Aggregate four-step & disaggregate agent-based modelling approaches, but what is in between?: Development of an intermediate Modelling approach

Doctoral Dissertation

Technische Universität München

Santhanakrishnan Narayanan

TUM School of Engineering and Design
Technische Universität München

Aggregate four-step and disaggregate agent-based modelling approaches, but what is in between?: Development of an intermediate modelling approach

Santhanakrishnan Narayanan

Vollständiger Abdruck der von der TUM School of Engineering and Design der Technischen Universität München zur Erlangung des akademischen Grades eines

Doktors der Ingenieurwissenschaften (Dr.-Ing.)

genehmigten Dissertation.

Vorsitz:
Prof. Dr.-Ing. Rolf Moeckel

Prüfer*innen der Dissertation:
1. Prof. Dr. Constantinos Antoniou
2. Prof. Dr. Haris Koutsopoulos, Northeastern University
3. Prof. Dr. Steven Travis Waller, Technische Universität Dresden

Die Dissertation wurde am 27.09.2022 bei der Technischen Universität München eingereicht und durch die TUM School of Engineering and Design am 24.01.2023 angenommen.

Abstract

Shared mobility services are slowly penetrating cities. Given that many cities, especially small- and medium-sized ones, continue to use the traditional four-step modelling approach and such an approach does not have the necessary capacity to model these services, there is a need to extend them. Therefore, this dissertation proposes an extended modular framework, called intermediate modelling approach, by the addition of modules for synthetic population generation and fleet management. Furthermore, modules are suggested for estimation of emissions, car-ownership and induced demand, as such measures are increasingly expected by cities. The framework is software agnostic, as the models used for the additional modules in this dissertation can be replaced with alternative equivalent models, provided the inputs and outputs are consistent.

The intermediate modelling approach accommodates a bilevel procedure for mode choice calculation, to allow cities to use their existing mode choice model. At the upper level, a disaggregate mode choice model allows the estimation of the modal split between conventional modes-as-a-whole, bike-sharing, car-sharing and ride-hailing. To the best of my knowledge, no existing study focuses on such a joint mode choice model, and therefore, a multinomial logit model is estimated. This model shows that the probability of choosing bike-sharing decreases with the increase in household cars. Since a specific emphasis on the mode shift of private car users towards a bike-sharing service is missing in the literature, this dissertation also focuses on the identification of factors influencing such a shift. On a different note, the aforementioned multinomial logit model can be utilised when the modal split for a service is substantial. However, an alternative framework is required when a service is operated at a small-scale, especially at earlier stages. Consequently, this dissertation addresses the methodological challenge of modelling such a car-sharing service, by developing a multi-method demand framework.

The intermediate modelling approach includes a step for the calculation of household car-ownership. To the best of my knowledge, a comprehensive analysis on car-ownership, especially dealing with emerging mobility solutions, is still missing in the pertinent literature. Therefore, this dissertation strives to estimate pertinent (city specific and generic) multinomial logit models. One of the estimated models shows that the probability of owning a car reduces with the ownership of a cargo bike. Therefore, this dissertation also explores the car substitution potential of cargo cycles, by estimating models for the actual purchase decision and the intention to purchase cargo cycles.

While the development of frameworks and models are interesting contributions to the literature, their worthiness cannot be fully realised, unless they are exploited. Therefore, this dissertation aims to adapt the intermediate approach and utilise the mode choice model, the multi-method demand framework and the car-ownership model for a case study on the city of Regensburg. To conclude, the methodological concepts from this dissertation, the results obtained and the (behavioural, policy, operational and modelling) insights derived can help cities to integrate shared mobility services and design Mobility-as-a-Service (MaaS) platforms, devise policies to shape their mobility plans and promote sustainable urban mobility.

Zusammenfassung

Gemeinsame Mobilitätsdienste dringen langsam in die Städte ein. Da viele Städte, vor allem kleine und mittelgroße, weiterhin den traditionellen vierstufigen Modellierungsansatz verwenden und ein solcher Ansatz nicht die nötige Kapazität für die Modellierung dieser Dienste hat, besteht die Notwendigkeit, sie zu erweitern. Daher wird in dieser Dissertation ein erweiterter modularer Rahmen, ein so genannter intermediärer Modellierungsansatz, vorgeschlagen, der um Module für die synthetische Bevölkerungsentwicklung und das Flottenmanagement ergänzt wird. Darüber hinaus werden Module für die Schätzung von Emissionen, Autobesitz und induzierter Nachfrage vorgeschlagen, da solche Maßnahmen von den Städten zunehmend erwartet werden. Der Rahmen ist softwareunabhängig, da die in dieser Dissertation für die zusätzlichen Module verwendeten Modelle durch alternative, gleichwertige Modelle ersetzt werden können, sofern die Eingaben und Ausgaben konsistent sind.

Der intermediäre Modellierungsansatz sieht ein zweistufiges Verfahren zur Berechnung der Verkehrsmittelwahl vor, so dass die Städte ihr bestehendes Verkehrsmodell verwenden können. Auf der oberen Ebene ermöglicht ein disaggregiertes Verkehrsmittelwahlmodell die Schätzung des Modal Split zwischen den konventionellen Verkehrsträgern als Ganzes, Bike-Sharing, Car-Sharing und Ride-Hailing. Soweit mir bekannt ist, gibt es keine Studie, die sich mit einem solchen gemeinsamen Verkehrsmittelwahlmodell befasst, und daher wird ein multinomiales Logit-Modell geschätzt. Dieses Modell zeigt, dass die Wahrscheinlichkeit, sich für Bike-Sharing zu entscheiden, mit der Zunahme des Pkw-Bestands im Haushalt abnimmt. Da in der Literatur ein spezifischer Schwerpunkt auf der Verkehrsmittelwahl von Pkw-Nutzern hin zu einem Bike-Sharing-Angebot fehlt, konzentriert sich diese Dissertation auch auf die Identifizierung von Faktoren, die eine solche Verlagerung beeinflussen. Andererseits kann das oben erwähnte multinomiale Logit-Modell verwendet werden, wenn der Modalsplit für einen Dienst erheblich ist. Ein alternativer Rahmen ist jedoch erforderlich, wenn ein Dienst in kleinem Umfang betrieben wird, insbesondere in früheren Phasen. Diese Dissertation befasst sich daher mit der methodischen Herausforderung, einen solchen Carsharing-Dienst zu modellieren, indem sie einen Multi-Methoden-Nachfragerahmen entwickelt.

Der intermediäre Modellierungsansatz beinhaltet einen Schritt zur Berechnung des Autobesitzes der Haushalte. Soweit ich weiß, gibt es in der einschlägigen Literatur noch keine umfassende Analyse des Autobesitzes, insbesondere im Hinblick auf neue Mobilitätslösungen. In dieser Dissertation wird daher versucht, einschlägige (stadtspezifische und allgemeine) multinomiale Logit-Modelle zu schätzen. Eines der geschätzten Modelle zeigt, dass die Wahrscheinlichkeit, ein Auto zu besitzen, mit dem Besitz eines Lastenrads sinkt. Daher wird in dieser Dissertation auch das Autosubstitutionspotenzial von Lastenrädern untersucht, indem Modelle für die tatsächliche Kaufentscheidung und die Absicht, Lastenräder zu kaufen, geschätzt werden.

Die Entwicklung von Rahmenwerken und Modellen ist zwar ein interessanter Beitrag zur Literatur, ihr Wert kann jedoch nur dann voll ausgeschöpft werden, wenn sie auch genutzt werden. Daher zielt diese Dissertation darauf ab, den intermediären Ansatz zu adaptieren und das Verkehrsmittelwahlmodell, den Multi-Methoden-Nachfragerahmen und das Pkw-Besitzmodell für eine Fallstudie über die Stadt Regensburg zu nutzen. Zusammenfassend lässt sich sagen, dass die methodischen Konzepte dieser Dissertation, die erzielten Ergebnisse und die abgeleiteten Erkenntnisse (Verhalten, Politik, Betrieb und Modellierung) den Städten dabei helfen können, Shared-Mobility-Dienste zu integrieren und Mobility-as-a-Service (MaaS)-Plattformen zu konzipieren, politische Maßnahmen zur Gestaltung ihrer Mobilitätspläne zu entwickeln und eine nachhaltige städtische Mobilität zu fördern.

Acknowledgements

The completion of this dissertation would have not been possible without the support and guidance I got throughout the past three years. First and foremost, I would like to express my sincere gratitude to my supervisor, Prof. Dr. Constantinos Antoniou. I believe that there are numerous things that can be done during a doctorate and therefore, several paths to travel. Again, it is my belief that a supportive supervisor allows a student to explore and choose a path that he/she desires and at the same time maximising the benefits achieved. Prof. Antoniou has been one such and I am glad to have had him as my supervisor. A special thanks to Dr. Emmanouil Chaniotakis for pushing me to do a doctorate. I received the best research paper award from TRB during my masters and yet, I was not interested in a doctorate. Dr. Chaniotakis kept convincing me that I am in a right track for a doctorate and I should not miss pursuing it.

I am deeply grateful to all my colleagues and friends that have helped me to complete my dissertation. To begin with, I would like to thank the entire consortium of EU H2020 project MOMENTUM, whose support have enriched my doctorate. I would also like to thank Dr. Johannes Gruber from DLR for the fruitful collaborations during my doctorate. Similarly, I would like to thank the entire TUM fraternity for supporting me at various capacities, especially the IGSSE team for shaping me through various elements, such as the courses on soft skills. The image in the front cover is a black and white sketched version of a figure from CoMoUK and I thank them for allowing me to adapt and use it.

I would like to thank my brother, with whom I live in Munich and who has been supporting me right from the day I landed in Germany. I would also like to extend my thanks to my parents, who have unconditional faith in me and boundless love towards me. Additionally, I would like to thank my wife and sister-in-law for having been supporting me during the last stages of my doctorate. With apologies to those that are not mentioned, I am grateful to the Almighty for bestowing what is always best for me in a given situation and environment. Finally, I would like to dedicate this dissertation to my soon-to-be-born baby.

Contents

List of Figures

List of Tables

Overview of the standalone models

Model	Short description	Dataset	Est. procedure	Est. results	Insights
MS	Mode choice b/w conventional modes-as-a-whole, BS, CS & RS	Madrid	Sec 4.3.2.1	Tab 5.1	Sec 7.1
MB1	Mode choice b/w private car & BS: Generic coefficients for travel cost and time	Alexandrou-polis	Sec 4.3.2.2	Tab 5.2	
MB2	Mode choice b/w private car & BS: Alternative specific coefficients				
MC1	Demand for a small-scale station-based CS: Frequency of use of the CS service	Regensburg	Sec 4.3.2.3	Tab 5.3	
MC2	Demand for a small-scale station-based CS: Total demand per day for the CS service			Tab 5.4	
MC3	Demand for a small-scale station-based CS: Station level demand per day			Tab 5.5	
MR1	HH car-ownership in Regensburg: Independent variables based on a HH representative (oldest member)	Regensburg	Sec 4.3.2.4	Tab 5.7	Sec 7.2
MR2	HH car-ownership in Regensburg: Independent variables based on a HH representative (member with highest car use)				
MR3	HH car-ownership in Regensburg: HH level variables used as independent variables				
MM1	HH car-ownership in Madrid: Independent variables based on a HH representative (oldest member)	Madrid		Tab 5.8	
MM2	HH car-ownership in Madrid: HH level variables used as independent variables				
ML	HH car-ownership in Leuven	Leuven		Tab 5.9	
MG	A global HH car-ownership model based on the pooled datasets from multiple cities	Regensburg, Madrid, Leuven		Tab 5.10	
MCC1	Purchase intention towards cargo cycles	Germany	Sec 4.3.2.5	Tab 5.14	Sec 7.3
MCC2	Actual purchase of cargo cycles				

Note: BS - Bike-sharing; CS - Car-sharing; RS - Ride-hailing; HH - Household

Acronyms

AIC	Akaike Information Criterion.
AV	Autonomous Vehicle.
B2B	Business-to-Business.
B2C	Business-to-Consumer.
BIC	Bayesian Information Criterion.
BRT	Bus Rapid Transit.
BS	Bike-sharing.
CO	Carbon monoxide.
CO_2	Carbon dioxide.
CS	Car-sharing.
DCM	Discrete Choice Model.
EFA	Exploratory Factor Analysis.
EU	European Union.
ICT	Information and Communications Technology.
IPU	Iterative Proportional Updating.
KPI	Key Performance Indicator.
LV	Latent Variable.
MaaS	Mobility-as-a-Service.
MCC	Micro-hub/Micro Consolidation Centre.
MNL	Multinomial Logit.
MNP	Multinomial Probit.
MVN	Multi-Variate Normality.
NGO	Non-Governmental Organisation.
NOx	Nitrogen oxides.
OD	Origin-Destination.
OL	Ordered Logit.

