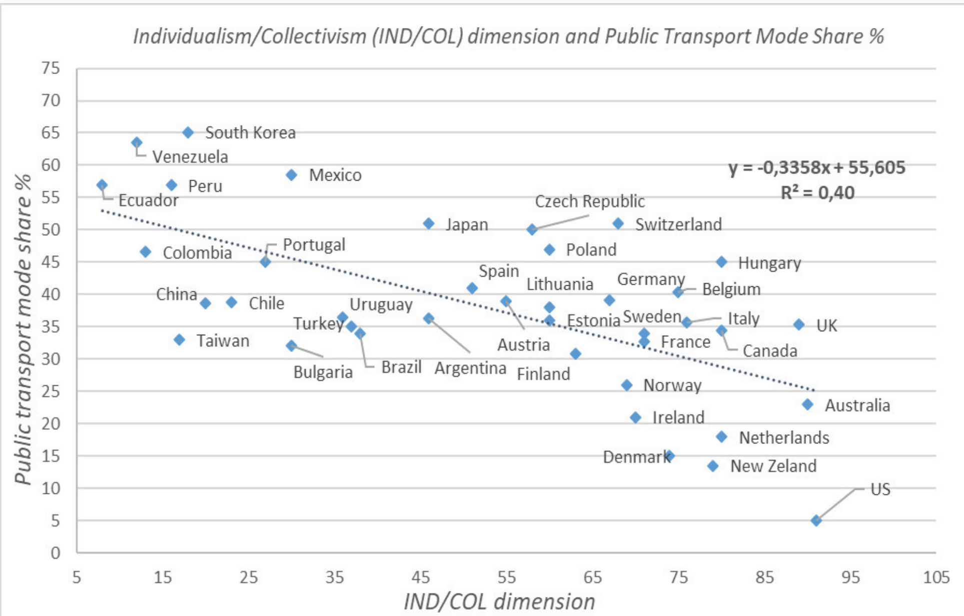

Figure 4.5 Public transport mode share over the individualism/collectivism (IND/COL) dimension.

Table 4.3 Results of the linear function model Eq. (1). $R^2 = 0.38$, sample size N=39.

	Coef	Std Err	**Beta**	T	**P>|t|**
C	16.429	4.834		3.399	0.002
D	0.411	0.084	0.615	4.875	0.000

Table 4.4 Results of the linear function model Eq. (2). $R^2 = 0.20$, sample size N=39.

	Coef	Std Err	**Beta**	T	**P>|t|**
C	11.871	3.807		3.118	0.003
D	0.209	0.066	0.450	3.143	0.003

Table 4.5 Results of the linear function model Eq. (3). $R^2 = 0.42$, sample size N=39.

	Coef	Std Err	**Beta**	T	**P>|t|**
C	158.878	42.551		3.734	0.001
D	3.929	0.743	0.646	5.289	0.000

Table 4.6 Results of the linear function model Eq. (4). $R^2 = 0.40$, sample size N=39.

	Coef	Std Err	**Beta**	T	**P>|t|**
C	55.605	3.924		14.172	0.000
D	-0.336	0.067	-0.634	-4.984	0.000

As seen from Tables (4.3–4.7), the IND/COL dimension exerts high influence in the urban travel patterns at perfect significance. The highest influence of individualism is seen in terms of car ownership. Communities with a high individualism shape their travel environment for individual transportation, and, in turn, these areas are developed by individualistic travel needs. A decrease in individualism means an increase in collectivism in the society. It is seen in Table 4.5 that an increase in collectivism results in greater usage of the public transport. Table 4.6 demonstrates the results of the multiple linear regression model on the prediction of the public transport mode share. R^2 is higher than linear function model Eq. (4), and all the coefficients are significant. Fig. 4.6 shows a normal P-P plot of the regression standardized residual for linear function model Eq. (5). The plot demonstrates that the residuals of multiple regression follow a normal distribution. The results of the model indicate that, in case of nations, an increase in three culture dimensions is observed: collectivism, uncertainty and masculinity results in greater usage of public transport. The masculinity and uncertainty dimensions have a similar level of influence on the public transport usage, which is less than an increase in individualism which decreases the public transport usage.

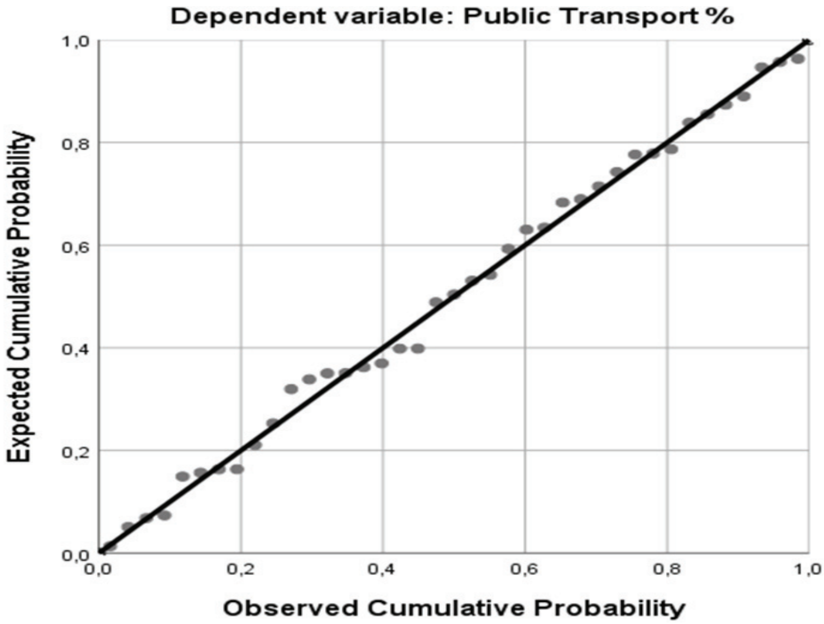

Figure 4.6 Normal P-P Plot of Regression Standardized Residual for model Eq. (4).

Table 4.7 Results of linear function model Eq. (5). $R^2 = 0.55$, sample size N=35.

	Coef	Std Err	**Beta**	T	**P>|t|**
C	32.018	8.155		3.926	0.000
D	-0.267	0.067	-0.504	-3.979	0.000
E	0.154	0.072	0.249	2.147	0.039
F	0.180	0.084	0.279	2.152	0.038

4.2. Analysis and results of the influence of higher education on the travel mode choice

This section describes the analysis of the influence of the higher education level on the urban travel mode choice in the investigated cities. In the first step, correlations between the higher education level and the mode choices were checked with the collected data. Thereafter, the mode choices were modeled based on the higher education level while controlling the population density and GDP per capita.

Table 4.8 Pearson correlation coefficient between the travel mode choices and urban indicators.

	Education Level	**Population Density**	GDP per capita
Drive %	-0.68	-0.63	0.37
Public Transport%	0.62	0.59	-0.33
Active %	0.51	0.73	
Cycling %	0.45	0.65	
Walking %	0.46	0,60	-0.41

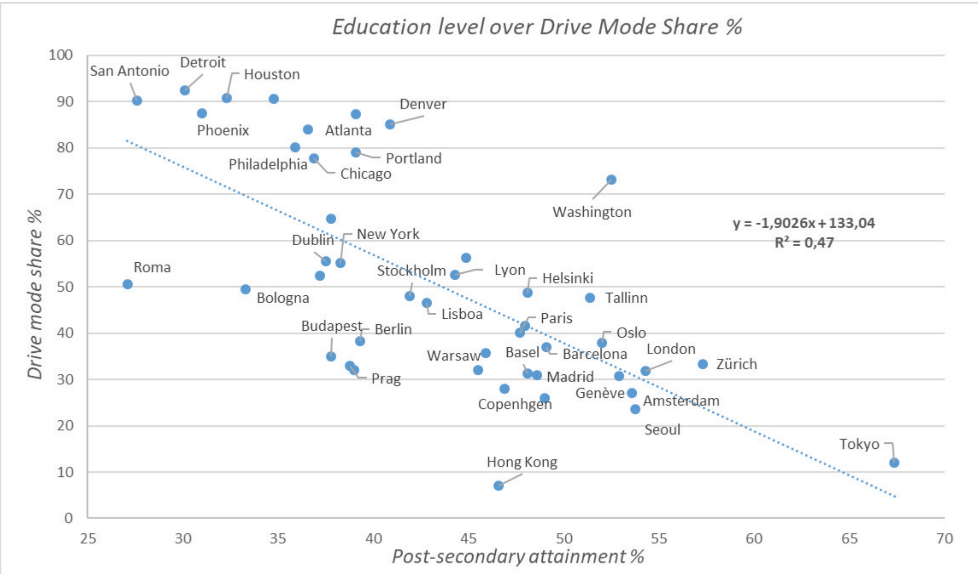

Figure. 4.7 Education level over the drive mode share.

The *Pearson Correlation Coefficient* between different indicators is shown in Table 4.1. Software *IBM SPSS 25* was used for the Pearson correlation analyses of variables. A strong negative correlation between the higher education level and driving is seen in Table 4.8. Also, the higher education level is positively correlated with the public transport usage at a high level. Furthermore, considerable positive correlation between the higher educational level and the active modes is shown in Table 4.1. These results confirm the previously mentioned findings between the education level and the mode choices with a larger sample size and more comparable data [28, 29 and 32]. One hypothesis could be that higher educated societies buy fewer cars, drive less, and use alternative mobility systems more due to environmental and health concerns.

As expected, the land use has high influence on the travel mode choices: there is a high positive correlation between the population density and the public transport mode share. Also, a strong negative correlation between the population density and driving is observed. The highest correlation with the population is shown for the active modes. Furthermore, the economic power is considerably correlated with the mode choices: cities with the higher GDP per capita drive more in a moderate level. However, there is no significant correlation between cycling and GDP per capita.

Figure 4.7 demonstrates a scatter graph with city labels in which the drive mode share over the higher education level is presented. Also, Figure 4.7 displays a linear model as the linear line showed the best fit with considerable R^2. A similar linear relationship is seen between the public transport mode share with a slightly lower R^2. Following the strong correlation values, two calibrated multiple regression models are proposed below thus quantifying the relation between the mode shares, the education level (EDU), the population density (PD) and GDP per capita.

$$\text{Drive mode share } \% = \text{c} + \text{d EDU } + \text{e PD} + \text{f GDP} \tag{6}$$

$$\text{Public Transport mode share } \% = \text{c} + \text{d EDU } + \text{e PD} + \text{f GDP} \tag{7}$$

Table 4.9 Results of linear function model Eq. (6). $R^2 = 0.62$, sample size N=44.

	Coef	Std Err	**Beta**	T	**P>|t|**
C	99.600	15.344		6.491	0.000
D	-1.372	0.313	-0.493	-4.382	0.000
E	-0.003	0.001	-0.315	-2.734	0.009
F	0.000	0.000	0.232	2.347	0.024

Table 4.10 Results of the linear function model Eq. (7). $R^2 = 0.52$, sample size N=43.

	Coef	Std Err	**Beta**	T	**P>|t|**
C	3.700	13.368		-0.277	0.783
D	0.919	0.278	0.430	3.308	0.002
E	0.002	0.001	0.312	2.327	0.025
F	0.000	0.000	-0.201	-1.762	0.086

Coefficients *d*, *e and f* quantify the reduction in the mode shares due to an increase/decrease in independent variables in Table 4.9 and Table 4.10. As units are different, we take into account standardized Beta coefficients for assessing. The results of linear function model Eq. (6) demonstrate that an increase in the education level has the highest effect on dropping the drive mode share in cities, while an increase in the population density reduces the drive mode share more than an increase in GDP per capita boosts it. R^2 is higher than the presented linear model in Figure 4.7, and the coefficients are significant. In addition, the public transport mode share estimation resulted in a similar fit of the data, but the statistical significance is lower.

4.3. Analysis and results of the transport indicators and comparison of 151 urban areas

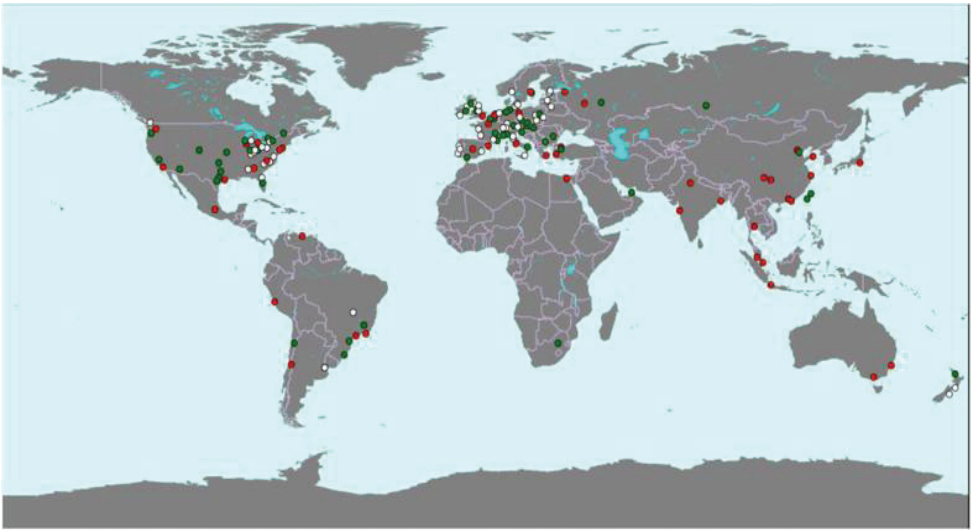

Figure 4.8 Distribution of the analyzed cities (white = small cities, green = mature cities, red = metropolises).

In this section, various analyses are performed, and their results are discussed below. Relations between the indicators are identified through correlations, and regression models are calibrated thus quantifying the relation between the transport infrastructure and performance indicators. Three sub-categories of cities with different population sizes (small cities, large cities and metropolises) are defined and studied individually. In addition, qualitative analysis is performed thus putting five different indicators into relation.

4.3.1. Correlations within city groups

In order to render the city comparison more comparable, cities are divided into three sub-groups: cities with a population under 800,000 are defined as ‘small cities’ (51 cities), cities with a population between 800,000 and 3 million are defined as ‘mature cities’ (56 cities), and cities with a population over 3 million are defined as ‘metropolises’ (44 cities). The distribution of the considered cities with the respective group-type is shown in the world map in Fig. 4.8.