OP	Ordered Probit.
PCE	Passenger Car Equivalent.
PM	Particulate Matter.
PT	Public Transport.
RMSE	Root Mean Square Error.
RS	Ride-hailing.
RVV	Regensburger Verkehrsverbund.
SAV	Shared Autonomous Vehicle.
SMOTE	Synthetic Minority Over Sampling Technique.
TAZ	Transport Analysis Zone.
TP	Transit Point.
UCC	Urban Consolidation Centre.
UDA	User-Defined Attribute.
VOC	Volatile Organic Compounds.
W-H	Work-Home.

1 Introduction

Contents

1.1 Background and motivation

Rapid technological developments have resulted in innumerable changes in today's world. One the of the major domains that faces the effects of rapid growth of technology is the urban mobility. On one hand, the way people move is changing, i.e., there is an alteration in the travel demand patterns. On the other hand, the choices available for the people to move are also changing. Developments in Information and Communications Technology (ICT) has brought new mobility options such as bike-sharing and car-sharing. These mobility options further accelerate the change in demand patterns and modal split, along with impacts on the transport supply. As a consequence, cities are facing an uncertain future.

Although emerging mobility options can help in moving towards a more sustainable and resilient mobility system, they can also lead to issues such as induced demand and mode shift from Public Transport (PT). Hence, planners and decision makers have to evaluate the impacts of different mobility options and pertinent policies under a range of possible alternative futures, or they risk being unprepared. If the drivers for the adoption and the use of the emerging mobility solutions, and their impacts on the transport system are not well understood, transport policy decisions are likely to be ineffective and may lead to undesired effects. Therefore, planners and decision makers are required to have access to suitable transport models that allow them to anticipate the possible impacts of emerging mobility systems and pertinent policies.

Transport models have been in existence for decades, as powerful tools to evaluate alternative policies and transport management solutions under a range of future supply and demand scenarios. Modelling of shared mobility calls for agent-based approaches. This can be observed in the existing pertinent literature, which are mostly based on agent-based modelling approaches (e.g., Ciari et al., 2016; Martínez et al., 2017). However, many cities, especially small- and medium-sized ones continue to use the traditional transport modelling approach (i.e., the four-step approach), which are not capable of adequately evaluating the impacts brought by the shared mobility services and other emerging mobility solutions. Furthermore, there is an inertia to change due to several reasons, including but not limited to, insufficient data, deficit of technical expertise and the convenience of simpler models (Givoni et al., 2016).

Considering the aforementioned facts, there is a need for a modelling approach, which adopts the disaggregate modelling principle from agent-based approach, and integrates the same into the traditional strategic modelling approach. However, such an approach is still missing in the existing literature and the primary focus of this dissertation is to close this gap by developing an intermediate modelling approach. The positioning of this dissertation is elucidated in Figure 1.1. This dissertation was possible through the collaborations in European Union (EU) H2020 projects "MOMENTUM" and "IRIS", German project "Ich entlaste Städte" under National Climate Initiative and TUM IGSSE project "MO3" and the datasets collected therein. As such, the datasets from these projects also act as a motivation for setting the research objectives of this dissertation.

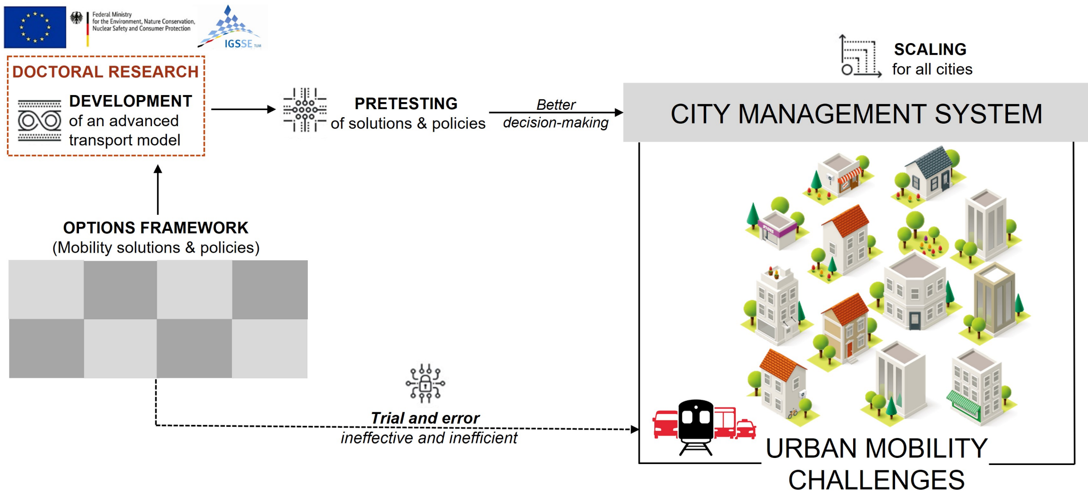


Figure 1.1: Positioning of this doctoral research

1.2 Objectives and framework

One of the twin-fold primary objectives of this dissertation (*Objective 1*) is to develop an intermediate modelling approach, an approach which stands in between the agent-based and traditional aggregate four-step approaches as shown in Figure 1.2. Based on a survey of planning practitioners (the end users), Te Brommelstroet (2010) state that there is a need to have a shift in the approach from "developing for" to "developing with" cities. They conclude that the model developers should not only focus on scientific rigour, detail and comprehensiveness, but also should try to achieve a balance between rigour and relevance, in order to increase the implementation success of advanced models. The intermediate modelling approach has been developed along these lines.

The specific focus is to integrate the disaggregate principles of the agent-based approach with the traditional aggregate four-step approach in a pragmatic manner, along with addition of steps for estimating emission, car-ownership and induced demand, as well as maintaining the balance between the complexity needed for modelling shared mobility services and the relative simplicity expected by the planners and decision makers. Furthermore, this framework is designed to be modular, so that it can be easily adapted according to the needs and use cases. The other primary objective of this dissertation (*Objective 7*) is to adapt and apply the developed framework for a case study on the city of Regensburg, focusing on evaluating the impacts of dedicated bus lanes, autonomous shuttles, bike-sharing and car-sharing services, within the limits of available data.

The aforementioned primary objectives lead to three different secondary objectives. The intermediate modelling approach has been formulated to accommodate a bilevel procedure for mode choice calculation. At the upper level, a disaggregate mode choice model allows the estimation of the modal split between conventional modes-as-a-whole, bike-sharing, car-sharing and ride-hailing. Such a model enables to uncover the distinc-

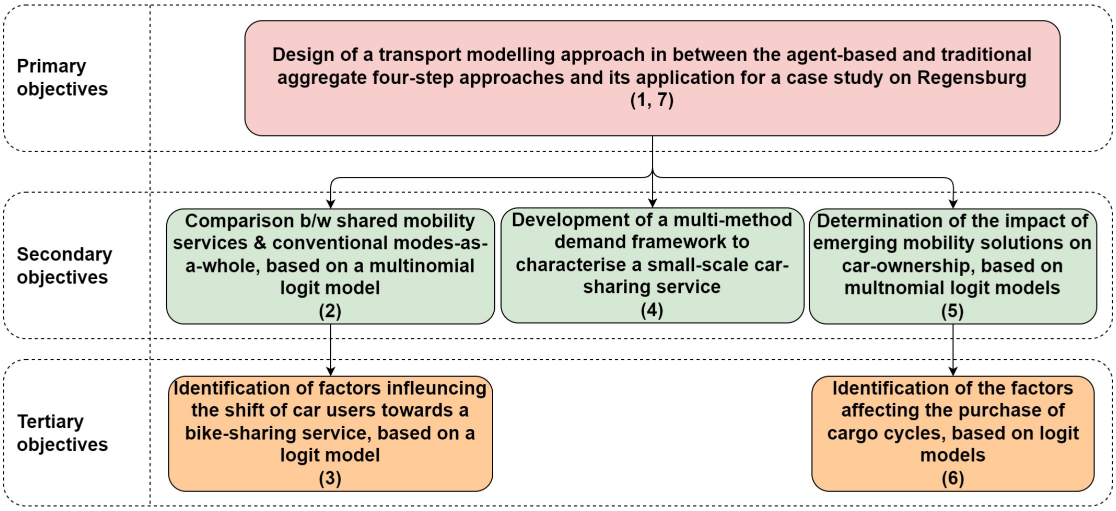


Figure 1.2: Research objectives

tive traits of shared mobility users and use, as against the conventional modes, based on the factors identified in the model. This comparison through the estimation of a multinomial logit model and ascertaining the policy and operational implications encompass *Objective 2*.

The Objective 2 leads to a tertiary objective, focusing specifically on the use of private cars and shared bikes. The disaggregate mode choice model, which is meant to estimate the modal split for the shared mobility services, shows that the probability of choosing a bike-sharing service decreases with increase in the number of household private cars. However, many cities envision to reduce private car use through the introduction of bike-sharing services. Therefore, *Objective 3* of this dissertation is to study the mode shift pattern of car users towards bike-sharing and identify the relevant influencing factors through the development of binary logit models.

When a car-sharing system is operated at a small-scale, the modal split for the service will be very low, especially at earlier stages. For example, in Regensburg, the number of shared vehicles in the car-sharing service is less than 10 and the total demand per day is less than 50 trips. This leads to a situation wherein it is not possible to account the demand for the service through the traditional mode choice models. Therefore, one of the secondary objectives (*Objective 4*) is to develop a data-driven multi-method demand estimation framework, to be integrated with the intermediate modelling approach for the case study on Regensburg. This framework also provides the opportunity to characterise the users and the use of small-scale station-based car-sharing services, such as the one in Regensburg.

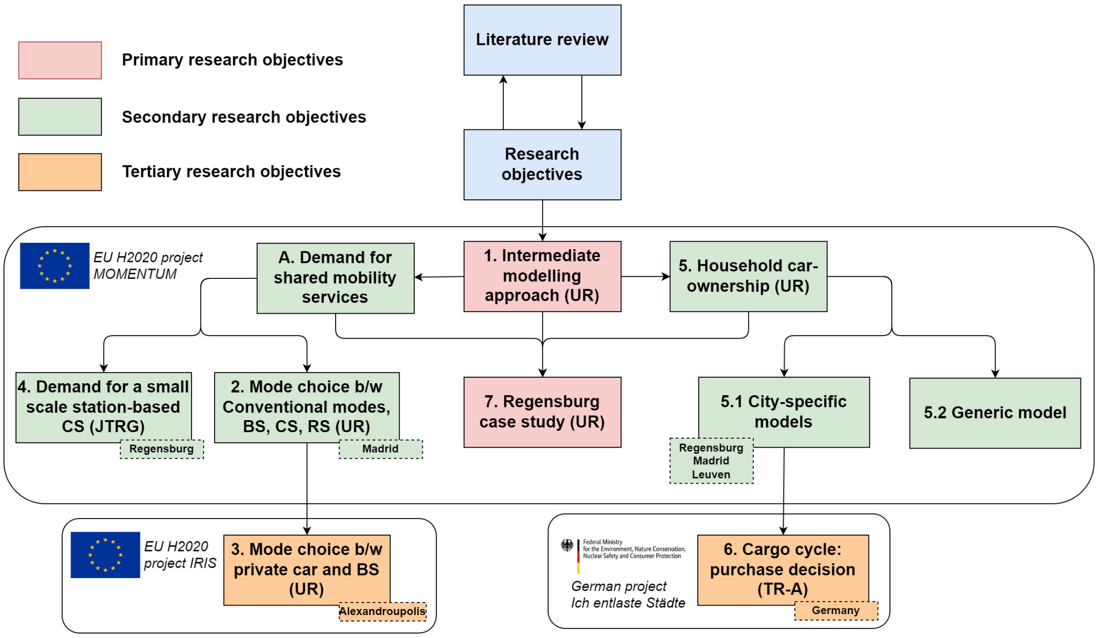
Given the interests of cities towards private car-ownership reduction, the intermediate modelling approach has been formulated to accommodate a disaggregate household car-ownership model. Therefore, this dissertation also strives to estimate relevant multinomial logit models, to determine the influence of shared mobility services on car-ownership and derive policy implications (*Objective 5*). Different models are estimated, based on the datasets from the cities of Regensburg, Madrid and Leuven. Furthermore, a generic model has also been estimated by pooling the datasets from the three cities.

Similar to Objective 2, Objective 5 also leads to a tertiary objective, focusing on the potential of cargo cycles to substitute cars. One of the multiple disaggregate car-ownership models (estimated in this doctoral research) shows that the probability of owning private cars reduces with the ownership of a cargo bike. Therefore, *Objective 6* of this dissertation is to explore the car substitution potential of cargo cycles through a framework combining Exploratory Factor Analysis (EFA), k-means clustering and binary logit models estimated for actual purchase decision and purchase intention. To the best of my knowledge, there was no suitable dataset in the field of passenger transport, during the course of this doctoral research. Hence, as an alternative, appropriate datasets from the field of commercial transport was identified and utilised to fulfil this objective.

Each of the seven objectives of this dissertation (indicated with numbering in Figure 1.2) is a research of its own and consequently, has lead to a standalone paper, as shown in Figure 1.3. The seven objectives leading to seven publications form the basis of this dissertation. Objectives (and Papers) 1, 2, 4, 5 and 7 are accomplished using datasets from EU H2020 project "MOMENTUM". Objective (and Paper) 3 is realised based on a dataset from EU H2020 project "IRIS". Finally, Objective (and Paper) 6 is achieved based on datasets from a German project "Ich entlaste Städte". The first paper, which focuses on the design of intermediate modelling approach (Objective 1) and acts as foundation stone for this dissertation, is currently under review (Narayanan et al., 2022e). Similarly, the second paper, which is based on the disaggregate mode choice model and Objective 2, is under review (Narayanan & Antoniou, 2022c).

The third paper, concerning the mode shift of car users to a bike-sharing service (Objective 3), is also under review (Narayanan et al., 2022c). The fourth paper, encompassing the development of a multi-method framework to characterise a small-scale car-sharing service (Objective 4), is published in "Journal of Transport Geography" (Narayanan & Antoniou, 2022b). Publications 2, 3 and 4 share a common aspect and hence, in Figure 1.3, they are grouped under "Demand for shared mobility services". The fifth paper, wherein multiple data sources from multiple cities are combined to estimate several car-ownership models for comparison, fulfils Objective 5 and is currently under review (Narayanan et al., 2022d).

Within the sixth paper, in accordance with Objective 6, the factors affecting the purchase of cargo cycles is assessed and the implications are discussed, within which the car substitution potential of cargo cycles is also explored. This paper is published in "Transportation Research Part A: Policy and Practice" (Narayanan et al., 2022b). The novelty of this paper lies in the methodological framework combining data integration, EFA, k-means clustering and logit models. The final publication, which supports Objective 7 and focuses on the adaptation and the application of the intermediate modelling framework for a case study on Regensburg (which focuses on the evaluation of dedicated bus lanes, an autonomous shuttle service for first/last mile and shared mobility services), is under review (Narayanan et al., 2022a).



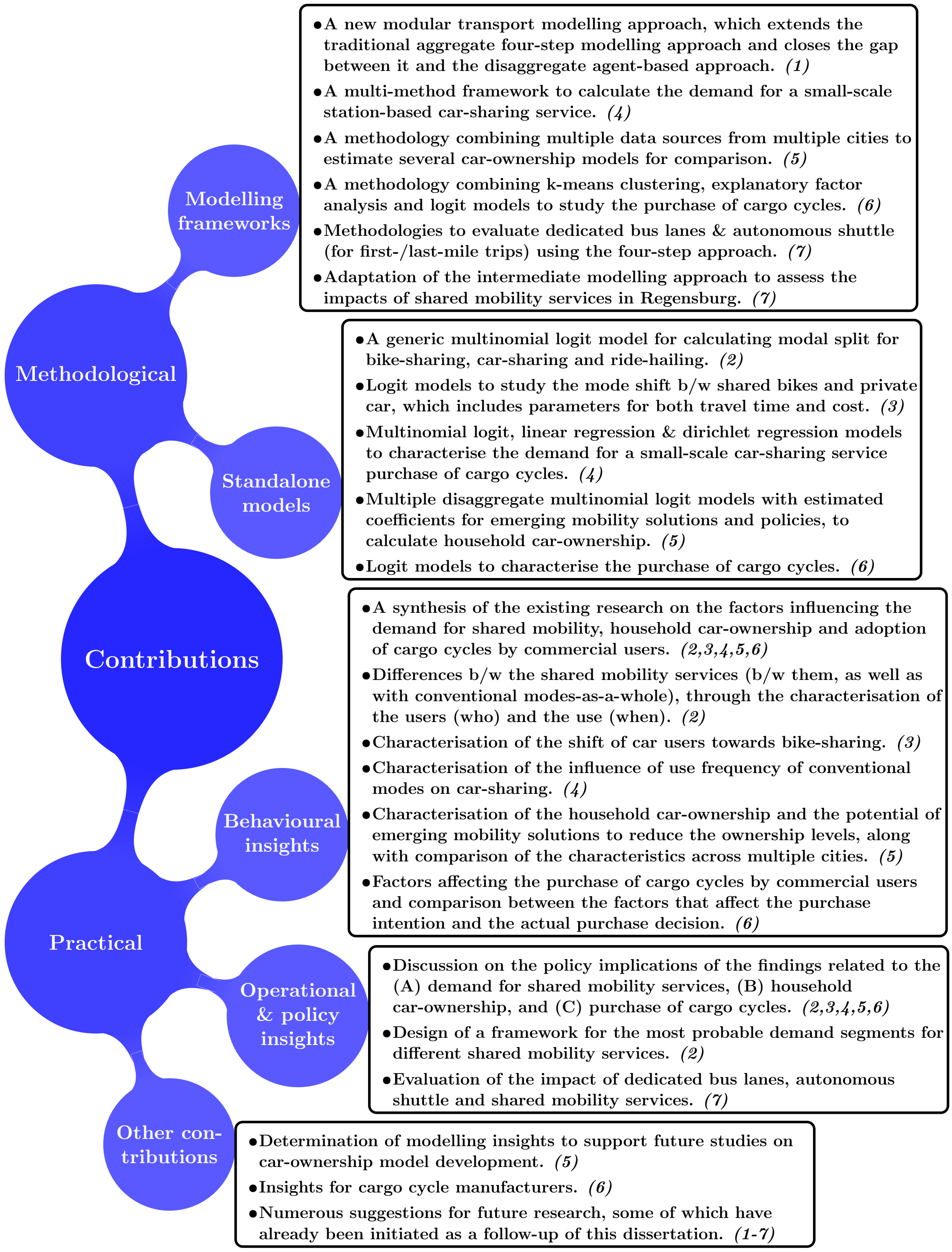
Note: BS - Bike-Sharing; CS - Car-Sharing; RS - Ride-hailing; UR - Under review and the preprint is available in SSRN. Numbers 1 to 7 represent seven independent publications, which form the basis of this dissertation and can be mapped to the seven objectives mentioned in Figure 1.2.

Figure 1.3: Research framework

1.3 Contributions

This dissertation consists of a number of methodological and practical contributions, as summarised in Figure 1.4. The methodological contributions can be bifurcated as “modelling frameworks” and “standalone models”. While the design and the development of new methodological frameworks fall into the former category, the standalone models estimated for various purposes (e.g., the multinomial logit model for calculating the modal split for bike-sharing, car-sharing and ride-hailing services) fall under the latter category.

The practical contributions include the synthesis obtained from the literature review of the relevant topics, the insights derived based on the factors and their coefficients in the estimated models, and the impact evaluation results from the Regensburg case study. These contributions can be grouped as “behavioural insights”, “Operational and policy insights”, and “other contributions”. These will be of high interest to practitioners, service operators, planners and policymakers. More details about each of the contributions are included in the subsequent paragraphs.



Note: Numbers 1 to 7, included in the information boxes, represent the seven independent publications listed in Figure 1.3, which form the basis of this dissertation and can be mapped to the seven objectives mentioned in Figure 1.2.

Figure 1.4: Contributions of this dissertation

1. Intermediate transport modelling approach
The intermediate transport modelling approach extends the traditional aggregate four-step modelling approach and closes the gap between the traditional aggregate and the disaggregate agent-based approaches. Cities can adapt and integrate this to their existing four-step model for evaluating the shared mobility services. The intermediate modelling approach has been designed to be modular and software agnostic. It is less data-hungry compared to the agent-based frameworks and also has the flexibility to be adapted according to the limits of the available data. Furthermore, several cities expect certain indicators at a disaggregate level and prefer other indicators at an aggregate level (H2020 MOMENTUM consortium, 2020) and the intermediate modelling framework caters to such needs with minimalistic input requirements. In addition, it will also act as a bridge between the worlds of simple and complex modelling approaches and pave the way for reducing the reservations of the cities towards complex approaches and prepare them for a smoother transition in future.

2. Mode choice between conventional modes-as-a-whole and shared mobility services
The generalised multinomial logit model (disaggregate mode choice model) can be used by several cities, as a complementary model to their existing mode choice model. This is a critical primary step towards the inclusion of the three shared mobility services (i.e., bike-sharing, car-sharing and ride-hailing) in transport network simulations, to analyse and predict their impact at the system level. While the cities can use this disaggregate model for estimating the demand for the shared mobility services, they can continue using their existing model to calculate the modal share for conventional modes. The characterisation of the users and the use of the shared mobility services using the parameters from the model, and the differences observed between them (as well as with the conventional modes) clarify the potential of the shared mobility services to achieve the mobility goals of the cities, and support evidence-based policy-making. Furthermore, the policy and the operational measures formulated based on the implications of the characterisation enable policymakers to promote sustainable usage of the services. Finally, the framework designed for the most probable demand segments for the three services, allows service providers to optimise their operations and integrate their services along with PT, aiming towards the establishment of MaaS platforms.

3. Mode choice between private car and bike-sharing
The logit model has been specifically estimated using a stated preference survey data pertaining to the car users and it can be used by several cities to study the mode shift pattern of car users towards a bike-sharing service. This model includes parameters for both travel time and cost, and hence, can be utilised to study pricing strategies. The characterisation of the mode shift pattern, based on the parameters, enable to assess the car substitution potential of the shared bikes. Furthermore, the policy measures formulated based on the implications of the characterisation can help to reinforce and improve the car substitution potential.

4. Demand framework for a small-scale station-based car-sharing system
The multi-method demand framework (consisting of linear regression, dirichlet regression and multinomial logit models) can be adapted and used by several cities around the world, who are caught in a dilemma towards how to characterise the use and the users and expand their car-sharing service during earlier stages. Though the framework has been developed aiming at a car-sharing service, I believe that it can be adapted to study, characterise and evaluate many other emerging mobility solutions with different business models. The characterisation of the users and the use, especially the influence of the use frequency of conventional modes on the car-sharing, can support in integrating the car-sharing service with other modes, in the form of a MaaS platform. Furthermore, the operational and policy measures, derived based on the implications of the characterisation, pave way for the sustainable growth of car-sharing services.

5. Household car-ownership
The methodological framework combining multiple data sources from multiple cities to estimate several car-ownership models for comparison can be reproduced to study other concepts (e.g., mode choice). The disaggregate multinomial logit models, with estimated coefficients for emerging mobility solutions, can be integrated with existing transport simulation tools for determining household car-ownership. Especially, the generic model, which has been estimated based on the common factors identified in multiple cities, can be utilised by several cities. The behavioural insights (obtained based on the estimation results) and the policy measures (derived from the behavioural insights) pave the way to clarify the potential of emerging mobility solutions, to reduce household car-ownership and to design proper policies to reduce household car-ownership. Finally, the modelling insights distilled from the comparison of the multiple models support future studies on the development of car-ownership models.

6. Cargo cycle: purchase decision
The methodological framework combining data integration, EFA, k-means clustering and logit models can be replicated to assess other emerging transport modes, both in commercial and passenger transport [e.g., Autonomous Vehicles (AVs)]. The estimated parameters in the logit models can help to understand the underlying reasons for the purchase of cargo cycles, especially clarifying the car substitution potential. The comparison between the factors that affect the actual purchase decision and the purchase intention can throw light on the rationale behind the differences in the intention and the actual decision. Finally, the insights for policymakers and industry can support them in fostering cargo cycle penetration, and reduce the reservations against their use.