The Pearson Correlation Coefficient between different indicators together with the number of samples is shown for different city sizes in Table 4.11. We note that the indicator correlations of small cities are often low, probably due to their heterogeneous sizes, land-use and transport networks.

The clearly positive correlation between the spatial city area and the population growth rate for metropolises, mature cities and all the cities is trivial as the number of newborns is proportional to the population size. Also, the fact that congestion levels (ADETT) increase with the higher population density is not surprising and confirms that cities are struggling to keep the transport infrastructure in pace with the increasing traffic intensity (trips per sq. km). It is of interest to note the negative relationship between the population density and GDP per capita, suggesting that economically weaker cities experience more congestions – this is particularly true for metropolises. The correlation between GDP per capita and the road infrastructure accessibility (IA) is strong for metropolises, and a little weaker for mature cities. The relationship between GDP per capita and rail IA and between GDP per capita and cycle IA is less pronounced.

Table 4.11 Pearson correlation coefficient and the number of samples (N) between different indicators.

	Metropolises	**Mature Cities**	**Small Cities**	**All Cities**
Spatial city area and annual pop. growth	0.53 (N = 44)	0.52 (N = 55)	–	0.45 (N = 150)
Population density and ADETT	0.52 (N = 37)	0.55 (N = 55)	–	0.50 (N = 143)
Population density and GDP per capita	-0.53 (N =42)	-0.28 (N = 56)	–	-0.40 (N =139)
GDP per capita and ADETT	-0.51 (N =36)	-0.30 (N = 55)	–	- 0.33 (N=132)
GDP per capita and road IA	0.71 (N = 42)	0.57 (N = 56)	–	0.56 (N = 139)
GDP per capita and rail IA	0.58 (N = 38)	0.48 (N = 47)	–	0.36 (N = 124)
GDP per capita and cycle IA	0.47 (N = 30)	0.34 (N = 43)	–	–
ADETT and road IA	-0.61 (N =37)	-0.75 (N = 55)	-0.59 (N = 51)	-0.66 (N = 143)
ADETT and train IA	-0.63 (N = 34)	-0.34 (N = 46)	–	-0.39 (N = 127)
ADETT and cycle IA	-0.36 (N = 27)	-0.30 (N = 43)	-0.43 (N = 42)	-0.34 (N = 112)

The strong relationship between road IA and ADETT is clearly seen for all the city sizes. For metropolises, the increase of the rail infrastructure shows a similar de-congesting effect tho that of an increase in the road infrastructure, while, for small cities, the rail infrastructure is less correlated with congestions. One hypothesis could be that smaller cities are less congested, and there is less pressure to change from the private car to rail. These results confirm the previously mentioned finding that the rail infrastructure has a relaxation effect on the road traffic for metropolises [95, 111], presumably by shifting from car trips to rail trips. Combining the relations between road/rail IA, the congestions and GDP per capita, it could be hypothesized that economically strong metropolises can afford to expand road, rail and bicycle infrastructure and are more successful in reducing congestions.

4.3.2. Statistical models

As IA and ADETT are generally well correlated, some statistical models were calibrated with the entire set of cities as well as on specific subsets. The best fit between the road infrastructure accessibility RIA and ADETT of all the cities was achieved with an exponential function of the shape:

$$ADETT = a\ exp(b\ RIA) \tag{8}$$

However, the fitting errors with a linear model are only slightly superior. The results of this calibration are shown in Table 4.12. Despite the high noise levels in the data, coefficient *b* is negative, which means decreasing congestions with the increasing road IA. This model was applied for the three city sub-groups and plotted together with the data points in Figs. 4.9, 4.10, 4.11.

A further model is built which includes both the road infrastructure accessibility *RIA* and the train infrastructure accessibility *TIA*:

$$ADETT = c + d\ RIA + e\ TIA \tag{9}$$

As *RIA* and *TIA* have the same unit, coefficients *d* and *e* quantify the reduction in traffic congestions due to an increase/decrease in the road infrastructure or the train infrastructure, respectively. The interesting question is how coefficients *d* and *e* behave in cities with high and low population densities. Table 4.13 shows the calibration results of coefficients *d* and *e* for cities with a high population density (above 1500 per sq. km) while Table 4.14 shows the same calibration for cities with a low population density (below 1500 per sq. km). The population density division at 1500 per sq. km was chosen arbitrarily. The main idea was to isolate the extreme space oriented cities in the US and Australia. However, the division at 1500 per sq. km can be varied within reasonable bounds without changing the core message of the results, as detailed below.

The results for high density cities in Table 4.13 show that *e* is significantly more negative than *d* (four times more negative), and that both coefficients are significant. This result means that the increase in the train infrastructure per person reduces more congestion than the increase in the road infrastructure per person.

One reason why rail lines combat congestion more effectively is probably due to the fact that the rail infrastructure was implemented primarily along the most congested corridors of the city. Therefore, the result of the model does not mean that extending the rail network beyond the main traffic corridors will continue to reduce the traffic congestion.

Table 4.12 The calibration results of exponential function model Eq. (8) for all cities. $R^2 = 0.52$, sample size N = 147

Calibration results	Coef	std err	t	P>|t|	[95.0% Conf. Int.]	
Log(a)	3.7734	0.037	100.773	0.000	3.699	3.847
B	-0.0101	0.001	-12.232	0.000	-0.012	- 0.009

Table 4.13 Calibration results of linear function model Eq. (9) for cities with population densities above 1,500 per sq. km. $R^2 = 0.27$, sample size N = 88

Calibration results	Coef	std err	t	P>|t|	[95.0% Conf. Int.]	
C	45.3582	2.122	21.375	0.000	41.139	49.577
D	-0.2386	0.083	-2.880	0.005	-0.403	-0.074
E	-0.9706	0.246	-3.950	0.000	-1.459	-0.482

Table 4.14 Calibration results of linear function model Eq. (10) for cities with population densities below 1,500 per sq. km. $R^2 = 0.64$, sample size N=39.

Calibration results	Coef	std err	t	P>|t|	[95.0% Conf. Int.]	
C	45.3582	2.122	21.375	0.000	41.139	49.577
D	-0.2386	0.083	-2.880	0.005	-0.403	-0.074
E	-0.9706	0.246	-3.950	0.000	-1.459	-0.482

The situation for low density cities, as shown in Table 4.14, is less clear: *e* is only slightly more negative than *d*, and *e* is statistically not significant (a high *P* value). This means that railway building for low density cities appears less effective in reducing congestions with respect to the cities denoted by high density.

4.3.3. Multi-variant comparison

In an attempt to pursue the holistic approach, the relations among five different indicators are shown in a bubble-type graph where each bubble represents a city: the x-axis represents Road IA, and the y-axis represents the ADETT, the fill color indicates Train IA, the bubble border color indicates Cycle IA, the color of the starred city labels indicates BRT IA. The color scaling is summarized in Table 4.15. The bubble graph was generated for each of the city groups: metropolitan cities in Fig. 4.9, mature cities in Fig. 4.10, and small cities in Fig. 4.11 For each city group, the model from Eq. (8) was calibrated, as the exponential curve showed the best fit. The regression curve and R^2 are also indicated in each bubble graph.

The regression analyses for all the city groups (Figs. 4.9–4.11) show R^2 values between 0.4 and 0.6, which indicates a good fit considering the many error sources mentioned in the Data collection and processing section and the diversity of street layouts, public transit service characteristics and mobility cultures. In the figures of all the three city groups, the cities can be divided in two groups at Road IA of approximately 35 m/(10Inh): most cities below this threshold have a higher population density comparing with the cities above this threshold. It is evident that many cities with low population densities built large road networks and succeeded in reducing congestion. On the other hand, cities with higher population densities appear to be facing space constraints and cannot extend their road network.

Table 4.15 Scaling of multi-variant graphs in Figs 4.9–4.11.

Urban Train IA [km railway per 10 inh]:	*Bubble fill color:* *red=Train IA>1100* *orange =223 < Train IA<1100* *green = Train IA < 223* *non-color= absence of urban rail*
Cycle IA [m cycleway per 10000 inh]:	*Bubble border color:* *red = Cycle IA > 1500* *orange =200< Cycle IA<1500* *green =10< Cycle IA<200* *blue = Cycle IA<10*
BRT IA [m BRT per 10000 inh]:	*Starred Marker (*) color of city labels:* *red = BRT IA > 150* *green = BRT IA < 150*

When looking closer at cities with higher population densities, it is apparent that the cities with a more extensive train network per person (the red and orange colors) have generally lower congestion levels. This result is consistent with the models in the last section. However, there are also many exceptions: Dublin and Bucharest have high Train IA but also high congestion levels, while Madrid and Sao Paulo have low Train IA and low congestion levels. Furthermore, the small cities give a less clear picture regarding Train IA and congestions. Some of the small cities with a higher population density stand out for their low congestion level most likely due to the presence of a high level of cycling infrastructure; examples are Malmo, Zwolle and Fresno, but there are not enough example cities with a high level of cycling to show a general trend.

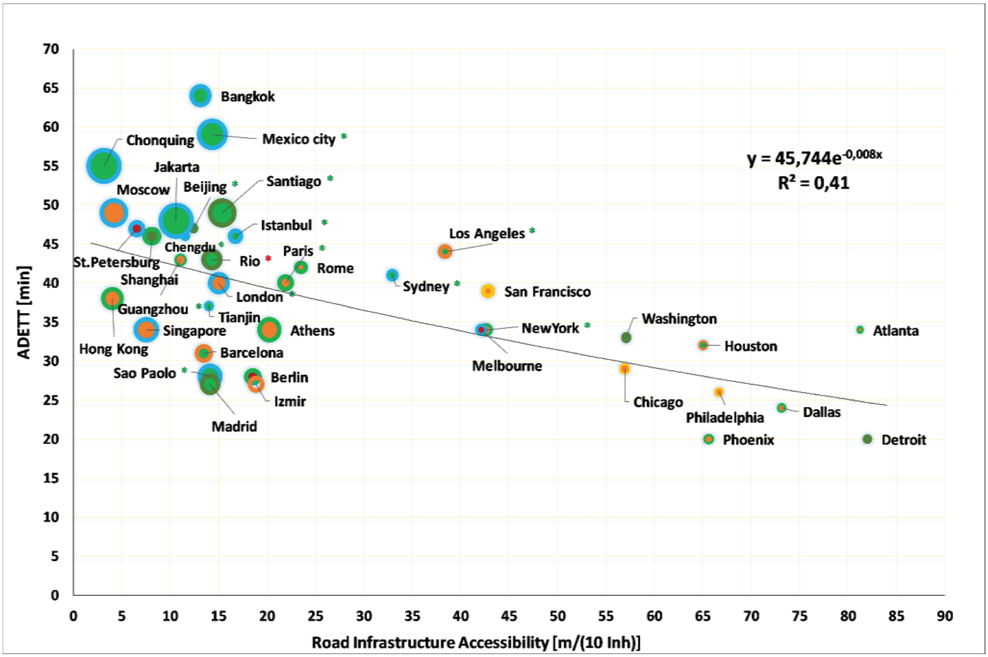

Figure 4.9 Multi variant diagram of metropolises. Congestion level (ADETT) over Road IA; the bubble size is proportional to the population density; the filled color indicates Train IA, the bubble border color indicates Cycle IA, the color of the starred city labels indicates BRT IA. For color scaling, see Table 4.15. The dotted line represents the fitted exponential curve from Eq. (8).

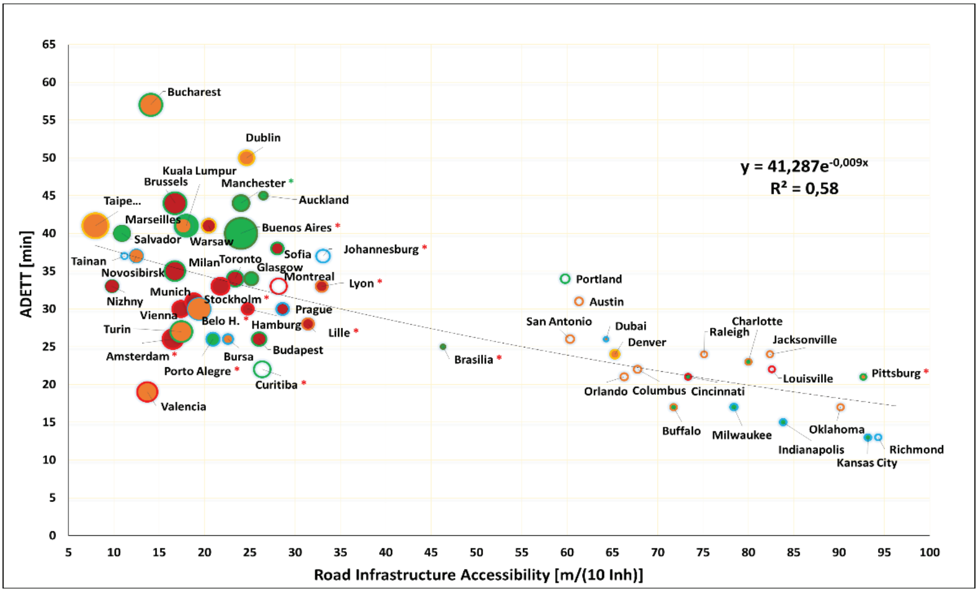

Figure 4.10 Multi variant diagram of mature cities. Congestion level (ADETT) over Road IA; the bubble size is proportional to the population density; the filled color indicates Train IA, the bubble border color indicates Cycle IA, the color of the starred city labels indicates BRT IA. For color scaling, see Table 4.15. The dotted line represents the fitted exponential curve from Eq. (8).