7. Regensburg case study
The methodologies implemented for dedicated bus lanes and autonomous shuttles (in the existing PTV Visum model of the city of Regensburg) can act as a motivation for other cities, to evaluate such options using tools based on the traiditional four-step modelling approach. Similarly, the adaptation of the intermediate modelling approach to assess

shared mobility services can act as an example to other cities, to adapt this approach and extend the four-step modelling approach for their use case. The insights obtained from the evaluation of dedicated bus lanes, autonomous shuttles, and shared mobility services on the PT use will help to channelise the urban mobility in Regensburg, as well as support shaping mobility in other small- and medium-sized cities.

1.4 Dissertation structure

The structure of this dissertation is summarised in Figure 1.5, which also shows the connections with the objectives and the publications introduced in Figure 1.2 and Figure 1.3, respectively. The remaining chapters in this dissertation are as follows:

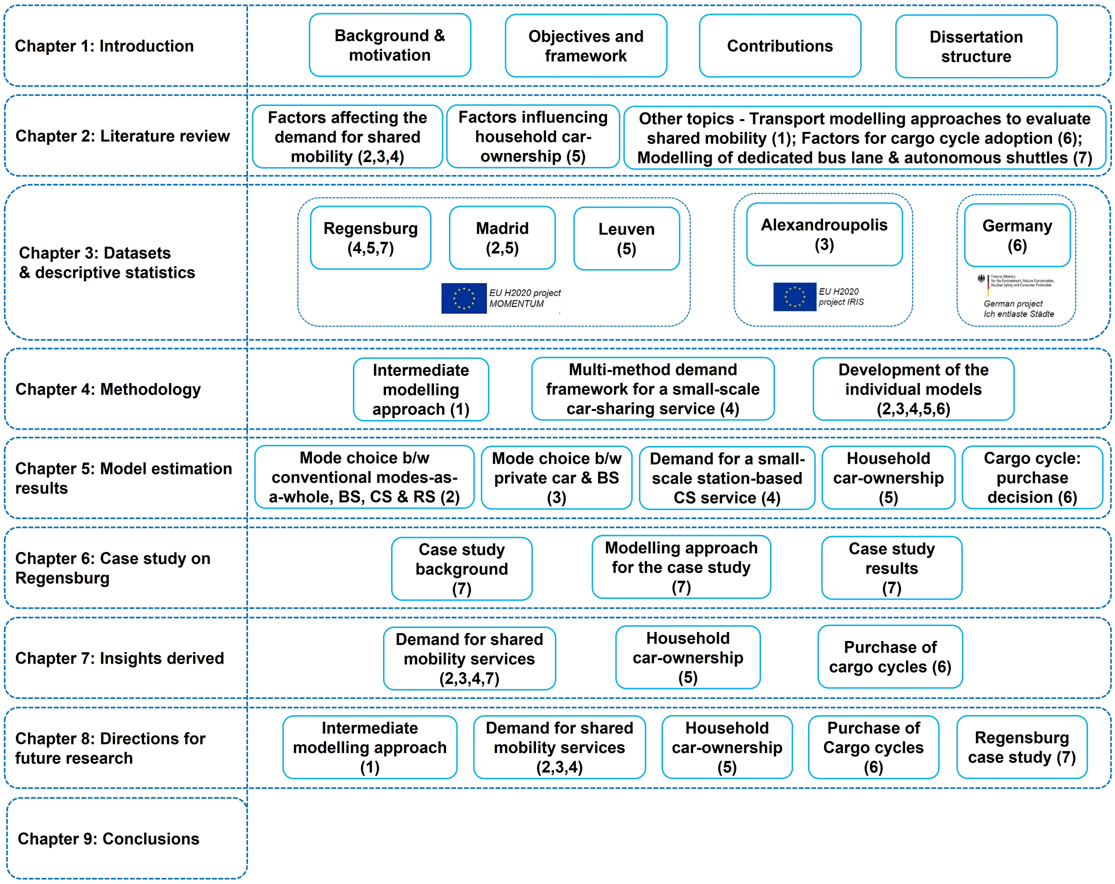
Chapter 2: Literature review This chapter provides an overview of the existing works, a targeted presentation of topics pertinent to this dissertation. At first, the literature review is performed on the factors affecting the demand for the three shared mobility services explored in this dissertation, which are bike-sharing, car-sharing and ride-hailing. Subsequently, the existing knowledge on the factors influencing household car-ownership is presented. Afterwards, other relevant topics, such as the transport modelling approaches for evaluating shared mobility services, factors governing the adoption of cargo cycles, the modelling of dedicated bus lanes and autonomous shuttles, are outlined. The studies were collected by querying the Scopus database using an open source python script[1] from Narayanan & Antoniou (2022a).

Chapter 3: Datasets and descriptive statistics This dissertation uses several existing datasets, whose details are included in this chapter. The datasets were collected as part of multiple projects and corresponds to the cities of Regensburg (Germany), Madrid (Spain), Leuven (Belgium) and Alexandroupolis (Greece). However, the spatial scope of the cargo cycle related datasets extends across Germany. Besides the information about the datasets, their descriptive statistics are also included in this chapter.

Chapter 4: Methodology This chapter focuses on the methodological aspects of this dissertation. Starting with the intermediate modelling approach, the schema for the high and low penetration scenarios of shared mobility services are formulated. Then, the multi-method demand framework for a small-scale station-based car-sharing service is described. Afterwards, the chapter proceeds with the discussion on the methodology followed for the estimation of individual standalone models (e.g., the multinomial logit model for disaggregate mode choice between conventional-modes-as-whole, bike-sharing, car-sharing and ride-hailing).

Chapter 5: Model estimation results The estimation results for the different individual models are summarised in this chapter. This includes the estimation results of

[1] https://github.com/nsanthanakrishnan/Scopus-Query



Note: BS - Bike-Sharing; CS - Car-Sharing; RS - Ride-hailing. Numbers 1 to 7 represent the seven independent publications listed in Figure 1.3, which form the basis of this dissertation and can be mapped to the seven objectives mentioned in Figure 1.2.

Figure 1.5: Dissertation structure

the (i) model for the mode choice between conventional-modes-as-a-whole, bike-sharing, car-sharing and ride-hailing, (ii) models for the mode choice between private car and bike-sharing, (iii) the models proposed as part of the multi-method demand framework for a small-scale station-based car-sharing service, (iv) multiple household car-ownership models and (v) models for the purchase intention and the actual purchase of cargo cycles.

Chapter 6: Case study on Regensburg One of the primary objectives of this dissertation is to adapt and apply the intermediate modelling approach for a case study on the city of Regensburg. At first, a background on the case study in presented. Then, the modelling approach implemented for the case study is detailed. This includes details about existing Regensburg PTV Visum model, the methodologies followed to model dedicated bus lanes and autonomous shuttle, and the adaptation of the intermediate modelling approach to model shared mobility services. Finally, the evaluation results are elucidated. Based on the objectives of the Regensburg city council, the results will include (i) the impact of dedicated bus lanes, autonomous shuttles and shared mobility services on the PT use, (ii) the influence on dedicated bus lanes on local emissions and (iii) the combined effect of shared mobility services on household car-ownership.

Chapter 7: Insights derived Based on the implications of the results obtained in the preceding two chapters, insights are derived, focusing to move towards a sustainable urban mobility and towards implementation of a MaaS platform. This will include suggestion of measures to (i) channelise the demand for shared mobility services, (ii) reduce household car-ownership and (iii) foster the penetration of cargo cycles.

Chapter 8: Directions for future research Naturally, this dissertation has its limitations and also generates several new research questions, which can lead to numerous future studies. As a consequence, limitations are listed and potential topics for future research are proposed in this chapter. The possibilities are discussed under the following topics: (i) intermediate modelling approach, (ii) demand for shared mobility services, (iii) household car-ownership, (iv) cargo cycles and (v) Regensburg case study.

Chapter 9: Conclusions The last chapter of this dissertation provides an overview of the objectives investigated, methods formulated and the results achieved, along with an outline on the implications and suggestions for sustainable urban mobility. Finally, the dissertation is concluded with a few summarising remarks.

Note: The chapter on datasets is presented at first and the methodology later, which is less common. The individual datasets are abstracted for different models and would have to be referred in the methodology section. For example, car-ownership models are estimated for multiple cities and naturally, different datasets are used. Another specific situation is the following: For the disaggregate mode choice model, all the records from the Madrid household survey is utilised, while for the Madrid car-ownership models, a subsample of them (households where the data for all the members are available) is considered (reasons will be discussed later in the methodology chapter). Hence, the sequence of having data description at first and then the methodology is followed for better readability and to introduce the datasets as a background and motivation for the methodological framework.

2 Literature review

Contents

2.1 Factors affecting the demand for shared mobility services

The majority of the existing literature focus on the use of shared mobility services using operator data. Therefore, in this section, the literature related to both the mode choice (based on stated preference surveys) and the use (based on operator datasets) of shared mobility services are examined. Studies exploring multiple of these are limited, and hence, studies that concentrate on at least one of them are also reviewed. The common and distinct characteristics observed between multiple modes are of higher importance than the factors influencing the use of single shared mode. Therefore, studies focusing on multiple shared modes, simultaneously, is presented at first, followed by literature related to single shared mode.

2.1.1 Studies exploring multiple shared mobility services

Starting with the studies that investigate multiple shared modes, Lee et al. (2021) use a zero-inflated negative binomial regression model to study the frequency of use of car-sharing, bike-sharing and shared ride-hailing (ride-sharing) services. Several variables are found to influence the use frequency, including, but not limited to, travel distance, age, gender and education. Education is found to have a positive relationship with the frequency. Male and young individuals are also associated with higher use frequency. Similarly, Becker et al. (2020), using MATSim, have conducted a joint simulation of car-sharing, bike-sharing and ride-hailing services for the city of Zurich. Parameters for the shared modes in the mode choice model are decided based on those of PT, conventional bike and car modes and few other assumptions. Variables in the mode choice specification include travel time, age, cost, access time and waiting time. Sweet & Scott (2021) analyse the adoption of on-demand ride-hailing, car-sharing and bike-sharing services using trivariate ordered models. They conclude that the adoption of the car-sharing service is higher among males, younger individuals and students.

Focusing on car-sharing and bike-sharing services, Li & Kamargianni (2019) have developed a choice and LV model. The utility specification of the shared modes in the final model consists of travel time, travel cost, education, age and air pollution level. As one would expect, travel time and cost have negative influences, especially higher influence of the latter for less educated individuals. In a subsequent study, Li & Kamargianni (2020) conduct a simulation analysis to evaluate modal substitution patterns. The modes considered in their study include bike-sharing, car-sharing, private car, taxi, bus and electric bike. The coefficients in the mode choice model are observed to differ according to trip distance, which is distinguished as middle and long distances. Furthermore, the number of walking trips has been observed to be very low, when the distance is above 2 km, while taxi trips are rarely observed for distances below 2 km. Thus, three different distance categories appear to exist, low (less than 2 km), middle (2 to 5 km) and long (greater than 5 km).

Wielinski et al. (2017) compare the travel behaviour of members of bike-sharing and car-sharing, using data from two web-based OD travel surveys. Age, gender, household size, car ownership and possession of PT pass are found to influence the use of the two shared mobility services. Picasso et al. (2020) has conducted a stated choice experiment to analyse the demand for a car-sharing system and its interaction with a bike-sharing system. They conclude that car-sharing and bike-sharing systems may attract different users, with longer trips being served by the former and shorter trips by the latter.

2.1.2 Studies exploring a single shared mobility service

Looking at the existing literature specific to bike-sharing services, gender and age are found to play a significant role for the use of bike-sharing service in Oslo, Norway (Böcker et al., 2020). The system is less used by women and older age groups. Similarly, based on a survey of 3000 individuals in Raux et al. (2017), the majority of bike-sharing users in Lyon (France) are male and hold higher social positions, when compared to the general population. Focusing on the difference between Millennials', Gen Xers' and Baby Boomers' bike-sharing ridership, Wang et al. (2018) conclude that most of the bike-share trips are made by older Millennials (born between 1979 and 1988). Furthermore, weather factors are shown to have less of an impact on younger Millennials' use of bike-sharing systems. These findings are based on zero-inflated negative binomial models, which are developed using New York's Citi Bike system data. However, based on a stated preference survey conducted in Beijing (China), Campbell et al. (2016) conclude that bike-sharing systems will draw users from across the social spectrum.

Based on a review of multiple studies related to bike-sharing systems, Fishman et al. (2013) identify convenience and cost to be significant factors for using bike-sharing service. Cost is also found to be a significant factor in Ma et al. (2020), whose conclusion is based on a binary logit model, with the dependent variable being whether or not a survey respondent shifts his/her commuting mode to a bike-sharing system. Tran et al. (2015) use linear regression models to predict station level demand for the bike-sharing system in Lyon (France). The authors conclude that long term subscribers use the system often together with trains for commuting trips, whilst short term subscribers' trip purposes are more varied. Furthermore, students are determined to be an important group among bike-sharing users. When it comes to the fleet size of bike-sharing systems, Shen et al. (2018b) observed that a larger bike fleet is associated with higher usage. In addition, easy access to PT, more supportive cycling facilities and free-ride promotions are concluded to positively influence the use of bike-sharing systems. Other factors that influence the demand for bike-sharing services are traffic safety concerns and limitations in the existing cycling infrastructure (Bakogiannis et al., 2019).

Becker et al. (2017) compare the user groups and usage patterns of the car-sharing schemes in Switzerland. They conclude that both free-floating and station-based car-sharing systems attract younger and highly educated people. In addition, males and individuals with university degree are more probable to use the system. Furthermore, the reduction in private vehicle ownership is observed for a significant share of members of both the schemes, with an influence towards a transit-oriented lifestyle. Education is also found to be a significant factor for car-sharing use in Zhou et al. (2020b). Similar to Becker et al. (2017), Yoon et al. (2017) compare the factors influencing the choice of one-way and round-trip car-sharing systems. They have found that the most significant factors for both the schemes are the cost gap (difference between the cost of original mode and the cost of using a car-sharing system) and car ownership. Another study comparing the round-trip and one-way services is Le Vine et al. (2014), wherein a round-trip system is concluded to complement PT.

Developing a random utility model for park-and-car-sharing, Cartenì et al. (2016) observe the significant influence of total travel time, cost, gender and age on the demand for the service. de Luca & Di Pace (2015) study the impact of an inter-urban car-sharing program on mode choice behaviour. They conclude that car-sharing could be a complementary mode to PT during the periods in which the PT service is not guaranteed or efficient. Wang et al. (2021) use gradient boosting decision tree to predict the travel demand for a station-based car-sharing service. They found that the demand varies according to the days of a week, with a peak on Fridays. A seasonal variation is also observed. Furthermore, the number of picked-up vehicles is higher in the morning and evening peak hours, while the return time is concentrated in the late evening. In addition, the number of vehicles picked up and returned increases with an increase in the number of stations. Similarly, Namazu et al. (2018a) conclude that provision of more car-sharing vehicles is likely to have the highest impact on car-ownership reduction, than waiving membership fees. Analysing the operator data of a German car-sharing system, Schmöller et al. (2015) conclude that changes in the weather conditions have only a short-term impact and socio-demographic characteristics are more suitable for long-term demand prediction. Finally, Costain et al. (2012) investigate the users' behaviour towards a car-sharing service and state that the service provides a segment of the population with enhanced accessibility.

When it comes to ride-hailing services [both exclusive (single customer) and shared rides (ride-sharing)], Alemi et al. (2019) state that socio-demographic variables are good predictors for the adoption of the service. Dong et al. (2018) examine empirical data to explore travel patterns of ride-sharing trips. They conclude that ride-sharing is a supplement to traditional taxi service, particularly for home-to-work or work-to-home commuting during rush hours. Results from Alonso-González et al. (2020) show that the share of individuals who prefer to share rides is mainly influenced by the trade-off between time and cost that they experience, rather than by the on-board discomfort related to the presence of strangers. Also, in Frei et al. (2017), cost and travel time are shown to influence the probability of using a ride-sharing service, along with travel distance. Similarly, Habib (2019) observes a significant impact of cost and travel time on the probability of choosing ride-hailing services (Uber), besides the higher likelihood of use by younger people. However, gender is found to be insignificant. The estimated mode choice model indicates that a mere consideration of a ride-hailing service as a feasible travel mode (by an individual) has a positive influence on choosing it. Furthermore, such services are stated to fill gaps in transit services.

Loa & Habib (2021) focus on both the exclusive and shared ride-hailing services. They conclude that individuals belonging to the age groups 30 years or less and between ages of 31 and 40 are more probable to use the two services. Based on a household travel survey, Young & Farber (2019) have found out that the users of ride-hailing services are mostly between 20 and 39 years old and such services are often used at times when transit ridership and service are already at their lowest level. Similarly, Lavieri & Bhat (2019) conclude that the age group 20 to 44 will be more probable to use the ride-hailing services, especially with policies targeting variety-seeking behaviour (such as personalised trip plans in mobility-as-a-service apps that offer multiple travel choices and include shared ride-hailing). Furthermore, highly educated individuals use a combination of exclusive and shared ride-hailing services as they see best fit for specific trips. Lavieri & Bhat (2019) state that educational campaigns, targeting the increase of tech-savviness among older population segments, will make ride-hailing services (both exclusive and shared) more accessible to this segment. Gilibert et al. (2019) analyse the usage of MOIA shared ride-hailing service and concluded that the users of the service are mostly 18 to 29 years old and without a driving license. The service effectively serves areas which are not efficiently covered by PT. The results from Acheampong et al. (2020) show that most ride-hailing trips tend to cover relatively shorter travel times (≤30 min). Furthermore, ride-hailing tends to be used alone for full door-to-door journeys, instead of complementing existing modes in serving first/last mile access.

2.1.3 Summary and research opportunities

To summarise, although subtle differences exist between the three shared mobility services (and the different schemes under them), they also share several common traits (i.e., user groups and use characteristics). Several significant determinants of demand for all the three shared mobility services have been identified in the existing literature: socio-demographic characteristics (age, education, car ownership and possession of PT pass), trip-related variables (distance, travel time and cost) and supply parameters (fleet size). Furthermore, weather conditions have only a short-term impact and socio-demographic characteristics are more appropriate for long-term demand prediction.

According to trip distance, the demand for shared mobility services can be segmented into three, namely, short (≤ 2 km), middle (2 to 5 km) and long (> 5 km) distance trips. While bike-sharing is expected to be used for low distance trips, car-sharing will be seldom used for this distance category. Similarly, based on travel time, the demand can be segmented into two, namely, shorter (≤30 min) and longer (>30 min) travel time trips. The shared mobility services are expected to be used more for shorter travel time trips. According to age, the user groups for shared mobility services can be divided into three categories, namely young (<20), middle-aged (20 to 44) and older (>44) groups, with higher use probability for the middle-aged group. While gender is a significant factor for using bike-sharing and car-sharing services, it may not play a significant role for ride-hailing services. Nevertheless, the absence of a driving license may increase the probability of using ride-hailing services.

Several policy related aspects are also found in the existing literature. For example, long term bike-sharing subscribers use the system often together with PT for commuting. Similarly, car-sharing systems can have an influence towards transit-oriented lifestyle. On the other hand, ride-hailing services are often used during the times and at places of low ridership, thereby effectively serving areas that are not efficiently covered by PT.

Thus, ride-hailing services may fill gaps in transit services and tend to be used more for door-to-door journeys.

The review leads to an understanding of the gaps in the existing literature. To the best of my knowledge, except from Becker et al. (2020), no other mode choice model existed at the time of research, which covered bike-sharing, car-sharing and ride-hailing services simultaneously. Becker et al. (2020), themselves, state that the combination of partial mode choice models used in their study only has limited validity, and estimating and utilising a choice model based on a survey data, capturing all the modes simultaneously, will be a superior approach. Therefore, one of the secondary objectives of this dissertation is to develop a disaggregate mode choice model, which combines all the three shared mobility services. Besides, policy and operational implications will be derived from the estimated coefficients, based on which different measures will be formulated to promote sustainable usage of shared mobility services. In addition, a specific focus on the characterisation of the (plausible) shift of car users to bike-sharing is still missing in the literature and one of the tertiary objectives of this dissertation is to close this gap.

There is a growing popularity for the different shared mobility solutions and multiple methodologies exist to study their potential, as can be observed above. However, in reality, several services do not get going and experience setbacks. There are many failure stories. Hamann et al. (2019) observe that several bike-sharing systems deployed around the world are not successful. However, they also state that these systems are subject to strong growth in some parts of the world and more regulation is necessary to channelise their growth. Nicholas & Bernard (2021) examine 17 different electric car-sharing programs which began their operations in the last decade and note that 6 of them are no longer operating. They state that there is no one business model that fits all; rather, the right model depends on the objectives of both the local municipality and the operator.

Many shared mobility service deployments have not been as successful as they could have been, in part, due to often-contentious roll out, without a systematic introduction. As a result, cities around the world are now moving towards regulating the emerging mobility solutions and implementing an incremental approach for their deployment. For example, Copenhagen developed a strategy in 2017 to enhance car-sharing in the city. This strategy focused only on round-trip car-sharing, because the city council determined that existing research has only been able to demonstrate the impact of round-trip schemes on congestion and car ownership (Nicholas & Bernard, 2021). Likewise, Paris has different strategies and regulations in place for free-floating and round-trip car-sharing. Similarly, Regensburg is following an incremental approach for the introduction of a car-sharing service.

It is imperative to characterise the new mobility solutions in early stages of the incremental implementation, to understand the utilisation of these services and streamline their growth through proper regulations. Otherwise, these services could run out of gas before they get anywhere or might lead to unsustainable use. However, their introduction is often planned in an exploratory way, based more on instinct and intuition, rather than on rational decision-making. For example, many cities have moved through trial and error stages for the entry of e-scooter sharing services (Hahn et al., 2020). This is partly due to the challenges in including these services in the conventional travel demand forecasting initiatives. This is a prime concern especially during the initial stages of small-scale operation, during which the data remains sparse and it is not possible to analyse the small use case with the existing methods.

Such an analysis is unique and calls for special approaches, since several constraints exist due to limited data availability. Therefore, another secondary objective of this study is to develop a suitable framework for estimating the demand for small-scale car-sharing services and characterise the users and the use case, which will be integrated with the intermediate modelling approach, when investigating the Regensburg case study. In addition, the influence of the use frequency of conventional modes on the car-sharing use has also not been explicitly assessed, which can support in integrating the car-sharing service with other modes, in the form of a MaaS platform, and support in improving transport equity. Thus, this gap will also be closed, as part of the research on the development of the framework.

2.2 Factors influencing household car-ownership

Understanding car-ownership is of great relevance for different actors in the transportation field. The private sector (e.g., car manufacturers and oil producers) is interested in forecasting the future demand of its products, whereas the public sector seeks to develop more effective transportation, environmental and taxing policies (Jong et al., 2004). Thus, in the scientific literature, car-ownership has been modelled from many different perspectives and for varied purposes.

2.2.1 Existing review works on household car-ownership

Fortunately, there are multiple review works discussing the existing methodologies. Jong et al. (2004) provide a comprehensive overview of the modelling types, including aggregate time series models, aggregate car market models, static disaggregate models and pseudo panel models. Potoglou & Kanaroglou (2008a) and Anowar et al. (2014) describe different disaggregate modelling approaches. These disaggregate models have higher computation and data requirements than aggregate ones, but they do not face difficulties due to the correlation between aggregate variables.

Potoglou & Kanaroglou (2008a) review models focused on vehicle-ownership levels (number of vehicles per household), vehicle type choice, vehicle holding, and vehicle transactions. Anowar et al. (2014) distinguish four groups of models depending on (i) whether they include vehicle-ownership as independent of other decisions or not (exogenous vs endogenous) and (ii) whether they consider changes in the decision process over time or not (static vs dynamic). In this dissertation, the emphasis is on disaggregate static models, using which the car-ownership decisions at the household level are studied, leading to more detailed and policy-relevant results.