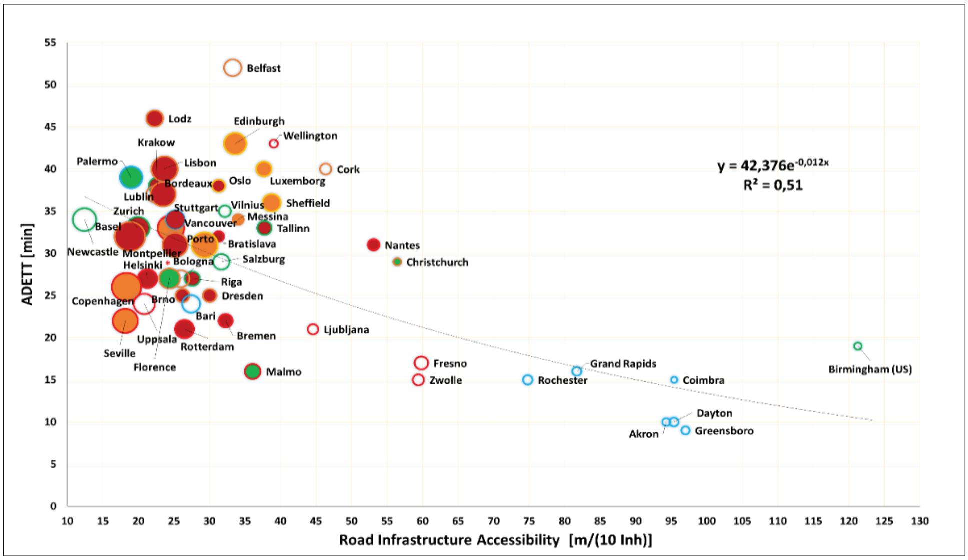

Figure 4.11 Multi variant diagram of small cities. Congestion level (ADETT) over Road IA; the bubble size is proportional to the population density; the filled color indicates Train IA, the bubble border color indicates Cycle IA, the color of the starred city labels indicates BRT IA. For color scaling, see Table 4.15. The dotted line represents the fitted exponential curve from Eq. (8).

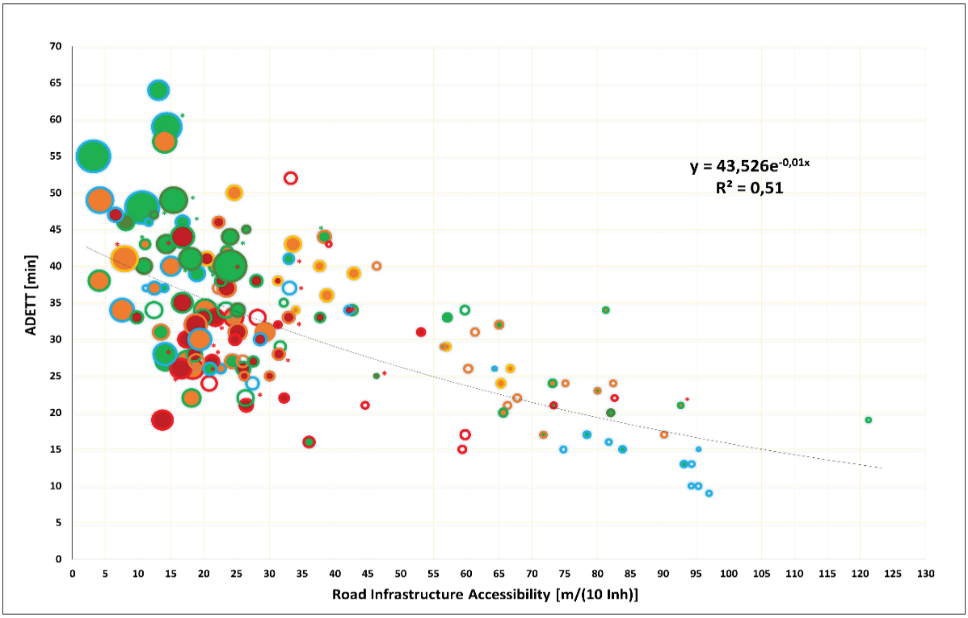

Figure 4.12 Multi variant diagram with a holistic view. Congestion level (ADETT) over Road IA

Fig. 4.12 demonstrates a holistic view including all the cities. In the ADETT interval of 14–34 minutes, one can see a cluster of cities below the logarithmic trend line with a common characteristic: a medium level GDP per capita, high urban railway and cycleway infrastructure accessibility but relatively low road infrastructure accessibility. Within the same range of travel delays, there is also a cluster of cities above the trend line: these cities feature generally a higher GDP per capita, a high road infrastructure accessibility, and a low level of railway infrastructure accessibility or total absence of urban railways. All of the cities above the trend-line are also denoted by low population densities. In this ADETT interval, most cities under the trend line are European cities, while most cities above the trend-line are US cities. In the ADETT interval of 34–44 minutes, cities have a generally average GDP per capita, a lower road infrastructure accessibility and a lower cycleway infrastructure accessibility. In this ADETT interval, cities are in various regions of the world. The highest congestion delays with over 44 minutes of the average daily extra travel time show cities with a low network infrastructure accessibility, a low GDP per capita, and a low bicycle infrastructure accessibility (none of these cities is among the 25% of the cities with the highest cycleway accessibility). Most of the highly congested cities are located in Asia. It is surprising to see that the cities with a high BRT infrastructure accessibility are more frequent in the cluster in the 14–34 minutes ADETT interval and under the logarithmic trend line – in the cluster with the highest multi-modal infrastructure accessibility. Generally, the cities with a high BRT infrastructure accessibility are in South America. We note that Amsterdam has one of the lowest road infrastructure accessibility levels amongst cities, but it has the highest multi-modal infrastructure accessibility and railways, cycleways and BRT lines, which appear to reduce congestion levels.

4.4. Analysis and results of the influence of the network design on the urban transportation performance

Figure 4.13 Distribution of the analyzed cities

This section strives to determine important network indicators, such as connectivity, centrality and clustering measures for different network types (road, rail and cycleway) from 86 urban areas and 32 countries, based on comparable, directly observable open-source data such as the *OpenStreetMap* (OSM) and the *TomTom* congestion database. Relations between the indicators are identified through correlations, and regression models are calibrated thus quantifying the relations of the infrastructure accessibility and the network indicators with the delay times. To the best of the author's knowledge, the indicator *average road connectivity over average road circuity* (RCRC) has not been studied before, which is proposed in this research. In this section, different analyses are performed, and their results are discussed. The distribution of the considered cities is shown in the world map in Fig. 4.13.

4.4.1. Correlations

The Pearson correlation coefficient among different indicators together with the number of samples is shown in Table 4.16 and Table 4.17. Software *IBM SPSS 25* is used for the Pearson correlation analyses of variables.

Significant negative correlations between ADETT and infrastructure accessibility types have already been shown in the previous section, and also regression models between ADETT & infrastructure accessibility have been presented. A considerable negative correlation between the road network connectivity indicators and ADETT is seen in Table 4.16. As expected, the reduction of choke points in the road networks can increase the continuity of traffic flows and in turn can reduce the traffic congestion. All the road connectivity indicators strongly correlated with each other at the similar level; thus only gamma connectivity is picked to show the inter-correlations between the connectivity measures. Only eta connectivity did not show any considerable correlation with any variants. The average circuity of road and rail networks (ARC and ATC) positively correlated with ADETT. As expected, the network connectivity negatively correlated with the network circuity for both network types.

Table 4.16 Pearson correlation coefficient between congestion and infrastructure indicators.

Pearson Correlation	ADETT	RIA	TIA	CIA	Γ	B	A	ANC	ARC	ATC
ADETT		N=87 -0.69	N=85 -0.41	N=86 -0.32	N=87 -0.49	N=87 -0.49	N=87 -0.49	N=87 -0.49	N=87 0.29	N=87 0.39
Γ					N=87 0.99	N=87 0.99	N=87 0.99	N=87 0.95		
ARC	N=87 0.29				N=87 -0.36	N=87 -0.36	N=87 -0.36	N=87 -0.36		

Table 4.17 Pearson correlation coefficient between congestion and distance-based network connectivity indicators.

Pearson Correlation	RCRC	ARCC	AWTCC	ACCC
ADETT	N=87 -0.50	N=87 -0.39	N=54 -0.47	N=29 -0.45
Γ	N=87 0.99	N=87 0.43		
ARC	N=87 -0.48	N=87 -0.40		
ATC			N=54 -0.36	
RCRC		N=87 0.46		

Networks can be well connected but at the same time be poor in terms of directness. This confirms that connectivity and directness are independent and can be coupled effectively as suggested in [180]. Table 4.17 demonstrates the relation between distance-based network connectivity measures (ARCC, ATCC and ACCC) and ADETT with some interrelations. The average closeness centrality is negatively correlated with ADETT for road and cycle networks (ARCC and ACCC). Another distance-based indicator proposed here as *average road connectivity over average road circuity* (RCRC) is correlated with ADETT with a coefficient of -0.50. As ARCC and RCRC are similar types of measures, they are strongly correlated with each other. Presumably, high average short distance accessibility of road networks decreases the low permeability choke points and distributes the road traffic more homogeneously, and consequently eases the road traffic. The average weighted clustering coefficient demonstrates distance-based directness of the network as it is evident that AWTCC correlates negatively with ADETT with a coefficient of 0.47 and negatively correlates with the average rail circuity.

4.4.2. Comparative view

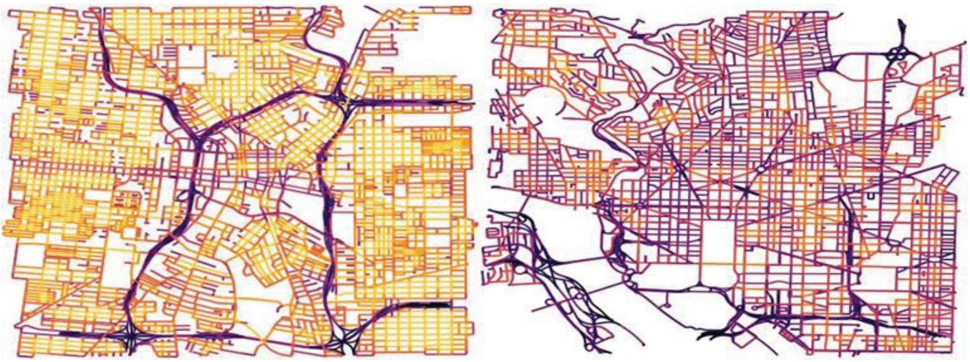

Figure 4.14 Road network connectivity maps of San Antonio and Washington D.C.

Figure 4.15 Road network connectivity maps of Berlin and Marseille.

Figure 4.16 Road network connectivity maps of Manchester and Dublin.

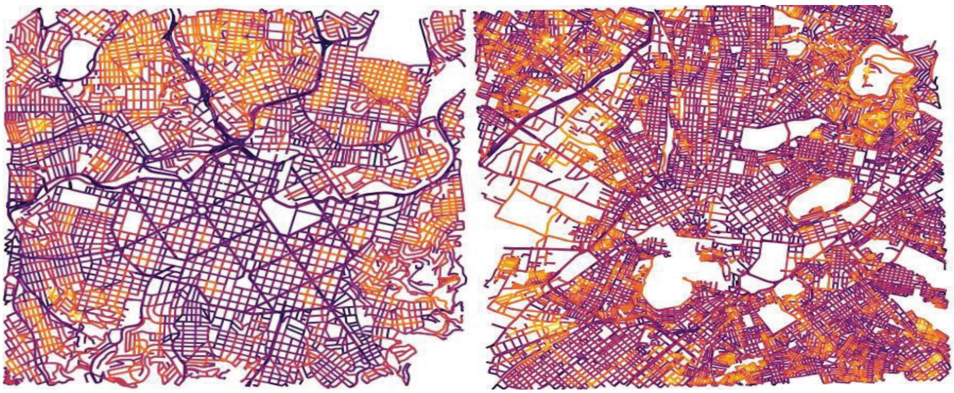

Figure 4.17 Road network connectivity maps of Belo Horizonte and Athens.

Table 4.18 Comparison of the selected cities.

Cities	RIA	TIA	CIA	ADETT	Population Density	ARC	ANC	Γ	RCRC
San Antonio	60.309	2.613	0.387	26	1312	1.0216	5.887	0.9817	0.9609
Washington	57.105	1.893	0.344	33	1446	1.0284	4.932	0.8225	0.7998
Dublin	24.645	1.453	0.262	50	3716	1.0736	3.945	0.6579	0.6128
Manchester	24.021	1.643	0.115	44	4236	1.0469	4.698	0.7832	0.7481
Berlin	18.550	6.477	0.080	28	3700	1.0276	5.032	0.8392	0.8166
Marseille	17.651	3.177	0.025	41	4040	1.0608	4.229	0.7050	0.6646
Athens	20.243	0.878	0.062	34	7436	1.0154	4.388	0.7315	0.7203
Belo Horizonte	19.398	0.194	0.010	30	7464	1.0229	4.834	0.8060	0.7879

Road network connectivity maps of some cities (50 km^2 cores) are plotted with the dual graph approach where streets are represented as nodes, and intersections are represented as edges in Figs. 4.14–4.17. These pairs of cities were selected for comparison as each pair has similar peer sociodemographic and infrastructure indicators, as shown in Table 4.18. Their similarity allows to put in evidence regarding the influence of the network structure. Qualitative color maps increasing luminance through blue, purple, and yellow hues are produced to interpret the graphs more efficiently. As it is clearly seen in the plotted maps and in Table 4.18, cities with higher RCRC and higher road network connectivity achieve lower congestion.