Table 2.1: Literature review - Factors influencing household car-ownership

Study	Analysis area & year	Model type	Dep. variable	Explanatory variables & effects	
Bhat & Pulugurta (1998)	Datasets from US (1990-91) and one from the Netherlands (1987)	Multinomial Logit (MNL) and Ordered Logit (OL)	Discrete with options 0,1,2,3,4+(US) 0,1,2+(Nether.)	SD	N. working adults (+) N. non-working adults (+) Single-family housing units (+) Income (+)
				Urb.	Urban and suburban location (-)
Matas & Raymond (2008)	Spain, 1980, 1990, 2000	Ordered Probit (OP) and MNL	Discrete with options 0,1,2,3+	SD	N. adults (+) Total household expenditure (+) HH representative: male (+) HH representative: Age <25 or >65 y.o (-)
				TR	PT quality (-)[*1]
Potoglou & Susilo (2008)	Baltimore (US) 2001	OL, OP, MNL, Multinomial Probit (MNP)	Discrete with options 0,1,2,3+	SD	Single family housing units (+) Income (+) Couple w/ & w/o children (+)[*2] Single parent (-) Retired (+)[*3] Caucasian race (+)
				Urb.	Population density (-)
	Netherlands 2005		Discrete with options 0,1,2,3+	SD	N. of workers (+) Couple w/ & w/o children (+) Retired (+)[*3]
				Urb.	Population density (-)
	Osaka (Japan) 2000		Discrete with options 0,1,2,3+	SD	Couple w/ & w/o children (+) Single parent (-) Retired (-)
				Urb.	Urbanisation level (-)
Potoglou & Kanaroglou (2008b)	Hamilton (Canada) 2005	MNL and OL	Discrete with options 0,1,2,3+	SD	Single family house (+) N. adults (+) N. full time workers (+) N. part time workers (-) Couple w/ & w/o children (+; only for "2") Income (+) N. of individuals working >6 km (+)
				Urb	Density (-)
				TR	N. of bus stops <500 m (-; only for "3+") % of individuals with driving license (+)
Clark (2009a)	United Kingdom 2002, 2003, 2004	Rough Sets	Discrete with options 0,1,2,3+	SD	Income (+) HH size (+) HH composition[*4]
				Urb.	Urban area type[*4]
Clark (2009b)	United Kingdom 2001	Multiple data mining methods	Discrete with options 0,1,2,3+	SD	HH tenure (owned/rented)[*4] Housing type: (semi)detached, flat[*4] N. of earners[*4] HH representative: economic position[*4]
Matas et al. (2009)	Madrid and Barcelona (Spain) 2001	MNL and OP	Discrete with options 0,1,2+	SD	Age (+; non-linear) HH Size (+) N. adults (+) Education level (+) HH representative: man/married/employed (+) HH representative: manager/self-employed (+) HH representative: unskilled worker/migrant (-) Rented house (-) Ownership of a second residence (+) Unemployment rate in neighbourhood (-)
				Urb.	Located in central city (-) Accessibility to jobs (-)
Yamamoto (2009)	Kyoto-Osaka-Kobe (Japan) 2000 and Kuala Lumpur (Malaysia) 1997	Trivariate Binary Probit (TBP) and MNL	TBP: own/not own a vehicle; MNL: 7 alternatives: own car, bike, motorcycle, car-and-bike, ...	SD	N. of working adults (+)[*5] N. non working adults (+) N. retired members (+) N. of children (+) Income (+)
				Urb.	Distance to city center (+/-)[*6] Population density (-) Land-use mix (+/-)[*6]
				Urb.	PT accessibility (+/-)[*6]
Cirillo & Liu (2013)	Maryland (US) 2001, 2009	MNL	Discrete with options 0,1,2,3,4+	SD	Income (+) N. of workers (+; only "3" and "4+") N. of drivers (+) Education level (+ ; only "1" and "2")
				Urb.	Urbanisation (-) Population density (-) Urban size (-)

Table 2.1: Literature review - Factors influencing household car-ownership

Study	Analysis year & area	Model type	Dep. variable		Explanatory variables & effects
Ritter & Vance (2013)	Germany 1999-2009	MNL	Discrete with options 0,1,2,3+	SD	HH Size (+) Age (+; non-linear) Income (+; log)
				Urb.	Share of open space in vicinity[*7] (+)
				TR	Walking distance to closest PT stop (+) Cost of PT (+) Availability of rail services (-) Availability of company car (-)
				Other	Fuel price (-; log)
Wong (2013)	Macao (China) 2009	MNL	Discrete with options 0,1,2+	SD	N. working adults (+) N. non-working adults (-; only “1”) N. young individuals (-; only “1”) N. children (+) Income (+)
				Urb.	Old town or historical location (-)
Liu et al. (2014)	Maryland, Virginia and District of Columbia (US) 2009	MNP	Discrete with options 0,1,2,3,4+	SD	Income (+) N. drivers (+) HH representative: female (-)
				Urb.	Urban size (-) Housing density [units/mile^2](-)
Liu & Cirillo (2016)	US census regions 2009	MNP	Discrete with options 0,1,2,3,4+	SD	Income (+) HH Size (+) N. of workers (+) Owned house (+)
				Urb.	Population density (-)
Maltha et al. (2017)	Neetherlands 1987, 1991, 1995, 1999, 2003, 2010, 2014	OL and MNL	Discrete with options 0,1,2,3+	SD	Income (+) HH Size (+) HH representative: age (-)[*8] HH representative: female[*8/*9] Dummy working (+) Education level (+)
				Urb.	Urbanisation (-)
Paredes et al. (2017)	Singapore 2008, 2012	MNL and multiple machine learning algorithms	Discrete with options 0,1,2+	SD	HH size (+) Two or more children (+) Income (+) Any member >60 y.o. (-) Any self-employed member (+) Any full time worker member (-) Any CEO member (+) Owned house (+) Public housing (-) Chinese descendent (+) Malay, Indian or another race (-)
				TR	Availability of motorcycle (-) Distance to MRT station (-) Ownership of a Taxi (-)
Soltani (2017)	Fars province (Iran) 2012	Nested Logit (NL)	Discrete with options 0,1,2,3+	SD	HH Size (+) N. working adults (+) Owned house (+) Income (+) Housing type: apartment (-) Member works in management (+) Any member works >5 km (+)
				Urb.	Land use mix (-)
Ma et al. (2018)	Xiaoschan district (China) 2015	Multivariate Ordered Probit (MOP)	Discrete with options 0,1,2+ and 4 types of vehicles (bike/e-bike/car/motorcycle)	SD	Income (+) HH Size (+) Owned house (+) Age (+) Education level (+)
				Urb.	Population density (-)
				TR	Availability of driving license (+)

Table 2.1: Literature review - Factors influencing household car-ownership

Study	Analysis year & area	Model type	Dep. variable	Explanatory variables & effects	
Shao et al. (2022)	Zhongshan (China) 2022	Gradient Boosting Decision Tree (GBDT)	Discrete with options 0,1,2+	SD	Income (+) Owned house (+) HH size (+)
				Urb.	Distance to city centre (+) Population density (-) Land use mix index (+)*10 Street density[km/km^2] (+)
				TR	Ownership of e-bike (-) Ownership of motorcycle (-) PT supply (-)

Notes:

- Studies are sorted by year and then alphabetically on authors
- (+) indicates direct and (-) indicates inverse relationship
- *1 Only significant in large cities; *2 Alternative "1 Car" is less likely than "0 Car"; *3 'Single' is considered as the base category; *4 Coefficient's sign is not explicitly given; *5 Negative sign when income variable is included in the model; *6 Different sign for different cities; *7 Proxy variable – inverse of population density; *8 Decreasing importance over time; *9 Different sign for different years. *10 The unexpected sign might be a result of the correlation with unobserved household wealth-related variables.
- Abbreviations: SD: Socio-Demographic variables; Urb.: Urban-related variables; TR: TRansport-related variables; w/: with; w/o: without; HH: Household; PT: Public Transport; CEO: Chief Executive Officer; MRT: Mass Rapid Transit.
- Studies are sorted by year and then alphabetically by authors.

2.2.2 Factors influencing household car-ownership

In this section, the literature is reviewed to ascertain the suitability of Multinomial Logit (MNL) models and identify the factors influencing household car-ownership. Table 2.1 summarises the literature reviewed, including details such as the type of model studied, explanatory variables and their effects. Bhat & Pulugurta (1998) prove MNL models, based on random utility theory, to be more appropriate for studying car-ownership than Ordered Logit (OL) models. They also state that factors such as the number of adults in a household (particularly working adults) and the income level have positive effects on car-ownership, whereas living in urban areas has negative effects. The suitability of MNL models for car-ownership estimation is also concluded in Potoglou & Susilo (2008), wherein the performance of several model types (MNL, OL, and Multinomial Probit) are compared using datasets from North American, Asian, and European cities.

Multiple studies state that the accessibility to jobs and PT stations, the cost of different transportation alternatives, and the availability of company cars influence the car-ownership level of a household (Potoglou & Kanaroglou, 2008b; Ritter & Vance, 2013). Belonging to a racial minority and the "life cycle" status of the household (single/couple, with/without children, retired/working) are stated to be influential too (Potoglou & Susilo, 2008; Matas et al., 2009; Paredes et al., 2017). Similarly, higher education, ownership of one or more residences and the characteristics of built environment (land-use type, decreasing urban size and decreasing population density) increase the odds of owning a car (Matas et al., 2009; Cirillo & Liu, 2013; Liu & Cirillo, 2016; Soltani, 2017).

The possible effects of owning other types of vehicles (e.g., bicycles, motorcycles, and e-bikes) have been analysed in the literature, particularly in Asian cities (Sanko et al., 2009; Yamamoto, 2009; Ma et al., 2018). These observed effects may have a lesser impact in western countries, as there are important transport supply and cultural differences (Wong, 2013). Furthermore, the role of gender has been frequently studied. In most cases, males are observed to be linked to higher car-ownership levels (Matas & Raymond, 2008; Matas et al., 2009; Liu et al., 2014). However, this effect might be becoming less relevant (Sanko et al., 2009; Maltha et al., 2017).

Matas et al. (2009), Ritter & Vance (2013) and Maltha et al. (2017) state that variables such as income and age have a non-linear relationship with car-ownership (logarithmic and quadratic, respectively). Finally, alternatives to Discrete Choice Models (DCMs) have been explored to study car-ownership at the disaggregate level. For example, data mining methods such as decision trees, support vector machines or rough sets may outperform DCMs on prediction, but at the expense of poorer –if any– interpretability (Clark, 2009a,b; Paredes et al., 2017; Shao et al., 2022)).

2.2.3 Summary and research opportunities

Summing up, the following explanatory variables have been identified in the literature, which influences household car-ownership: (i) socio-demographic characteristics (e.g., age, life cycle status, employment, housing tenure, and type), (ii) urban characteristics (e.g., urbanisation density, land use), (iii) transport-related variables (e.g., PT supply, road infrastructure, availability of alternative vehicles), and (iv) others (vehicle price, policy regulations, petrol price). Furthermore, MNL models are more appropriate than OL models for studying household car-ownership.

The above analysis and the information in Tables 2.1 contribute to understanding the existing gaps in scientific research. To the best of the my knowledge, there is scarce research considering the effects of shared mobility supply on car-ownership. There are, however, available studies analysing the willingness to sell/replace/defer private cars among car-sharing users (Giesel & Nobis, 2016; Kim et al., 2019; Le Vine & Polak, 2019; Jochem et al., 2020; Zhou et al., 2020a). Although their outcomes cannot be directly extrapolated into the car-ownership models, they can be employed to validate the results.

The role of alternative transport modes is insufficiently studied in the existing literature, particularly the use and availability of bikes (including cargo bikes). Furthermore, a comprehensive comparison of the car-ownership characteristics across multiple cities from different countries is not yet performed. One of the secondary objectives of this dissertation is to close the aforementioned gaps, thus helping modellers and policymakers to estimate the household car-ownership more accurately and to devise policies to reduce private car-ownership and promote sustainable urban mobility.

2.3 Other topics

2.3.1 Transport modelling approaches for evaluating shared mobility services

Existing literature related to the modelling of shared mobility services generally demonstrates the use of agent- and activity-based approaches. For example, Martínez et al.

(2017) developed an agent-based model to simulate one-way car-sharing systems in Lisbon. They incorporated the operation side of the system in the agent-based model, along with a stochastic demand model. Similarly, Ciari et al. (2016) presented the use of MATSim (an activity-based multi-agent simulation system) for modelling car-sharing systems. In a subsequent study, Becker et al. (2020) use MATSim to conduct a joint simulation of bike-sharing, car-sharing, and ride-hailing services, focusing on the city of Zurich.