4.4.3. Statistical models

Some statistical models were calibrated between ADETT and the distance-based road connectivity measures (DBRC) with the entire set of cities. ADETT as a function of DBRC appears to be of the exponential shape:

$$ADETT = a\, exp(b\, DBRC) \tag{10}$$

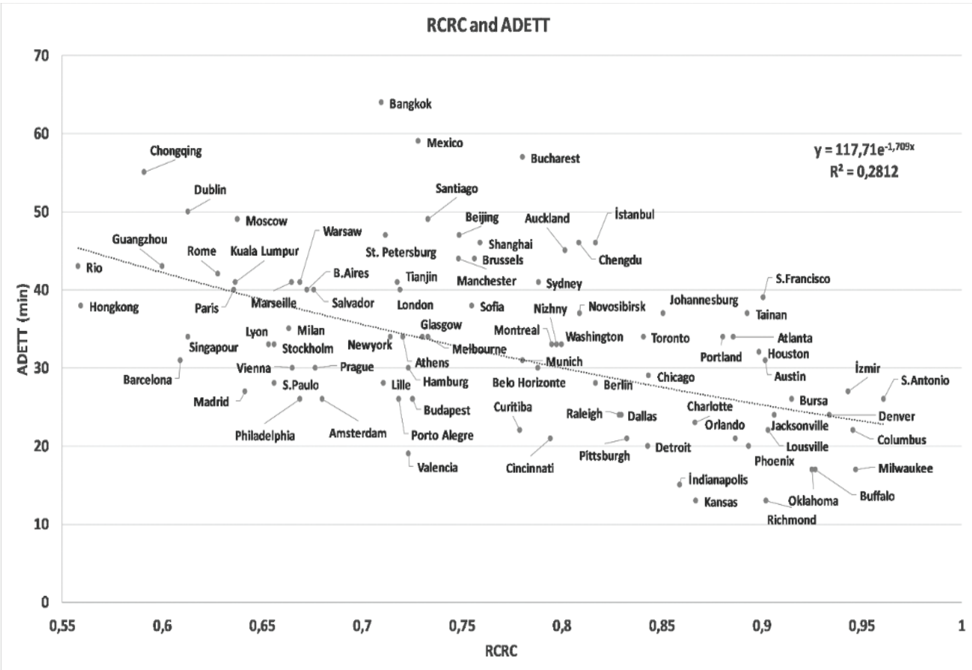

Figure 4.18 Scatter graph, average road connectivity over average road circuity (RCRC) and congestion level (ADETT) of cities; the dotted line represents the fitted exponential curve from Eq. (10).

However, the fitting errors with a linear model are only slightly superior. Fig. 4.18 demonstrates the exponential model which was calibrated from the exponential relation of Eq. (10). The best fitting exponential curve is also shown in Fig. 4.18. Even though $R^2 = 0.28$ is not particularly high, it shows a reasonable goodness of fit, and parameters are statistically significant. We note that a similar reasonable fit was also achieved for ADETT as a function of ARCC. Considering the fact that many different network attributes influence the demand and road congestions, the quality of this fit is reasonable. The influence of DBRC on congestion is minor for cities with very high population densities, such as Bangkok and Mexico City (see Fig. 4.18).

A question arises how the road-based coefficients behave in cities in the presence of different alternative infrastructures, such as railways and cycleways of different length and topology. Geometric variations of network structures, such as density and circuity, become more visible when the network complexity is at a maturated level. This makes the infrastructure density a good proxy when seeking to identify the level of the infrastructure maturity. Two subsets of cities were created based on the level of maturity of the alternative network systems. The rail infrastructure density division was set at 1km per km^2, and the cycle infrastructure density division was set at 0.4km per km^2. Both thresholds were chosen arbitrarily. The main idea was to isolate non-matured alternative network systems in cities. This will help to understand the network related factors of alternative network systems more accurately. All the cities possess a road network with a density over 10km per 1km^2. As IA and ADETT as well as DBC and ADETT are considerably correlated, some multiple linear regression models were attempted with the entire set of cities as well as on specific subsets (cities matured with railways – 53 cities, and cities matured with cycleways – 28 cities), while only the models with a P value below 0.2 for each attribute are shown in the tables below. Further models were built which include infrastructure accessibility indicators (infrastructure per capita) and DBC indicators:

$$ADETT = c + d\,RIA + e\,TIA + f ARCC \tag{11}$$

$$ADETT = c + d\,RIA + e\,TIA + f ARCC + g AWRCC \tag{12}$$

$$ADETT = c + d\,RIA + e\,TIA + f CIA + g ACCC \tag{13}$$

Coefficients *d*, *e*, *f* and *g* quantify the reduction in traffic congestions due to an increase/decrease of the independent variables. As the units are different, standardized Beta coefficients are considered. The results of the linear function model from Eq. (11) demonstrate that an increase in the average road closeness centrality reduces congestion at a similar level as does an increase in TIA. This is a useful finding which demonstrates that the network design is as important as increasing the infrastructure length of alternative networks. The significance of *e*, *f*, *g* is less clear. However, the results of linear function model Eq. (12) demonstrate that an increase in $AWTCC$ decreases the road congestion at a similar level as does an increase in the average road closeness centrality. The results of linear function model Eq. (13) demonstrate that the influence of RIA on congestion stays slightly lower compared with model Eq. (12), and CIA exerts the highest influence on congestion alleviation compared with an increase in RIA and TIA while considering cities with over 0.4 km per km^2 cycleway density. Furthermore, an increase in $ACCC$ decreases congestion more effectively than an increase in TIA. However the increase in $ACCC$ is slightly less effective in decreasing congestion than an increase in RIA. The influence of TIA is less significant in this model.

Table 4.19 Calibration results of linear function model Eq. (11) for all the samples. R^2=0.53, sample size N=85.

Calibration results	Coef	Std Err	Beta	t	P>|t|
C	68.192	10.034		6.796	0.000
D	-0.222	0.034	-0.556	-6.603	0.000
E	-0.682	0.312	-0.179	-2.186	0.032
F	-109818.3	46148.044	-0.193	-2.380	0.020

Table 4.20 Calibration results of linear function model Eq. (12) for cities matured with railways. $R^2 = 0.48$, sample size N=53.

Calibration results	Coef	Std Err	Beta	t	P>|t|
C	71.287	16.076		4.434	0.000
D	-0.161	0.041	-0.488	-3.926	0.000
E	-0.847	0.423	-0.206	-2.002	0.051
F	-121553	72324.044	-0.180	-1.681	0.099
G	-1017.27	764.075	-0.164	-1.331	0.189

Table 4.21 Calibration results of linear function model Eq. (13) for cities matured with cycleways. $R^2 = 0.59$, sample size N=28.

Calibration results	Coef	Std Err	Beta	t	P>|t|
C	46.366	2.803		16.163	0.000
D	-0.167	0.054	-0.461	-3.039	0.006
E	-0.684	0.393	-0.229	-1.571	0.130
F	-2.833	0.797	-0.472	-3.486	0.002
G	-20519.7	9563.210	-0.321	-2.127	0.044

4.5. Analysis and results of the transport-related energy consumption of urban areas

This section describes the analysis of the transport energy consumption per capita of the investigated cities. In a first step, the transport energy of cities is calculated as precisely as possible from the collected data. Thereafter, the transport energy is modeled based on infrastructure accessibility and population density.

4.5.1. Transport-related energy consumption

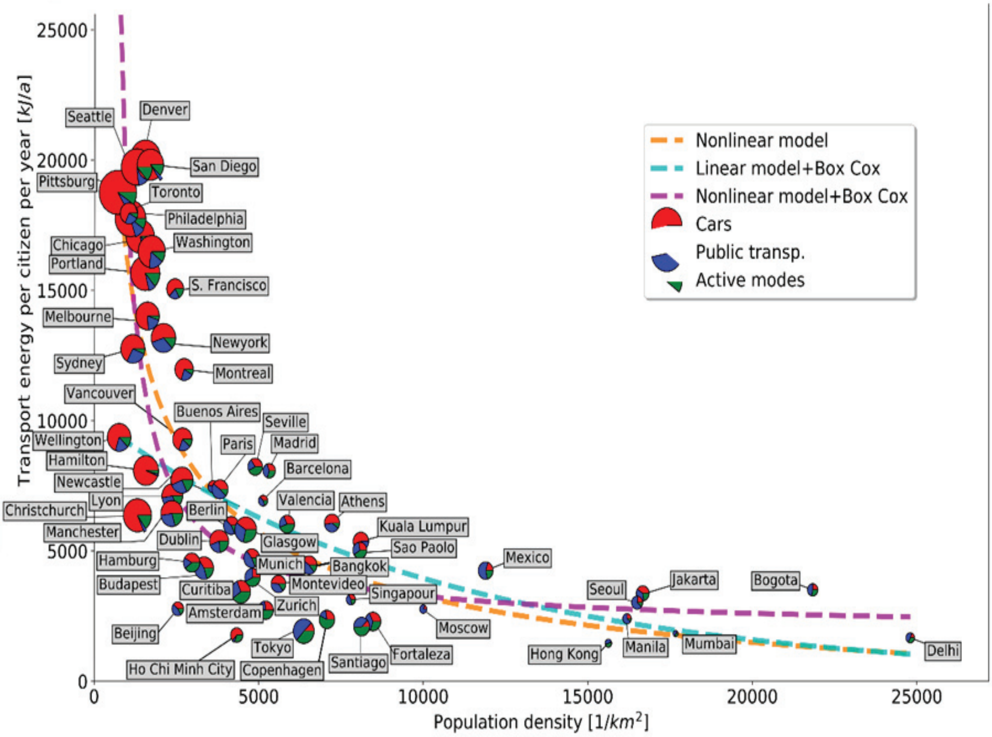

Figure 4.19 Transport related energy consumption per person in a year for commuting purposes, TE, over population density DPOP. For each city, also, the mode share of the private transport MSC (red), the public transport MSPT (blue), and the active mode share (MSA) are shown. The bubble size is proportional to the road infrastructure accessibility (RIA) of the respective city. The dashed lines represent different models which are derived in Section 4.5.2: The nonlinear model from Eq. (23) (dashed orange), the linear model with Box Cox back-transform from Eq. (24) (dashed light blue), and the nonlinear model with Box-Cox back-transformation from Eq. (25) (dashed magenta).

Considering the available data, the most precise estimate of the transport energy per person per year for commuting purposes $W_{T,i}$ in city i the can be determined by:

$$W_{T,i} = SWP_i(DC_i \cdot MSC_i \cdot WCC_i + DPT_i \cdot MSPT_i \cdot WCPT_i) \cdot 261 \quad (14)$$

where SWP_i is the share of the working population in the total population, DC_i is the daily average commuting distance to work by a private car, DPT_i is the daily average commuting distance to work by public transport, MSC_i is the mode share of private car trips, $MSPT_i$ is the mode share of trips with public transport, WCC_i is the average energy consumption per person km for a private car, $WCPT_i$ is the average energy consumption per person km for public transport, and one year corresponds to 261 working days.

Figure 4.19 shows the transport energy W_T and mode share versus the population density for each city. The same figure contains the hyperbolic shape of W_T which is similar to Newman and Kenworthy's curve. A cluster of cities can be seen at low population densities between 1000–2500 persons/km^2, where the majority are US and Canadian cities are positioned. These low population density cities are exhibiting a much higher transport related energy consumption comparing with the cities with a higher population density. Low population density cities are also characterized by a high road infrastructure accessibility (see the diameter of bubbles in Fig. 4.19), and a high car mode share (see the pie chart of bubbles in Fig. 4.20). What regards the mode shares of daily commuting in the US, the private vehicle mode share is over 85% of all trips, which is followed by 5.2% share of public transportation trips. Canadian, Australian and New Zealand cities, where car dependent mobility concepts are adopted, are denoted by on average a slightly lower road infrastructure accessibility and slightly higher public transport usage comparing with US cities.

A cluster with mainly European, Latin American cities and some Asian cities, such as Tokyo, can be seen at population densities between 2500–8000 persons/km^2 with medium level road infrastructure accessibility. The cities in this cluster consume noticeably less transport energy with respect to the first cluster. It is apparent that, in this cluster, the cities with the highest active mode share, such as Tokyo, Amsterdam and Copenhagen, consume the lowest transport energy. The cluster of the cities with population densities above 8000 persons/km^2 are mainly Asian cities with a low road infrastructure accessibility and a high public transport share.

The particularly sharp rise in energy consumption for decreasing population densities calls for some reasoning. The non-linear model shown in Fig. 4.19 is developed in the following section.

4.5.2. Transport infrastructure, population density and transport energy consumption

This section investigates how the transport infrastructure and population density determine transport energy consumption, as estimated in Eq. (14). The road infrastructure accessibility RIA and other infrastructure accessibilities **(**rail-track infrastructure accessibility TIA and bike infrastructure accessibility BIA, which can be calculated with the OSM data) are assumed to have an impact only on the respective mode shares MSC, MSPT and MSA, not on the other variables in Eq. (14). The energy efficiency of private and public transport will not be part of the modeling.

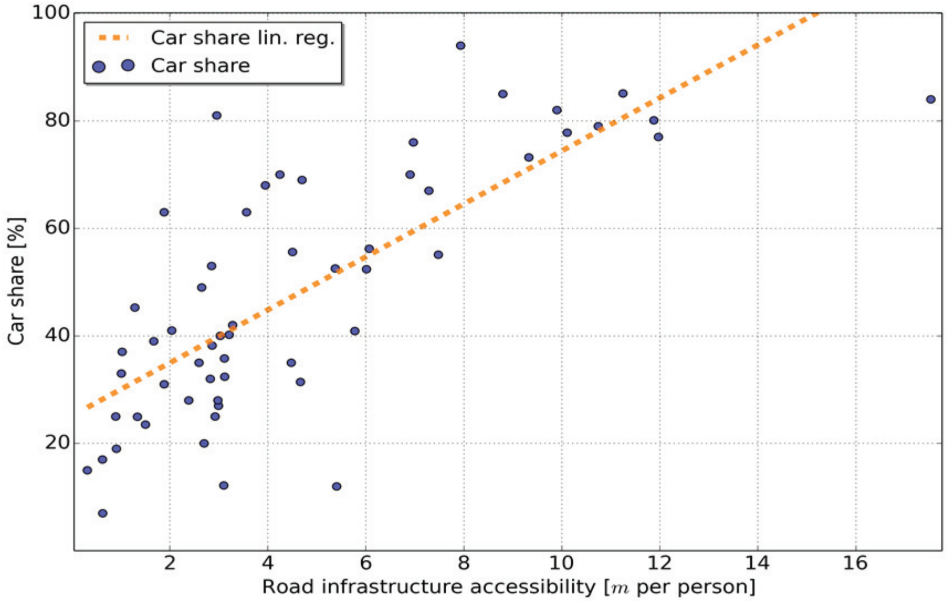

Figure 4.20 Car mode share MSC over road infrastructure accessibility RIA. The blue bubbles represent the car shares from the city database, while the dashed orange line represents a linear regression model from Eq. (15) ($R^2 = 0.58$).

What concerns the MSC, the data shown in Fig. 4.20 suggests a linear relation between the road infrastructure accessibility RIA and the car mode share MSC. MSC was estimated with the equation:

$$\widehat{MSC} = \beta_{C,0} + \beta_{C,1} RIA \tag{15}$$

where the parameters were estimated with linear regression, see Table 4.22. The fit with $R^2 = 0.58$ is relatively good considering the different error sources in the determination of RIA and MSC. The Harvey Collier test results in a p-value of 0.41, confirming that the null hypothesis that linear specification is correct should not be rejected. The skew is close to zero (0.198), and the p-value of the Jarque-Bera test is 0.62 thus indicating normally distributed residuals even though there are uncertainties due to the small sample size. However, the reason why the road length per inhabitant increases the car mode share in a proportional way is not clear.

Table 4.22 Linear regression results for private car mode share in Eq. (15)

	coef	std err	T	P>|t|	[95.0% Conf. Int.]	
$\beta_{C,0}$	25.12	3.320	7.567	0.000	18.470	31.778
$\beta_{C,1}$	4.93	0.570	8.642	0.000	3.787	6.073

What regards the public transport mode share MSPT, it is more difficult to establish a relation between the rail track length per inhabitant TIA and MSPT in the absence of more detailed information: the rail length represents only a part of all the public transport infrastructure, and, in any case, the rail usage is only a fraction of all the public transport trips. One interesting possibility is to test whether MSPT depends also on the road infrastructure. Indeed, the linear approach may be tested as:

$$\widehat{MSPT} = \beta_{PT,0} + \beta_{PT,1} RIA \qquad (16)$$

with regression parameters $\beta_{PT,0}$ and $\beta_{PT,1}$ shown in Table 4.23. The results show that RIA is significant, and, as $\beta_{PT,1}$ is negative, an increasing RIA decreases the public transport mode share as expected. With $R^2 = 0.47$, the fitting is less pronounced with respect to Eq. (15). The linear specification is correct as the p-vale of the Harvey Collier test equals 0.55, and it is likely that the residuals are normally distributed due to a skew close to zero and a Jarque-Bera p-value of 0.26.

Table 4.23 Linear regression results for PT mode share in Eq. (16)

	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
$\beta_{PT,0}$	46.177	2.816	16.396	0.000	40.533	51.821
$\beta_{PT,1}$	-3.372	-6.971	0.484	0.000	-4.342	-2.403

Further modeling showed that also the bike mode share is negatively correlated with RIA.

The population density is assumed to influence the average daily commuting distances by car, DC, and the average daily commuting distances by public transport, DPT. The linear regression model is as follows:

$$\widehat{DC} = \beta_{DC,0} + \beta_{DC,1} DPOP \qquad (17)$$

which shows that DC decreases with an increasing population density, the parameters are statistically significant, but the fit is very weak as $R^2 = 0.13$, see Table 4.24. The linear specification is correct as the p-value of the Harvey Collier test equals 0.92. The residuals are likely to be normally distributed due to a skew close to zero (0.165) and because of a Jarque-Bera p-value of 0.77. Parameter $\beta_{DC,1}$ has a relatively low absolute value, which means that the commuted distances are slightly sensitive to the population density. The influence of the population density on the PT commuting distance is not statistically significant for the present dataset.

Table 4.24 Linear regression results for average commuting travel distance in Eq. (17).

	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
$\beta_{DC,0}$	31.0955	1.697	18.326	0.000	27.695	34.496
$\beta_{DC,1}$	-0.0006	0.000	-2.917	0.005	-0.001	-0.000

Considering solely the road infrastructure accessibility RIA and the population density DPOP as independent variables, the transport energy estimate $\widehat{W}_{TA}$of a generic city shall be estimated by substituting the estimates of models from Eq. (15), Eq. (16) and Eq. (17) in the energy equation of Eq. (14). The resulting energy estimate can be presented in the shape of:

$$\widehat{W}_{TA} = \beta_{T1,0} + \beta_{T1,1} DPOP + \beta_{T1,2} RIA + \beta_{T1,2} DPOP \cdot RIA \tag{18}$$

where the following parameters are assumed to be constant and independent from *DPOP* and *RIA*:

$$\beta_{T1,0} = 261\, SWP\, (WCC\; \beta_{C,0} \beta_{C,0} + WCPT\; DPT\; MSPT\; \beta_{PT,0})$$

$$\beta_{T1,1} = 261\, SWP\, WCC\;\; \beta_{DC,1}\, \beta_{C,0}$$

$$\beta_{T1,2} = 261\, SWP\, (WCC\; \beta_{DC,0} \beta_{C,1} + \text{WPT MSPT DPT}\; \beta_{PT,0})$$

$$\beta_{T1,2} = 261\, SWP\, WCC\; \beta_{DC,0} \beta_{C,1} \beta_{C,1}$$

We note that city index *i* of the various parameters in Eq. (14) was dropped, and the respective quantities were replaced by average values. The beta parameters in Eq. (18) are determined by linear regression instead of using the above listed equations because doing so would lead to multiplicative errors. The regression results are presented in Table 4.25. This estimate fits well with the energy data as $R^2 = 0.68$, and the signs of the parameters meet expectations. However, parameter $\beta_{T1,1}$ related to DPOP is not statistically significant and takes positive values within the 95% confidence interval. In addition, the independent variables are not homoscedastic as the p-value of the Breusch-Pagan Lagrange Multiplier test is low, i.e., $9.59 \cdot 10^{-5}$. The Box-Cox transformation of the model with the optimal lambda value of λ = -0.036 is not able to improve this condition.

Table 4.25 Linear regression results for transport energy consumption per person per year of Eq. (18)

	Coef	std err	T	P>|t|	[95.0% Conf. Int.]	
$\beta_{T1,0}$	5.077e+06	1.32e+06	3.854	0.000	2.43e+06	7.72e+06
$\beta_{T1,1}$	-3.628e+05	1.16e+06	-0.312	0.757	-2.7e+06	1.97e+06
$\beta_{T1,2}$	1.196e+05	1.62e+04	7.402	0.000	8.72e+04	1.52e+05
$\beta_{T1,3}$	-1.788e+05	6.98e+04	-2.562	0.013	-3.19e+05	-3.88e+04

If dropping the explicit dependency on DPOP from Eq. (18), one ends up with the simple transport energy estimate:

$$\widehat{W}_{TB} = \beta_{T2,0} + \beta_{T2,1} RIA \tag{19}$$

with parameters $\beta_{T2,0}$ and $\beta_{T2,1}$ to be calibrated. Yet, as demonstrated below, RIA does depend on DPOP. The regression results in Table 4.26 demonstrate that both parameters are significant, with $R^2 = 0.62$, which is only slightly worse than the model in Eq. (18). The linear specification is correct as the p-value of the Harvey Collier test equals 0.30. However, the residuals are unlikely to be normally distributed as the skew is different from zero (0.712), and the Jarque-Bera p-value is 0.012, which is below 0.05.

Table 4.26 Linear regression results for average commuting travel distance in Eq. (19).

	coef	std err	t	P>|t|	[95.0% Conf. Int.]	
$\beta_{T2,0}$	1.91e+06	7.58e+05	2.519	0.015	3.9e+05	3.43e+06
$\beta_{T2,1}$	1.24e+05	1.3e+04	9.520	0.000	9.79e+04	1.5e+05

Attempts to include the rail-track infrastructure accessibility or the bike infrastructure accessibility in the transport energy estimation resulted in a better fit of the energy data, but statistical significance is still lacking.

4.5.3. The relation between population density and transport energy consumption

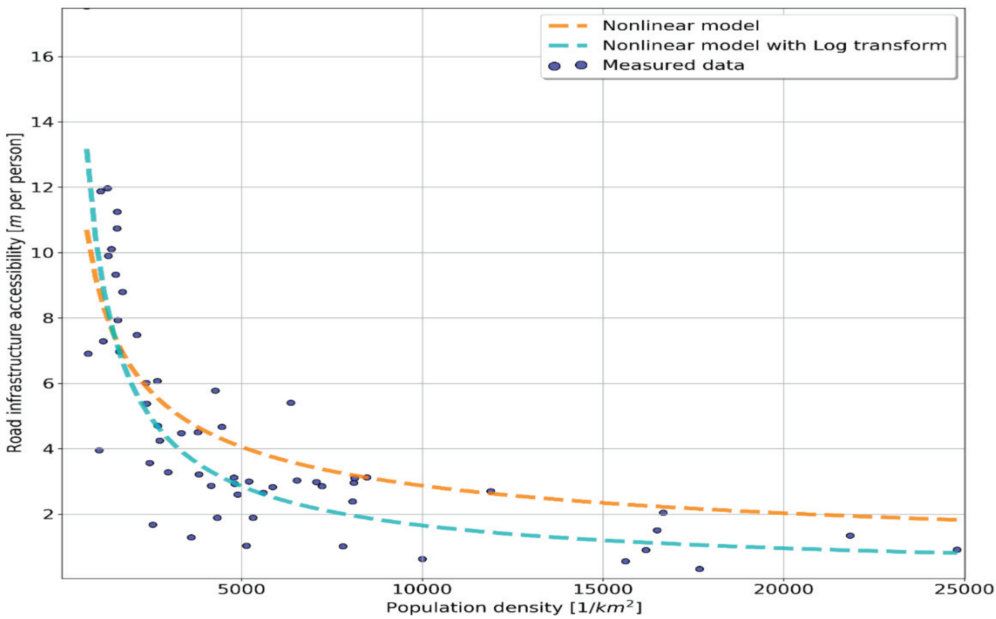

Figure 4.21 Road infrastructure accessibility RIA over population density DPOP. The orange dashed line represents the non-linear function of Eq. (20) with a goodness of fit of R^2=0.64. The light blue dashed line represents the back transformed Log model from Eqs. (21) and (22) with a goodness of fit of R^2=0.69.

It remains to be explained why the transport energy per person shown in Fig. 4.19 is increasing so sharply for a low population density. The previous section shows that the average travel distance DC is slightly sensitive to DPOP. Therefore, it must be the private car mode share MSC that increases in a non-linear fashion as DPOP approaches zero. However, if MSC increases linearly with RIA, as demonstrated in Section 4.5.1, then the relation between DPOP and RIA is necessarily of the non-linear nature. In fact, Fig. 4.21 shows that the RIA of the cities is rapidly decreasing as DPOP is increasing, similarly to the transport energy curve in Fig. 4.19.

The following approximations are an attempt to explain why the road length per person tends to increase so dramatically for cities with a low population density: we assume a city with a squared layout with side length L and a grid-like road network where all streets are W meters apart, as shown in Fig. 4.22, where the number of roads is $M = L/W$ in each coordinate and the total road length is $L_{TOT} = 2ML = 2\,L^2/W$.

Assuming further that the population is evenly spread over the city, then the population density is$DPOP = N/W^2$, and the total population becomes $POP = NM^2 = N(L/W)^2$. As the road infrastructure accessibility is defined by $RIA = L_{TOT}/POP$, RIA is obtained by replacing W with $W = \sqrt{N/DPOP}$:

$$\widehat{RIA}_A = \frac{2}{\sqrt{N}} \frac{1}{\sqrt{DPOP}} = \frac{2}{\sqrt{N}} \frac{1}{DPOP^{0.5}} \tag{20}$$

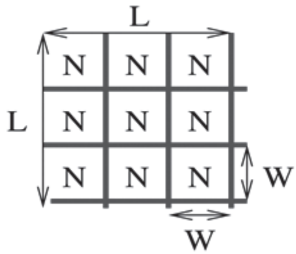

Figure 4.22 A simplified squared city with a street grid of $M = L/W$ roads in x-direction and the same amount of roads in y-direction. In each sub-square of size $W \times W$, there are N residents.

where $2/\sqrt{N}$ can be seen as a constant to be calibrated. Clearly, this equation determines the road length of cities with a varying population density, while limiting the road circuity constant to $\sqrt{2} = 1.41$, which is a typical value for US cities. We note that *RIA* is dropping sharply for the increasing *DPOP*, as expected from the city data. Applying an ordinary linear regression on the city data with DPOP in inhabitants per m^2, the term $2/\sqrt{N}$ is found to be statistically significant and within 0.256 and 0.316 when using the 95% confidence interval. The average value of $2/\sqrt{N} = 0.286$. Despite the simplicity of the grid-road model city, the estimate shows a goodness of fit with $R^2 = 0.64$ even though the residuals are unlikely to be normally distributed as the skew is different from zero (0.856), and the Jarque-Bera p-value is far below 0.05. The linear specification is correct as the p-value of the Harvey Collier test equals 0.92.

It is worth mentioning that the estimate fits well because the calibration is determined by US cities with a large RIA at low population densities and by Asian cities with a low RIA and high population densities. The dominant US cities are the ones best represented by the regular road grid which was assumed in the above model.

The results of Eq. (20) shall be verified by calibrating a non-linear model with a generic exponent β_{R1} of the shape

$$\widehat{RIA}_B = \frac{\beta_{R0}}{DPOP^{\beta_{R1}}} \tag{21}$$

and by comparing β_{R1} with exponent 0.5 in Eq. (20). With a log transformation, this problem can be transformed into a linear estimation problem of the form

$$\log \widehat{RIA}_B = \alpha_{R0} + \alpha_{R1} \log DPOP \tag{22}$$

where $\beta_{R0} = exp(\alpha_{R0})$ and $\alpha\beta_{R1} = -\alpha_{R1}$. The regression results of the log-model in Eq. (22) are shown in Table 4.27. The linear specification is correct as the p-value of the Harvey Collier test equals 0.24. However, the residuals are unlikely to be normally distributed as the skew is different from zero (-0.945), and the Jarque-Bera p-value is well below 0.05.

Table 4.27 Linear regression results for road infrastructure accessibility in Eq. (22).

	coef	std err	T	P>|t|	[95.0% Conf. Int.]	
α_{R0}	-3.1318	0.408	-7.668	0.000	-3.950	-2.313
α_{R1}	-0.7890	0.073	-10.797	0.000	-0.935	-0.643

Apparently, exponent β_{R1}= 0.78 from Eq. (21) is different from the exponent value of 0.5 in Eq. (20), which represents the square root. Also, β_{R0}= 0.44 is different, but in the same order of magnitude as $2/\sqrt{N} = 0.286$ from Eq. (20). The goodness of fit of the model in Eq. (21) with $R^2 = 0.69$ is marginally higher with respect to the model in Eq. (21). These minor differences are not surprising given the simplifying assumptions made during the derivation of Eq. (20). The results of the two models are plotted in Fig. 4.21.