Another example for the use of agent-based approach is the application of the travel demand model MobiTopp by Heilig et al. (2015), for modelling round-trip and free-floating car-sharing systems. In a subsequent study, Wilkes et al. (2021) used the MobiTopp framework to evaluate ride-hailing services. MaaSSim (Kucharski & Cats, 2022) is a new agent-based simulation framework, which also focuses on the modelling of shared mobility services. Agent-based approaches are also employed to evaluate the impacts of e-scooter services (Tzouras et al., 2022). Besides the agent-based simulation frameworks, agent-based optimisation models are also observed in the literature for the evaluation of shared mobility services (e.g., Nourinejad & Roorda, 2016)

While the aforementioned studies focus on conventional shared mobility services, agent-based approaches are also used to model Shared Autonomous Vehicle (SAV) services (Narayanan et al., 2020b). For example, Gurumurthy et al. (2020) employ an agent-based approach (POLARIS simulation tool) for analyzing the supply and demand aspects of an SAV service. SAV services are also modelled using a combination of discrete event and agent-based simulation approaches (e.g., Jager et al., 2017). Agent-based tools, such as MATSim and MobiTopp, have also been extended to study the impacts of SAVs (e.g., Boesch & Ciari, 2015; Heilig et al., 2017; Zwick et al., 2021). Furthermore, Shen et al. (2018b) developed an agent-based supply-side simulation framework to study the integrated PT-SAV system. On a different note, Lokhandwala & Cai (2018) propose an agent-based framework to compare conventional and autonomous mobility services.

The agent-based approaches are seen as a natural way to model shared mobility, since they offer the possibility of a more realistic representation of the fleet operations of shared mobility services. However, many European cities continue to use the traditional strategic four-step modelling approach, due to multiple reasons, including but not limited to, insufficient data for advanced models, deficit of technical expertise and the convenience of simpler models (Givoni et al., 2016). Nevertheless, the desire for the extension of the existing strategic models, rather than switching to the agent-based approaches, have been confirmed by cities in H2020 MOMENTUM consortium (2020). Therefore, there is a need to extend the conventional four-step approach, to make it more suitable for modelling shared mobility services. Existing pertinent literature in this direction include Friedrich & Noekel (2017), Friedrich et al. (2018), and Zhao & Kockelman (2018).

Friedrich & Noekel (2017) focused on the integration of car-sharing systems into the four-step approach, by incorporating the system in the timetable-based PT assignment. This approach does not consider the operation side of the sharing system. In a subsequent research, Friedrich et al. (2018) developed a matching algorithm for ride-hailing, which could be integrated within the four-step approach. Demand is based on fixed shares. Thus, a realistic consideration of the mode choice is not implemented. In Zhao & Kockelman (2018), an SAV service is evaluated using a modified four-step approach. Modifications include the use of a multinomial logit model for trip distribution and the replacement of a nested multinomial logit model with a simple multinomial logit model for mode choice, along with some alterations in the model parameters. Similar to Friedrich & Noekel (2017), the operation side of the sharing system is not considered.

Summary and research opportunities Literature findings show that there is no substantial research on the integration of shared mobility services into the four-step approach. The existing ones focus on single type of shared systems (car-sharing or ride-hailing), without a comprehensive approach. In addition, to the best of my knowledge, bike-sharing systems and models for deriving relevant Key Performance Indicators (KPIs), such as car-ownership and induced demand, are not integrated into the four-step approach. Therefore, one of primary objectives of this dissertation is on closing these gaps in the existing literature.

2.3.2 Cargo cycle adoption

This section consists of literature findings concerning the (i) purchase of cargo cycles (as well as their usage) by commercial users and (ii) comparison of purchase intention and the actual purchase of market products. Since there is no substantial literature on the purchase decision of cargo cycles, factors that affect the willingness-to-use will also be explored, with an assumption that such factors could also have an influence on the purchase decision.

Narayanan & Antoniou (2022a) reviewed the existing literature on cargo cycles and categorised the factors influencing cargo cycle adoption into six groups, namely vehicular, infrastructural, workforce, organisation, policy and operational factors. Thoma & Gruber (2020) enlist different LVs that could potentially influence the adoption. The enlisted LVs include vehicle limitations, soft benefits, worries and perils, cost benefits, urban advantages, riders' concerns, and infrastructure constraints. Heinrich et al. (2016) state that technical deficits have a decisive impact on the user acceptance of cargo cycles. Hence, adequate cargo cycle models are required to lower the technology failure likelihood. Utilisation of cargo cycles could affect the workplace dynamics, especially for the organisations that previously relied more on cars or vans (Faxér et al., 2018). Therefore, there could be a delay in the planning phase, discouraging the use of cargo cycles. For people to change, incentives are required. Furthermore, the following are found to influence cargo cycle penetration: lack of over-night storage facilities, cargo cycle design and the necessity to share the road with automobiles. Similarly, Nürnberg (2019) states that the vehicle specifications (e.g., suitable construction types) and local policy decisions (e.g., provision of better cycling infrastructure and public presentation of the cargo cycle benefits) could affect the introduction of cargo cycles into a city's logistics system.

Based on a survey, the perception of bike and car messengers on electric cargo bikes and the factors driving the willingness-to-use them are analysed in Gruber et al. (2014). The authors conclude that the critical factors for the implementation of electric cargo bikes include electric range, purchase cost and publicly available information. In another related study (Gruber et al., 2013), the bike and car messengers are found to state an improvement in their jobs' image and a better possibility to have on-the-job exercise (soft benefits), when electric cargo cycles are utilised. Also, the messengers are found to be in support for the use of innovative technology. Payload capacity of cargo cycles are stated to be sufficient. In Choubassi et al. (2016), application of cargo cycles in regions with high population density (e.g., city centre), provision of a dedicated right-of-way for them, policies that discourage the use of trucks and motorised vehicles, and monetary incentives to shift to cargo cycles are stated to be the contributing factors for cargo cycle use.

Concerning the comparison of purchase intention with the actual purchase decision, such a comparison for commercial decision-making (B2B) with respect to transport vehicles does not exist in literature, to the best of my knowledge. Hence, findings from B2C market research are summarised here. One of the earliest studies on the comparison between purchase intention and the actual purchase comes from 1959 (Namias, 1959). The study states that even if a research correctly ascertains a consumer's purchase intentions at any given time, unforeseeable events, spontaneous and external, may intervene and change those intentions. However, purchase intention is stated as a best predictor of actual purchase in Peter & Olson (2010). Interestingly, the literature review of Morwitz (2012) concludes that the purchase intention is correlated with the actual purchase, and predict future sales, but does so imperfectly. Concerning automobile market, purchase intention and the actual purchase decision for automobiles and household appliances are compared in Morrison (1979). The study suggests that the automobile purchase intention is more correlated with the actual purchase decision, when compared to the purchase intention of household appliances. Nevertheless, there is a clear difference between purchase intention and the actual purchase for both the products.

Summary and research opportunities Literature findings show that the adoption of cargo cycles as well as its use could be affected by a range of factors, including LVs. However, identifying and quantifying the factors that significantly influence the actual purchase decision is yet to be carried out. Furthermore, there is no existing research, which compares the factors that influence the purchase intention and the actual purchase. Such a comparison is necessary, as the literature from the B2C market research point towards the difference in factors influencing them. Therefore, one of the tertiary objectives of this dissertation is to close these gaps in the literature. Based on the literature findings, the major factors that should be explored for the purchase decision include organisational characteristics (i.e., location, work place dynamics, attitude towards technology and innovation, and provision of over-night facilities), vehicle characteristics (i.e., construction types and battery range), benefits (operational, soft and costs benefits) and issues associated with cargo cycles, and local transport policy (i.e., infrastructure, incentives and public promotion of the benefits). Apart from the aforementioned factors, this dissertation will also analyse the influence of other organisational characteristics such as business sector, fleet decision-making process (Nesbitt & Sperling, 2001) and fleet size currently utilised.

2.3.3 Modelling and impacts of dedicated bus lanes

A common strategy to improve bus operations is to dedicate a lane for bus use. The initial studies towards this direction involve the exploration of their impact as part of Bus Rapid Transit (BRT) operations. For example, Abdelghany et al. (2007) developed a dynamic traffic assignment-simulation modelling framework (DYNASMART-P) for evaluating BRT operations and service planning. They conduct a set of simulation experiments using the developed model, to study the impact of introducing a hypothetical service in the Knoxville area in Tennessee (USA). They found out that the provision of dedicated bus lanes reduces the average bus travel time by more than 60%. This improvement in the bus travel times, in turn, leads to increase in bus use (around 16% or 1.5 percentage points). Nevertheless, the results from the study also show that the allocation of one of the existing lanes as a dedicated bus lane leads to a greater congestion for the car users (increase by about 17%). A similar finding is also observed in Arasan & Vedagiri (2010), wherein a heterogeneous traffic microsimulation model (HETEROSIM) is utilised to study the possible impacts of dedicated bus lanes on the major roads of Chennai city (India). The results from the study show that the travel time reduction due to dedicated lanes is around 70%, and for other personal vehicles (e.g., cars), there is an increase in travel time varying between 3% and 8%.

Surprenant-Legault & El-Geneidy (2011) investigate the impact of dedicated bus lanes on the running times and on-time performance of two parallel bus routes in Montreal (Canada). They use automatic vehicle location and automatic passenger count data to build statistical models (linear regression for running time and binary logit for on-time performance) and conclude that dedicated bus lanes yield running time savings of 1.3% to 2.2%. Furthermore, such lanes lead to a decrease in the odds of being late by around 65%. In a subsequent study, Diab & El-Geneidy (2012) evaluate the impacts of implementing a combination of strategies, designed to improve the bus transit service. They also conclude that strategies, such as the dedicated bus lanes, lead to a decline in running time. In another study, Alam et al. (2014) analyse the impact on emissions along a busy corridor in Montreal, using data collected on-board for instantaneous speeds and stop-level ridership. The dedicated bus lanes are found to reduce bus emissions [greenhouse gases, Particulate Matter $(PM)_{2.5}$, Carbon monoxide (CO) and Nitrogen oxides (NOx)] by 14% to 18% and decrease average travel time by 2%.

Truong et al. (2015) assess the operational effects of bus lane combinations, to ascertain whether multiple bus lane sections create a multiplier effect. They perform their assessment using Vissim traffic mico-simulation tool, on a hypothetical 5.5 km-long main arterial and five intersections with minor roads, which resembles the typical suburban conditions of Melbourne (Australia) . The results from their study confirms the presence of a multiplier effect, i.e., bus travel time benefits are proportional to the number of links with a bus lane with a linear return to scale. However, there is an increase in the travel times for other traffic (of the order of 0.6% to 3.2%). A network wide scale, rather than a local scale, for dedicated bus lane provision is recommended to obtain a net positive result. Furthermore, it is possible to achieve a net benefit, in terms of total travel time, by implementing dedicated bus lanes at strategic locations. For an undersaturated demand condition in the network, it is preferable to implement bus lanes on all bus routes (Bayrak & Guler, 2021). Bayrak & Guler (2021) utilised a bi-level optimisation algorithm to determine the locations for dedicated bus lanes on a network. Their result is based on the application of this algorithm in a symmetrical grid test network with 133 nodes and 420 links. Similarly, Tsitsokas et al. (2021) formulate a combinatorial optimisation problem for dedicated bus lane allocation, in order to maximise traffic performance of an urban network, while balancing the trade-off between bus priority and regular traffic disturbance. They propose a framework based on a link-level dynamic traffic modelling paradigm. Application of this framework to a part of the traffic network of San Francisco (USA) central area shows that it is possible to improve travel time for both car and bus users, when the implementation of the dedicated bus lanes are optimised.

While the aforementioned studies focus mainly on time-related aspects, Currie & Delbosc (2011) explore the impact of service levels and the design of BRT on ridership. They employ a series of regression models estimated using data corresponding to BRT and non-BRT bus routes in Australia. Their results show that the boardings per vehicle kilometre increases significantly with higher proportion of dedicated bus lanes in the bus route. Similarly, Ben-Dor et al. (2018) evaluate the impact of dedicated bus lanes on the modal split for PT, using MATSim (an agent-based modelling framework). They performed their evaluation using Sioux Falls network. They conclude that dedicated bus lanes make PT characteristics during the peak hours similar to those during the off-peak hours. The results from the study show that around 18% modal shift occurs from car to PT during peak hours, due to bus lane implementation. Focusing on both time-related and ridership aspects, Russo et al. (2022) conclude that dedicated lanes reduce bus travel time by about 18% and rise the number of bus users by 26%. They use analytical equations and empirical data (data from loop detectors and bus micro-data) from Rome (Italy). Furthermore, they assume motor-vehicle and bus travel as substitutes and a value of -2.2 for the elasticity of bus demand with respect to the price of bus travel.