As the derived model in Eq. (20) reasonably explains the *RIA* of cities, Eq. (20) is substituted into the energy estimate of Eq. (19), which leads to a transport energy model as a nonlinear function of the population density. The shape of this transport energy estimate becomes

$$\widehat{W}_{TC} = \beta_{T3,0} + \beta_{T3,1} \frac{1}{\sqrt{DPOP}} \tag{23}$$

with parameters $\beta_{T3,0}$ and $\beta_{T3,1}$ to be calibrated with the transport energy data. The linear regression results in Table 4.28 indicate that both parameters are significant, the value of $\beta_{T3,1}$ is positive, as expected, and the fit is reasonable with $R^2 = 0.65$. The linear specification is correct as the p-value of the Harvey Collier test equals 0.24. The residuals are likely to be normally distributed due to a skew close to zero (-0.128) and a Jarque-Bera p-value of 0.41. This estimate explains the sharp rise of transport energies for low density cities as previously shown in Fig. 4.19.

In order to judge whether the particular non-linear shape of the model in Eq. (23) is a reasonable fit, two other modeling attempts were investigated: first, a linear Box-Cox model of the form

$$\widehat{W}_{TD}(\lambda) = \alpha_{T4,0} + \alpha_{T4,1} DPOP \tag{24}$$

was calibrated with an optimal $\lambda = -0.036$. The parameters from Eq. (24) are shown in Table 4.29. The outcome of the linearity test and the normal distribution test are equivalent to the results of the non-linear model from Eq. (23). After a back-transformation of Eq. (24), the obtained goodness of fit equals $R^2 = 0.37$.

Table 4.28 Linear regression results for transport energy in Eq. (23)

	coef	std err	T	P>|t|	[95.0% Conf. Int.]	
$\beta_{T3,0}$	-2.735e+06	1.12e+06	-2.439	0.018	-4.98e+06	-4.88e+05
$\beta_{T3,1}$	5.983e+08	5.93e+07	10.082	0.000	4.79e+08	7.17e+08

Table 4.29 Box-Cox linear regression results for transport energy in Eq. (24).

	coef	std err	T	P>|t|	[95.0% Conf. Int.]	
$\alpha_{T4,0}$	-2.735e+06	1.12e+06	-2.439	0.018	-4.98e+06	-4.88e+05
$\alpha_{T4,1}$	5.983e+08	5.93e+07	10.082	0.000	4.79e+08	7.17e+08

In a second attempt, a Box Cox transformed model with a non-linearity in $DPOP$ was calibrated, similar to the one in Eq. (23):

$$\widehat{W}_{TD}(\lambda) = \alpha_{T5,0} + \alpha_{T5,1} \frac{1}{\sqrt{DPOP}} \tag{25}$$

With the previously optimized $= -0.036$, the parameters from Eq. (25) are shown in Table 4.30. The outcome of the linearity test and the normal distribution test are again identical to the non-linear model from Eq. (23). After a back-transformation, the goodness of fit showed results in $R^2 = 0.42$.

Table 4.30 Linear regression results for transport energy in Eq. (25)

	coef	std err	T	P>|t|	[95.0% Conf. Int.]	
$\alpha_{T5,0}$	-2.735e+06	1.12e+06	-2.439	0.018	-4.98e+06	-4.88e+05
$\alpha_{T5,1}$	5.983e+08	5.93e+07	10.082	0.000	4.79e+08	7.17e+08

Apparently, the model in Eq. (23) fits best with the measured energy data. All the three models of the transport energy estimation are shown in Fig. 4.19.

4.5.4. Transport-related CO_2 emissions of cities

The final attempt is to shed light on how the analyzed cities' CO_2 emissions levels are varied by different urban indicators, such as the travel modal split, the population density, and the infrastructure accessibility. Considering the available data, the most precise estimate of the CO_2 emissions per person per year for commuting purposes CE (T,i) in city i can be determined by:

$$CE_{T,i} = SWP_i \cdot CO2e_i(DC_i \cdot MSC_i \cdot WCC_i + DPT_i \cdot MSPT_i \cdot WCPT_i) \cdot 261 \quad (27)$$

where SWP_i is the share of the working population in the total population, DC_i is the daily average commuting distance to work by private car, DPT_i is the daily average commuting distance to work by public transport, MSC_i is the mode share of private car trips , $MSPT_i$ is the mode share of trips with public transport, WCC_i is the average energy consumption per person km for a private car, $WCPT_i$ is the average energy consumption per person km for public transport, and $CO2e_i$ is kg CO_2e per MJ.

$$\text{CO2 emissions kg per person } = \text{c} + \text{d RIA} \quad (28)$$

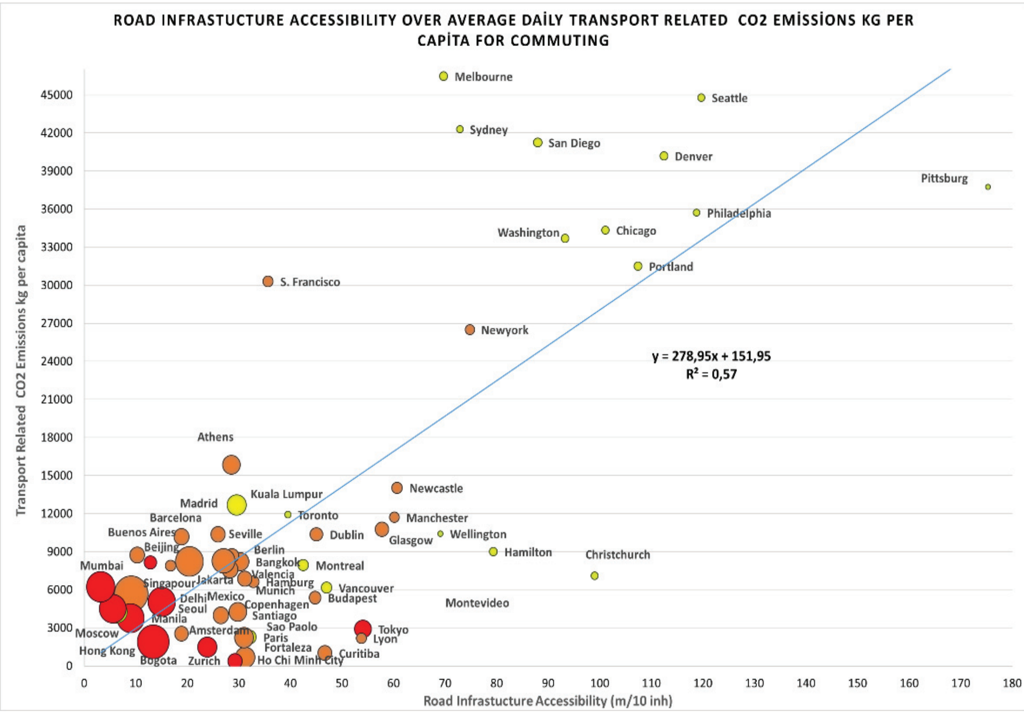

Figure 4.23 CO_2 emissions kg per person per year for commuting purposes, CE, over road infrastructure accessibility, RIA. The bubble size is proportional to the population density; the filled color indicates the share of sustainable modes. The dotted line represents the fitted linear line from Eq. (28).

Figure 4.23 demonstrates CO_2 emissions CE_T, the population density and the mode share versus the road infrastructure accessibility RIA for each city. The bubble colors represent the total percentage of the non-motorized mode share and the public transport mode share in cities. The filled bubble colors indicate, respectively: red=sustainable transport mode usage>70%, orange= 35%<sustainable transport mode usage<70% and yellow=35%<sustainable transport mode usage. The same figure contains the linear shape of CE_T as the linear line showed the best fit with a considerable R^2. A cluster of cities can be seen at low road infrastructure accessibility between 0–20 m/10 inh., where the majority are Asian cities. These low road infrastructure accessibility cities are showing much lower transport-related CO_2 emissions per capita compared to the cities with a higher road infrastructure accessibility. This cluster consists of cities with the highest population density, and these cities are also denoted by the highest sustainable usage of the modes. Another cluster of cities can be seen at medium road infrastructure accessibility between 20–60 m/10 inh., where the majority are European and South American cities. This zone consists of cities with a slightly lower population density and a lower alternative mode usage compared to the previous cluster, therefore, the transport-related CO_2 emissions are higher than average. There is also one more cluster at the high road infrastructure accessibility over 60 m/10 inh., where the majority are US, New Zealand and Australian cities. This zone consists of the cities with very high car usage and very low population density compared to the two previous clusters. The cities in this cluster emit noticeably the highest amounts of CO_2 gases with respect to the previous clusters. Holistically, Figure 4.23 indicates that an increase in the road infrastructure accessibility catalyzes the urban sprawl and boosts the car usage – in turn, the transport-related CO_2 emissions peaked in this segment.

4.6. Evaluation of the results

As stated in the EC mobility targets [14], focusing on people first rather than on the technical aspects was taken into account. Therefore, our analysis deeply investigated the mode choice under different socio-technical conditions so that to understand how to provide a shift towards cleaner and more sustainable transport modes. The modal shift is a very important piece of the chain since a prominent increase of the public transit and cycling significantly reduces the transport related energy consumption and traffic congestion, and, in turn, the air pollution level, emissions and the transport-costs would be lightened. When focusing on the technical part, our analysis deeply investigated two major technical factors: the infrastructure and the land use in order to understand how to create an accessible system providing social equity and how to minimize the socio-economic and environmental impact of urban mobility. The internal relationship between these two major factors and their relation with the other factors is investigated by questioning how these associations influence the modal shift, the congestion level and the transport-related energy consumption. The following paragraphs evaluate the findings based on the above mentioned investigations.

The limited literature availability focusing on the analysis of the culture effect on the travel behavior brings along a gap. In the past, to the best of the author's knowledge, no macroscopic analysis on the relationship between national culture and urban travel patterns has been conducted. In the present thesis, 87 cities distributed over 41 countries were analyzed in Section 4.1. The relationship between culture dimensions and urban travel patterns was investigated. Also, the relationship between culture and some demographic indicators (the population density and the GDP per capita) closely associated with the travel choices was demonstrated. Additionally, the relations between the urban travel mode choices (driving versus public transport) and some transport-associated indicators were shown as well.

Some countries showed very high individualism and very low driving, specifically, the Netherlands, Denmark and Hungary. The Netherlands and Denmark have already been focusing on biking for urban transportation for a long time. Cycling can be called an environmentally friendly individual travel mode. This may suggest that urban planners and policy makers should consider adaptation of the biking infrastructure so that to reduce car-dependent transportation in the countries with high individualism. Culture may potentially explain why public transportation is unsuccessful on patronage in places with high individualism. However, the study did not cover quantitatively the role of cycling and the bicycle infrastructure as the bike share was not available for most cities, which impedes drawing a certain conclusion. Hungary has one of the highest uncertainty levels among all the countries with high usage of public transport. Uncertainty is denoted by the second highest influence on the public transport usage after collectivism. This result suggests that investments in public transportation can be a good option for the places with high collectivism and high uncertainty so that to prevent car-dependent mobility.

One limitation of the presented models is certainly the use of culture at a country level. Describing culture at a country level is the only choice for now, while there is no culture scale for cities. Errors may occur due to possible issues related to group effects where several cities from the same country are included, thus this situation impedes more refined analysis. Also, errors may happen should a representative selection of the population be diverse in terms of the nation as some cities are denoted by a multinational community. Compatibility problems related to data stemming from different years and mixing data from several open sources are other relevant limitations.

Considering the many error sources and limitations listed above, good correlation values have been obtained between Hofstede's fundamental culture dimensions: IND/COL and the travel patterns were demonstrated with a reasonable goodness of fit. The analysis showed that the countries with a higher individualism score built a more individualistic transport-related environment, which, in turn, results in more driving. On the other hand, collective nations tend to use more public transportation. It is also noticeable that uncertainty and masculinity culture dimensions have a considerable effect on the public transportation usage. There is significant evidence that, in case of nations, there is an increase in three culture dimensions: collectivism, uncertainty and masculinity results in the greater usage of public transport. However, the highest influence on the public transportation usage is made by the IND/COL dimension. Lastly, Section 4.1 demonstrated that culture could be a key tool in urban transportation planning. If we can predict which alternative transport systems could be adopted in a city at peace, we can achieve sustainability in urban transportation.

The influence of the higher education level on the urban travel mode choices was examined with a large and diverse open data collection for 45 urban areas from 30 countries in Section 4.2. Also, a higher education level is controlled with the population density and income level which exert significant influence on travel behaviors. The main result demonstrated that an increase in the education level has the highest effect on dropping the drive mode share in cities, while an increase in the population density reduces the drive mode share more than an increase in GDP per capita boosts it. The result of this study clearly identified that the higher education level considerably affects the travel mode choices in cities. Presumably, one hypothesis could be that higher educated societies buy fewer cars, drive less, and use alternative mobility systems more due to environmental and health concerns. In summary, Section 4.2 demonstrated that educating citizens is an important path to the reduction of car dependence.

In the past, the limited availability of comparable data on socio-economics, transport infrastructure and transport performance of cities prevented holistic analysis with many indicators due to the lack of variety. These limitations were hereby overcome by analyzing the OSM data, the *TomTom* data, and the data from centralized internet databases in Section 4.3. To date, to the best of the author's knowledge, no systematic worldwide infrastructure analysis based on the OSM data has been performed. By using *Python* package *OSMnx*, it was possible to extract different network-types from the OSM data as downloaded from different urban areas of the world. The 151 analyzed cities are distributed over 51 countries in Section 4.3. The cities were analyzed as a whole and within subgroups of cities with distinct population sizes (small cities, mature cities and metropolises). The relationships between the socio-economic indicators, infrastructure accessibility and congestion level were investigated.

Good correlation values between the infrastructure accessibility, socio-economic indicators, and congestion levels were demonstrated with a reasonable goodness of fit. The clearly positive correlation between the spatial city area and the population growth rate for metropolises, mature cities and all the cities is trivial as the number of newborns is proportional to the population size. It is of interest to note the negative relationship between the population density and the GDP per capita suggesting that economically weaker cities experience more congestions – this is particularly true for metropolises. Also, the fact that congestion levels (ADETT) increase with a higher population density is not surprising, and it confirms that cities are struggling to keep the transport infrastructure in pace with the increasing traffic intensity (trips per sq. km). However, a highly positive correlation between the population density and the public transport, cycling, and walking mode shares was shown in Sections 4.1 and 4.2 suggesting that the denser cities are more successful in terms of the reduction of automobile dependence. The analyses further showed that cities with higher GDP built more infrastructure, which, in turn, results in lower congestion levels. The relation between the infrastructure accessibility and the congestion levels was quantified by using regression models. For cities with a low population density (below approximately 1500 inhabitants per sq. km), more roads per inhabitant lead to lower congestion levels. Metropolises and mature cities with a high population density have in general lower congestion levels where the rail infrastructure per person is higher. There is significant evidence that, in the case of high density cities, an increase in the train infrastructure accessibility is more decongestionating than an increase in the road infrastructure accessibility. Also, any rise in the cycle infrastructure per person alleviates the congestion significantly in 42 worldwide small cities below 800,000 inhabitants.

In the past, only limited holistic analysis was attempted to investigate the influence of the urban network topology on the transportation performance mainly due to lack of diversity in the data from alternative network types. We analyzed the influence of the topological indicators with multi-network layers on the network performance in Section 4.4. The 86 analyzed cities show sufficient diversity as they are distributed over 32 countries.

The relationships between network topology indicators and congestion levels were investigated. Good correlation values between topological variants and congestion levels were demonstrated. Multiple linear regression models were attempted with the entire set of cities as well as for specific subsets (cities with mature railways – 53 cities and cities with mature cycleways – 28 cities). Calibrated regression models were proposed thus quantifying the relation between the transport infrastructure, topology and performance indicators.

Some useful relationships between congestion and network indicators were identified. Open source data-related errors and data limitations were outlined and clarified. Some pre-assumptions were made as a result of the findings. The core message of the study is to demonstrate the influence of the network-design related factors on the road traffic performance. In the light of the findings, it is evident that short distance connectivity of the road network is important for reducing the traffic congestion. Another hypothesis is that distance-based connectivity of alternative networks *does* influence the travel mode choices, which, in turn, changes the road traffic volume. One particular question was addressed with regard to urban planning: what is more effective in terms of congestion alleviation in the light of sustainability to build well-connected road networks with low circuity or to build well-connected alternative networks with low circuity? Public transit networks are more circuitous than roads, which is one of the reasons behind the preference of auto usage over public transit [168]. The increase in the average circuity of public transit networks can drop the transit ridership and thus cause a mode shift towards road mobility. As alternative network systems become mature, road-based infrastructure indicators and DBC indicators have a lower impact on congestion. Presumably, it is due to the fact that in cities with a mature public transit or bike network, fewer people use cars, which lessens the importance of the road infrastructure. These useful findings suggest that the short distance connectivity of alternative network systems, such as railways and cycleways, may attract more car-drivers towards alternative modes. With the available average daily travel distance data for each mode, the study could be further exploited to determine the relationship between the DBC indicators and the travel distance.

Quality open source data from centralized databases allowed more consistent and complete analysis of transport networks from many cities around the world in Section 4.5. Up-to-date information on the urban area, population, average commuting distances for private and public transport, specific energy consumption and modal splits was obtained from various databases. Still, it was challenging to obtain homogeneous data from a sufficient number of cities. City boundaries, sampling dates, and calculation methods of certain quantities were not homogeneous. Instead of eliminating a large quantity of cities due to insufficient data, it was decided to estimate the missing data from alternative sources even though this may have distorted the obtained results. It was specified which data was estimated by with which method and for which particular city. The attributed extensive information on the transport infrastructure provided by *OpenStreetMap* (OSM) was used to extract the road length, rail length and bikeway length of the city's transport networks by means of the open source software *OSMNx*. From the collected city data, the transport related energy was calculated, which is an important sustainability benchmark of the city transport system. The transport energy consumption essentially depends on two quantities: the modal split and the the average commute distances.

The main focus of the analysis was to establish a quantitative and statistically significant relation between the population density, the transport infrastructure and the transport energy consumption. A particularity previously highlighted by Newman and Kenworthy [61] was investigated: the cities with a low population density from the USA, Canada and Australia are denoted by extraordinarily high transport energy consumption (2–4 times higher than the medium density European or Asian cities). The result of the present study clearly identified the high private car mode share as the main cause of the high transport energy usage of such cities, while the longer average commuting distance in the low population density cities exerts more modest influence on their transport energy consumption.

Two quantities were investigated which can significantly influence the transport energy of cities, see Eqs. (14, 15): the modal split and the average commuting distance. From the present city dataset, there is statistical evidence that private commuting travel distance is linearly decreasing with the population density, see Eq. (17). The model shows a ratio of approximately 50% between the commuting distance of cities with the highest and lowest population densities. However, the errors of this distance model are fairly large.

With regard to the modal shares, a significant linear relationship was found between the road infrastructure accessibility (RIA) and the car mode share (MSC), see Eq. (15). In this case, the ratio between the MSCs of cities with the lowest and the highest RIA is approximately 400%. This result means that RIA exerts a much stronger influence on the mode share than the population density has on the commuting distance. The public transport infrastructure can only be represented by the rail length extracted from the OSM data for each city. This information proves to be insufficient to establish a relation between the public transport infrastructure and the public transport mode share MSPT as rail constitutes only a part of all public transport trips. Instead, it was possible to demonstrate that MSPT is decreasing linearly with RIA. The linear relations between RIA, MSC and MSPT were only demonstrated empirically, and a model to explain this relation quantitatively was not found in literature. Nevertheless, as RIA *does* determine significantly both shares, i.e., MSC and MSPT, the transport energy was estimated with a linear regression that depends only on RIA, see Eq. (19). The failure of the attempts to include the rail infrastructure accessibility (TIA) or the bike infrastructure accessibility (BIA) in the transport energy estimation was probably due to the fact that either the OSM data is insufficiently precise or incomplete in order to explain the public transport or active mode share, respectively. However, including the rail and bike infrastructure accessibility reduces the errors in the model. Further tests revealed that TIA actually increases proportionally with the rail mode share (for 17 cities, $R^2 = 0.54$), and that BIA is proportional to the bike mode share (for 32 cities, $R^2 = 0.27$). These findings support the relationship between the usage and alternative infrastructures expansion presumably by shifting car trips to alternative modes, as demonstrated in [8, 90, 92] for rail and in [132, 133] for cycling. Better fits can be obtained when concentrating on a particular area: for example, the relation between BIA and the bike mode share has a better fit when using only European cities with respect to cities from all the countries available in the database. Still, the active mode share includes walk-trips and walk infrastructure; however, it is difficult to assess the values with the OSM data as footpaths are generally insufficiently modeled in OSM.

In Section 4.5.2, a non-linear function between the population density and RIA was derived based on simplifying the road-grid model, see Eq. (20). This calibrated model fits well with the empirical population density and the RIA data and shows a marked rise of RIA as the population density approaches zero. This model was verified by calibrating a more generic model whose parameters relaxed to the values similar to the derived model of Eq. (20). When combining the function in Eq. (20) to compute RIA from the population density with the linear relation from Eq. (19) which estimates the transport energy, it was possible to calibrate a statistically significant model that estimates the transport energy as a function of the population density, see Eq. (23). This model can explain the marked rise in the transport energy for cities with a low population density, as already established by Newman [65]. Nevertheless, there are some cities which do not fit well with the estimated energy curve: Hamilton, New Zealand, has a high car mode share (94%), but a relatively low energy use for its low population density. The reason is

Hamilton's relatively low average commuting distance. Also, Ho Chi Minh City has short commuting distances and therefore relatively low transport energy consumption. Wellington has low energy consumption for its population density, but, as the metropolitan area was used, the population density might be underestimated as most of the population lives in Wellington City. The Spanish cities Madrid, Seville and Barcelona demonstrate relatively high transport energy consumption despite a low car mode share due to an exceptionally high commuting distance.

Attempts to include the average commuting distance as a linear function of the population density resulted in a slightly improved fit of the transport energy, but the parameters became statistically insignificant and are not suited to explain the phenomenon.

Also, transport-related CO_2 emissions of urban areas were assessed to stress the environmental impacts. A linear model for transport-related CO_2 emissions of urban areas was presented. The linear model demonstrates that CO_2 emissions increase with an increasing RIA where an increase in RIA catalyzes the urban sprawl and boosts the car usage; in turn, the transport-related CO_2 emissions peak.

Cities with a low population density must provide a disproportionately high road length per inhabitant in order to cover the area and to limit longer detours with respect to the line of sight. This may suggest that line-oriented public transport cannot match the connectivity of the road network in low population density cities. In order to reduce the energy consumption in low density cities, either the energy efficiency of cars must increase, for example, by battery electric vehicles, or new forms of demand-responsive public transport systems need to become competitive in low density settlement areas.

One limitation of the presented models is surely the sole use of the population density and road infrastructure length to explain the transport energy consumption in cities. Such a simplification may hide the fact that transport energy consumption in cities with the identical population density can vary considerably. Some examples were discussed where cities with a low population density have a low energy density due to short commuting distances. Another limitation is the use of non-homogeneous data, particularly, the city boundaries are critical. The different criteria how city boundaries are drawn introduce large errors into the population density thus impeding more refined analysis.

Cities with medium to high population densities feature either a substantial public transport mode share, or a high active mode share, or both. This fact leads on average to lower energy consumption with respect to the cities with a low population density. The study did not cover quantitatively the role of cycling and the bicycle infrastructure as the bike share was not available for most cities. However, almost all cities with the lowest transport energy consumption have a high share of the active modes including cycling.

A systematic literature review and worldwide multivariate analysis of transport indicators was conducted above. The obtained results were evaluated and presented as a summary of the results of worldwide analysis and comprehensive literature review: interrelations among the socio-technical factors, their influence on the users and transport performance were presented in scheme Fig. 4.24 with a holistic and integrated view. In multi-dimensional analysis, a series of indicators and the interaction among them are identified through by using logic architectures [10]. The arrows in the developed scheme demonstrate how an increase in any socio-technical factor has influence on the following indicators with plus and minus signs. The first step of sustainable transport planning should be 'focusing on user profiles' in order to identify how to enhance the modal shift towards sustainable modes for any investigated city. The scheme is user-centered where transport user profiles are presented in the rectangle at the center of the scheme, such as private vehicle, public transport, and non-motorized. The main transport-performance indicators, such as the congestion level and the transport energy consumption, are presented on top of the scheme with their connection to the GHGs emission level, air pollution and transport costs. The outgoing arrows from the user preferences indicate that cities with well-established public transit or/and cycling infrastructure succeed in achieving lower transport-related costs, air pollution and emission levels; meanwhile, car-dependent cities are facing high socio-economic and environmental costs. The socio-composition in a city is vital when planning how to enhance the modal shift towards more sustainable modes. The left square in the scheme demonstrates the social factors in which the outgoing arrows show the influence of these factors on user mode preferences and technical factors in turn highlighting how these relations <u>indirectly</u> affect the transport related costs, air pollution and CO_2 emissions. The scheme demonstrates that the social variation in the urban areas shapes the travel mode choices along the factors such as 'culture', creates a general user profile, 'nature of demography' enforces transport users to undergo a modal shift, 'education level' changes the travel mode choices, and 'income level' can manipulate the travel mode choices. The right square in the scheme demonstrates technical factors. The outgoing arrows show that the technical factors induce the travel mode choices towards the factors such as: land use conditions, infrastructure accessibility, infrastructure design and innovations that <u>directly</u> affect the transport related costs, the air pollution and the GHGs level. Technology and policies act as system optimization tools. The arrows show that any change of infrastructure catalyzes the land area growth; therefore, these factors should be considered together in urban transport planning. The arrow associations demonstrate that cities getting sprawled and having low alternative network accessibility result in very high car usage, which in turn causes significant socio-economic and environmental costs.

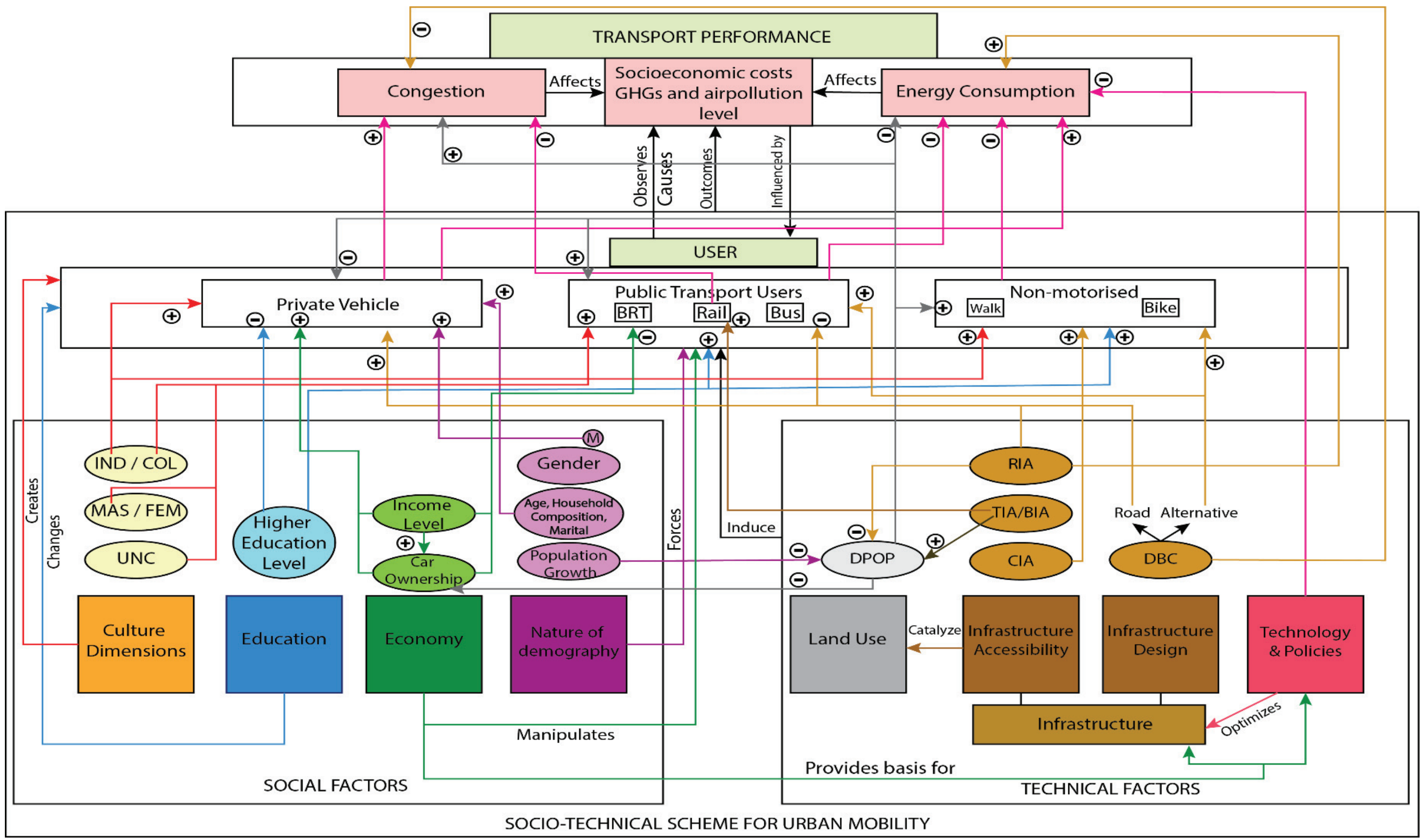

Figure 4.24 Socio-technical scheme for urban mobility

5. Conclusions

1. The present thesis demonstrated how to minimize the *socio-economic (inequity and travel costs) and environmental (transport-related energy consumption, CO_2 emissions and air pollution)* impacts of urban transportation. Examination of similarities and differences within worldwide cities and understanding how these cities are shaped by socio-technical factors demonstrated which mobility strategies could be sustainable under which socio-technical conditions.

2. User preference is vital since the travel mode shift towards public transit and non-motorized modes is one of the key paths to minimize *socio-economic and environmental impacts*. Understanding which alternative travel mode can be sustainable under specific socio-technical conditions and how to attract travel users towards the sustainable modes is the first step of sustainable transportation planning. The conclusions related to the first step of sustainable transportation are outlined as follows:

* The results showed that culture can be a key tool in urban transportation planning. Countries with higher individualism built a more individualistic transport-related environment which, in turn, results in more driving. On the other hand, collective nations tend to use public transportation more. Also, some countries with high individualism show a tendency to adapt to biking. Notable examples are the Netherlands and Denmark, where driving and public transport mode shares are low compared to other countries, but the individualism indexes are high with *the values of 82 and 74*, respectively.
* Additionally, Hungary is denoted by high individualism indices with *the value of 80* and at the same time Hungary demonstrates a high public transport mode share with the value of *45%*. It was noted that the uncertainty dimension is highly correlated with the public transport usage, and that Hungary has one of the highest uncertainty indices with *the value of 82* among all countries.
* There is significant evidence that the presented multiple regression model *Eq. (5) (R^2= 0.55)* demonstrated, in case of nations, an increase in three cultural dimensions: collectivism, uncertainty and masculinity results in a greater usage of the public transport. Prediction of alternative transport systems which could be adopted in a city at peace is important in order to bring down car dependence in a more sustainable manner.
* The results demonstrated that educating citizens is an important path towards reducing car dependence through creating awareness with the current issues. The linear function model *Eq. (6) (R^2= 0.62)* demonstrated that an increase in the education level has the highest influence on dropping the driving habits in cities comparing to the land use and income level factors. The influence of the education level on dropping the car usage level is approximately *2 times* higher than an increase in GDP per capita in terms of boosting the extent of driving.

* The obtained results demonstrated a negative correlation between the public transportation usage and GDP per capita while cities with a higher GDP per capita tend to drive more to a considerable extent. However, there is no considerable correlation between the income level and the non-motorized modes, especially for cycling. The implementation of a biking infrastructure would offer a sustainable service for the places with high income.

* A significant linear relation (*R^2= 0.58)* was found between the road infrastructure accessibility (RIA) and the private car mode share: the car mode share increases with an increasing RIA, which is reasonable for entire cities. Further tests revealed that TIA actually increases proportionally with the rail mode share *(for 17 cities, R^2= 0.54)*, and CIA is proportional to the biking mode share *(for 32 cities, R^2=0.27)*. An increase in any network accessibility results in an increase of its usage, while an increase in the population density results in higher public transport and active modes usage. Also, the results showed that well-connected alternative networks with short direct routes can trigger a mode shift from car to rail or bike, thus the resulting shift may lighten the road traffic volumes.

3. Understanding under which technical conditions an urban transport system can minimize its *socio-economic costs and environmental impacts* is the second step of sustainable transportation planning. Two key factors – land use and transport infrastructure and their interrelation – were demonstrated with details so that to explain the transport-related energy consumption, the CO_2 emission and the congestion level in the cities. Additionally, the effect of the infrastructure design on the congestion level was shown. The conclusions related to the second step of sustainable transportation are outlined as follows:

* The results showed that, in particular for the cities with a low population density *(below approximately 1500 inh. per sq. km)*, more road accessibility (roads per inhabitant) leads to lower congestion levels; cities with a high population density *(above approximately 1500 inh. per sq. km)* have, in general, lower congestion levels if the rail infrastructure per person ratio is high. Furthermore, these cities, by increasing the railway accessibility (railways per inhabitant), become more effective in reducing congestions than by increasing the road length per person (*approximately 4 times more*). Also, small cities increasing cycleways per person alleviate congestion considerably.

* The role of the network design was assessed in terms of the congestion performance with the controlling infrastructure accessibility and network density. The results demonstrated that an increase in the average short distance connectivity of road networks (average closeness centrality and RCRC) eases down road congestion, most likely because the road traffic is distributed more homogeneously over a network with fewer low permeability choke points.

* Furthermore, an increase in the average short distance connectivity of alternative network systems (the average weighted rail clustering coefficient, the average cycle closeness centrality) alleviates road congestion. In particular, for cities with a mature cycleway network *(cycleway density greater than 0.4 km per km^2)*, an

increase in cycleway closeness centrality decreases congestion with nearly the same effectiveness as an increase in the road infrastructure accessibility.

* A simplified phenomenological model was developed in order to explain the non-linear relation between the population density and RIA. RIA is dropping with one over *the square root* of the population density. Indeed, RIA acts as a catalyser for urban land. Based on the relationship between the population density and the infrastructure accessibility with their influence on the modal split and the average travel distances, a hyperbolic function *($R^2 = 0.65$)* between the population density and the transport energy was calibrated, which explains the rapid increase of the transport energy consumption of cities with low population densities.

* Transport-related CO_2 emissions of urban areas were calculated to assess environmental impacts. A linear model *($R^2 = 0.57$)* for transport-related CO_2 emissions of urban areas was calibrated where CO_2 emissions increase with an increasing RIA. The cities clustered in the highest RIA zone produce, on average, *4–5 times more* transport-related CO_2 emissions comparing to the other city clusters.

* The graph analysis also showed that an increasing RIA catalyzes the urban sprawl and boosts the car usage simultaneously; in turn, transport-related CO_2 emissions peak. This association is the main factor affecting the transport-related CO_2 emission levels in cities. As an example, Hong Kong is in the cluster of cities that have the lowest RIA, meanwhile, they also have the highest sustainable modes usage and the highest population density. The city emits around *4,500 kg per capita* of transport-related CO_2 emissions per year compared to Philadelphia City, which is in the cluster of cities that are singled out by the highest RIA, the highest car usage and the lowest urban density and emits around *40,200 kg per capita*, which is approximately *9 times more*.

Recommendations

1. **Social point of view:** When focusing on people, a transportation system must serve diverse demands. Looking through cities' demographical composition and culture values, we can detect the socio-economic condition(s) of cities and the social acceptance levels of alternative systems. The socio-economically disadvantaged people are the major part of the societies where geological and climate conditions are varied, while increasing the accessibility by alternative modes of transport promotes social equity. This means that the system should be multi-modal. To plan multi-modal systems, we should focus firstly on the people rather than on the transport systems so that to optimize the anatomy of trips and to minimize the travel costs and environmental impacts. Cities based on well-planned and suitable alternative mobility systems will result in travel mode shifts from car users, which, in turn, alleviates road congestion, travel costs and environmental impacts. The social influence will be higher in the cities where multi-transport services are fully integrated, and the travel time is minimized. The high social acceptability of rail-transit systems comes up with the faster mode shift from private vehicle users than other alternative systems may do, especially for dense cities. The user preference of the public transit and non-motorized systems increases with the concentration of

activities in the proximity. The densification of urban areas increases the functionality of the alternative systems. To further encourage the modal shift from car use, alternative networks should be designed with highly connected paths and less circuity so that to provide high-speed accessibility to the final destination and allow a reduction of the traffic volume.

2. **Technical point of view**: Especially for mature cities and metropolitan areas, high car usage in turn increases the traffic congestion and reduces the functionality of the conventional bus systems. The current situation suggests that building alternative mobility systems based on separated tracks is vital since rail transit and bus rapid transit systems provide high-speed accessibility. The use of different modes in combination can vary depending on the city size and geographical conditions; however, in order to provide optimal mobility, the system should offer high public transit accessibility or/and high cycling infrastructure accessibility, and, on top of that, the system should have high integration within its networks. Mature cities and metropolitan areas with high level rail infrastructure accessibility achieve high public transport ridership, lower car ownership, less traffic congestion, and lower environmental impacts. Also, cities with high level BRT infrastructure accessibility succeed in achieving high public transport ridership and significant travel time savings with the advantages of lower infrastructure costs comparing to railways. There is less pressure to change from private cars to public transit for small cities since they are less congested. Therefore, the adoption of the cycling infrastructure for small cities should be considered as the first option if the geographic and climate conditions are suitable. Provided a city is small, this situation allows an opportunity to grow its urban transportation within proximity areas based on the cycling mode. Small cities with high cycleway infrastructure accessibility achieve very low congestion levels and a high cycling share. Cycling is the most energy efficient mode; therefore, an increase in cycling usage considerably reduces the socio-economic and environmental impacts. The densification of urban areas increases the energy efficiency of urban transit systems. ***Mitigating land segregation towards increasing sustainable infrastructures accessibility*** is suggested critically since this is an important path towards reducing transport-related energy consumption; in turn, that will alleviate the CO_2 emissions and the travel costs considerably. There were significant shifts towards e-mobility in the leading countries over the recent years. The electrification of mobility systems appears to be the best choice in terms of energy efficiency and environmental impacts compared to other currently available technologies. Urban mobility systems should be supported with intelligent transportation systems so that to enable effective use of the travel information and vehicle use and to improve the network management. Integration of ICT systems increases the functionality of multimodality. Improved real-time monitoring systems, optimized timetables, integrated ticketing systems and reliable planning applications provide network usage optimization. Shared mobility schemes as well as limitations, pricing and proximity regulations significantly help to alleviate congestion while increasing the effectiveness of a public transit system.

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List of Scientific Publications on the Topic of the Dissertation

-Publications in journals included in Web of Science database with impact factor:

- **Transport indicator analysis and comparison of 151 urban areas, based on open source data**

European Transport Research Review, Open Access Journal
Ali Enes Dingil*, Joerg Schweizer, Federico Rupi and Zaneta Stasiskiene
https://doi.org/10.1186/s12544-018-0334-4
Published: 13 December, 2018

- **Updated models of passenger transport related energy consumption of urban areas**

Sustainability, Open Access Journal
Ali Enes Dingil*, Joerg Schweizer, Federico Rupi and Zaneta Stasiskiene
https://doi.org/10.3390/su11154060
Published: 27 July, 2018

-Publications referred in Scopus and other International databases:

- **The Role of Culture on Urban Travel Patterns: Quantitative Analyses of Urban Areas based on Hofstede's Culture Dimensions**

Social Sciences, Open Access Journal
Ali Enes Dingil*, Federico Rupi, Joerg Schweizer, Zaneta Stasiskiene, Kasra Aalipour
https://doi.org/10.3390/socsci8080227
Published: 29 July, 2018

- **A Macroscopic Analysis of Transport Networks: The Influence of Network Design on Urban Transportation Performance**

International Journal of Transport Development and Integration, Open Access Journal
Ali Enes Dingil*, Joerg Schweizer, Federico Rupi and Zaneta Stasiskiene
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- **Road network extraction with OSMNx and SUMOPy**

Published: June 25, 2018
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Mathematical Glossary

Pearson correlation	A number between -1 and 1 that demonstrates bivariate linear association between two variables *X* and *Y* for numerical variables.
Regression	An important tool for modeling and analyzing datasets. There are many types of regression. Shortly, it is used to predict the behavior of a dependent variable based on the behavior of independent variables.
Linear function	Linear functions are those whose graph is a straight line. $f(x) = a + bx$.
Non-linear function	The variables containing at least one equation that is not linear which contain a slope that varies between points.
Exponential function	A function whose value is a constant raised to the power of the argument where the constant is *e*. $f(x) = e^x$
Logarithmic function	An inverse of exponential function. y=logbx
Hyperbolic function	A function of an angle demonstrates a relationship between the distances from a point on a hyperbola to the origin and to the coordinate axes.
The P-P Plot of Normality Test	The cumulative probability plots of residuals are used to judge whether the distribution of variables is consistent.
Box-cox transformation	A method to transform non-normal dependent variables into a normal shape.
Harvey Collier Test	A statistical test for linearity intended to test whether recursive residuals have mean 0.
Jarque–Bera test	A goodness-of-fit test checking whether the dataset is normally distributed.
Breusch-Pagan Lagrange Multiplier test	This method is used to test for heteroscedasticity in a linear regression model.

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