Summary and research opportunities Studies focusing on dedicated bus lanes have been in existence for more than a decade. Nevertheless, the topic continues to enjoy prominence among policymakers and is still evolving in the research world. The findings from the reviewed studies reveal that the provision of dedicated bus lanes has a positive impact on time-related aspects (e.g., passenger travel times, bus delays and reliability), emissions and PT ridership. However, the positive impacts also depend on the locations of the bus lanes. Therefore, it is necessary to evaluate the introduction of such lanes in cities to ensure intended impacts. Furthermore, the majority of the existing studies focus on time-related impacts and the ones focusing on PT ridership and emissions are very limited. To the best of my knowledge, the evaluation of their impact on the overall modal split in a real city network is still missing in the literature. In addition, complex microscopic or agent-based models are generally used to evaluate the bus lanes and their assessment using aggregate four-step modelling approach, which the majority of the cities in the world continue to use, is not yet seen in the literature. Therefore, as part of one of the primary objectives of this dissertation (i.e., the Regensburg case study), a methodology to model dedicated bus lanes using aggregate four-step modelling approach will be framed and their implementation in Regensburg will be investigated, in terms of emissions and modal split.

2.3.4 Modelling and impacts of autonomous shuttles

Deployment of AVs for first- and last-mile services (i.e., integration of AVs with PT in the form of autonomous shuttles) can contribute to the sustainability of transportation systems (International Association of Public Transport, 2017). However, the majority of the existing studies related to AVs focus on evaluating them as independent systems (Narayanan et al., 2020b), e.g., private AVs or SAV services as a competition to PT services. Narayanan et al. (2020a) conclude that policymakers should plan proactively to integrate AVs with PT to avoid mode shifts. Consequently, the trend has been changing and the cities around the world have began to test autonomous shuttles in pilot projects to reinforce PT in their cities. For example, as of 2021, 25 countries around the world have bought more than 200 autonomous shuttles from Navya, a French company specialised in the design of such vehicles (Navya, 2022).

Although pilots with autonomous services for PT first- and last-mile are on the rise, studies pertaining to the impacts of such systems are still limited. Moorthy et al. (2017) assess the energy consumption and emissions for an integrated PT-SAV system, using life cycle assessment model. They focus on the provision of last-mile transit service between Ann Arbor and Detroit Wayne County Airport. They conclude that the SAV service decreases energy consumption and emissions. Recently, Huber et al. (2022) conducted an environmental life cycle assessment of electric automated shuttles and stated that the application of shuttles could lead to a reduction in environmental impacts. Shen et al. (2018a) analyse the effects of introducing SAV services for first-mile connectivity to train stations, during morning peak hours in Tampines area of Singapore. They use smart card data and AnyLogic simulation tool, and consider replacing bus systems in low-demand routes. They found out that the integrated PT-SAV system can reduce total vehicle miles travelled.

Salazar et al. (2018) develop a multi-commodity network flow (mesoscopic) optimisation model to explore the interaction between coordinated SAV and PT services. Electric SAVs are coupled with PT system and a congestion pricing scheme is designed to achieve maximum social welfare. They conclude that the integrated system investigated in their study can reduce traffic, emissions and transport cost of individuals. Pinto et al. (2019) propose a joint transit network redesign and fleet size determination problem. They implement a heuristic solution procedure to solve this problem, which consists of a non-linear programming solver and an iterative agent-based simulation approach. The results from their study indicate significant traveller benefits, in terms of improved average waiting times. A similar observation is also seen in Scheltes & de Almeida Correia (2017), wherein an agent-based simulation model has been developed and applied to a case-study on the connection between the train station Delft Zuid and the Technological Innovation Campus (Delft, Netherlands). Likewise, Gasper et al. (2018) conclude an improvement in the travel time in morning and evening hours, when an autonomous shuttle system is used for the last-mile in the research campus of the Robert Bosch GmbH in Renningen (Germany). They perform their investigation in SUMO.

Chee et al. (2020) examine the determinants of intention-to-use a first- and last-mile autonomous shuttle service, based on a survey during a trial operation in Stockholm (Sweden). They employ structural equation modelling in their study and conclude that the intention-to-use the service greatly increase, when the service frequency is comparable to the service frequency of a regular public bus service. Kassens-Noor et al. (2020) examine the views of public transit riders on the willingness to use autonomous shuttles. They conduct two surveys in Michigan and found out that a significant number of public transit riders are hesitant to ride in autonomous shuttles, because of concerns over safety and distrust in technology. A similar conclusion is also observed in Yap et al. (2016). However, recently, Beauchamp et al. (2022) observed that automated shuttles have safer interactions with lower speeds and higher time to collision. They base their study on the user trajectories obtained using video analysis of road users and automated shuttles that circulated in Montreal and Candiac (Canada). Multivariate regression is used to identify the relationship between the safety indicators and various factors analysed in their study.

While the studies pertaining to the impacts of PT-SAV systems are limited, studies that focus on the change in overall modal share for PT due to autonomous shuttles are scarcer. An example in this regard is Thorhauge et al. (2022), who build stated choice experiments to assess user preferences using mixed logit models. They conclude that almost no effect on the overall modal share is observed and autonomous driving technologies will have a limited effect for the entire trip chain. However, they also observe that the shuttle service has the potential to improve first- and last-mile services for PT. It should be noted that their results are based on a case study on the campus of Technical University of Denmark and scaling the service to a larger area may have a significant impact on the overall modal share. Supporting this notion, the simulations from Huang et al. (2021) show an increase of around 3.7% in transit use, when SAVs are coupled with real-time ride-sharing to and from transit stations. They use SUMO toolkit to examine the modal split, by simulating SAVs providing service to 10% of central Austin's tripmakers near five light-rail transit stations. Similarly, Lau & Susilawati (2021) observe a 3% increase in PT usage during the morning peak hour, because of the introduction of SAVs for first- and last-mile connectivity in Kuala Lumpur (Malaysia). The evaluation is conducted using a mesoscopic simulation model.

Summary and research opportunities Existing studies show significant advantages of introducing autonomous shuttles for first- and last-mile connectivity. Nevertheless, the literature on the evaluation of their integration with PT is sparse. Furthermore, to the best of my knowledge, modelling of autonomous shuttles (for the first- and last-mile of PT trips) using traditional aggregate four-step modelling approach is still missing in the literature. Therefore, as part of one of the primary objectives of this dissertation (i.e., the Regensburg case), a simplified and pragmatic approach for evaluating autonomous shuttles using aggregate four-step modelling approach will be developed and the impact of such a service in Regensburg will be investigated.

3 Datasets and descriptive statistics

Contents

3.1 Regensburg

3.1.1 Details about the datasets

The research sample from the city of Regensburg consists of a household travel survey and two car-sharing operator datasets, namely demand and supply. These were obtained through EU H2020 project "MOMENTUM"[1]. Besides these datasets, the supply data for the (planned) bike-sharing service, the locations of the dedicated bus lanes and the supply information for the autonomous shuttle service are also available.

3.1.1.1 Household survey

The survey is part of the eleventh edition in a series of household surveys that began in 1972 (Mobility in cities - SrV), wherein the traffic behaviour in selected cities and regions of the Federal Republic of Germany is studied. In Regensburg, the recent survey has been conducted between February 2018 and January 2019. For this study, the Regensburg urban area is divided into five sub-areas: centre, north, south, east and west. The dataset contains information, such as household and individual socio-demographic characteristics, along with mobility-related aspects (e.g., frequency of use of conventional modes and car-sharing), for a sample of 2,501 individuals from 1,116 households. After removing records with incomplete data, a total of 2,086 individuals are present in the sample.

With regards to the frequency of use of different transport modes, the following answers are possible: daily or almost daily, 3 to 4 days per week, 1 to 2 days per week, 1 to 3 days per month, 1 or 2 days per quarter, rare and never. For the car-sharing service, the categories "daily or almost daily" and "3 to 4 days per week" have only 0 and 1 samples, respectively, which is expected because of the small-scale of operation of the car-sharing service in Regensburg. Therefore, those two categories are discarded.

3.1.1.2 Car-sharing operator dataset

The supply dataset from the service operator contains details, such as the car-sharing station address (8 stations with 1 to 2 vehicles per station), latitude and longitude coordinates, start date of the station and vehicle model available in the station. The demand dataset consists of information related to all the trips performed using the small-scale round-trip station-based car-sharing service, between November 2016 to November 2019. The data is extracted from the operating tool used for providing the customer service and for tracking the vehicles. Details in the dataset include booking start and end date, booking start and end time, pick up and return station (same value because of round-trip system), vehicle make and model, distance travelled during the booking and finally, booking type (i.e., user booking or service trip). For the current analysis, only the user trips are considered from the demand data. Similarly, records with missing and

[1] https://h2020-momentum.eu

inappropriate values are discarded. After the initial processing, the dataset consists of details for 8,567 trips.

3.1.1.3 Other available information

A one-way station-based bike-sharing system is planned to be initiated with around 500 bicycles. The supply dataset of the bike-sharing service includes details, such as the station location (latitude and longitude coordinates) and the number of bikes planned per station. With regards to the dedicated bus lanes, the city is planning to introduce them in around 70 links, and the available data for this is a shape file containing their locations. Concerning the autonomous shuttle, the service has been implemented under a pilot scheme, as a feeder/collector service to the PT system. The autonomous shuttle line is a 1.3 kilometre circuit around an industrial park, located within a single Transport Analysis Zone (TAZ). The shuttle has a capacity of 6 people and runs with a headway of 10 minutes and average speed of 15 kmph.

3.1.2 Descriptive statistics

The descriptive statistics of the relevant variables from the household survey and the operator data are provided in this section and summarised in Table 3.1 and Figures 3.1 - 3.3. Starting with the household-related variables, as shown in Table 3.1, around 72% of the households in Regensburg have up to two members. Regarding income, a range of values is observed, with around 14% of the households having a monthly income of less than €1500 and 27% having more than €4600. When it comes to vehicle ownership, most households own one private car (around 59%). About 19% of the households have no car, while 22% of the households own multiple cars. On a different note, 64% of the households possess multiple bikes. Observing the statistics for the total number of trips per day, the mean value per household is 7.4.

Looking at the socio-demographic variables of the individuals in the sample, males and females are almost equally represented (though the share of females is slightly higher), which is true in the case of Regensburg population. The survey participants include students (around 21%), employed professionals (47%) and retired individuals (18%). Around 14% of the sample belong to the 'other' employment category (e.g., homemaker). Concerning the age distribution, all age groups are sufficiently represented, with the mean age being 41. There is also a significant representation of individuals with some form of mobility restriction (7%). When it comes to education, around 38% of the sample have an education level lower than vocational training. Conversely, around 12% of the sample have a vocational degree and 51% have a university degree.

With regards to the frequency of use of transport modes, most participants often (daily and frequent) use private cars (80%), while only 4% never use private car. Naturally, the share of license holders is high (93%). Bicycles are also often used (61%). By comparison, fewer individuals use PT often (30%) and around 25% own a PT ticket. For both bicycles and PT, a significant number of non-users are found (16% and 18%, respectively). Regarding the frequency of car-sharing use, given the small scale of operation, the majority of participants (94%) have never used the service. The average number of trips per person per day (mobility rate) is 3.3, which is representative for the Regensburg population.

The average daily demand for the entire car-sharing service is 8 and the maximum value observed is 30. A negative exponential distribution is observed for the trip distance (Figure 3.1), with around 60% of the trips being conducted for a distance of up to 20 km. The characterisation of the trip distances is based on the travel distance recorded in the operator dataset. This distance includes the whole round-trip. For characterisation, it is assumed that the destination is at a distance equal to half the kilometres recorded in the dataset, since the trips have the same pick-up and return station. This can lead to some bias, but given that there is no other information available, I believe that it is the best approach to characterise the trip distance.

With respect to the trip departure times, a bimodal distribution is seen (Figure 3.2), with crowns around the usual traffic peak hours. However, the arrival times show a unimodal distribution (Figure 3.3), with peaks during the late evening. Nevertheless, both of these distributions show that the car-sharing service is utilised during the usual peak hours, as well as beyond those hours. Especially, a significant use is also observed during the night times. Concerning the bike-sharing service, a total of 48 stations are planned. The number of bikes per station ranges between 6 and 30, with an average value of 10.

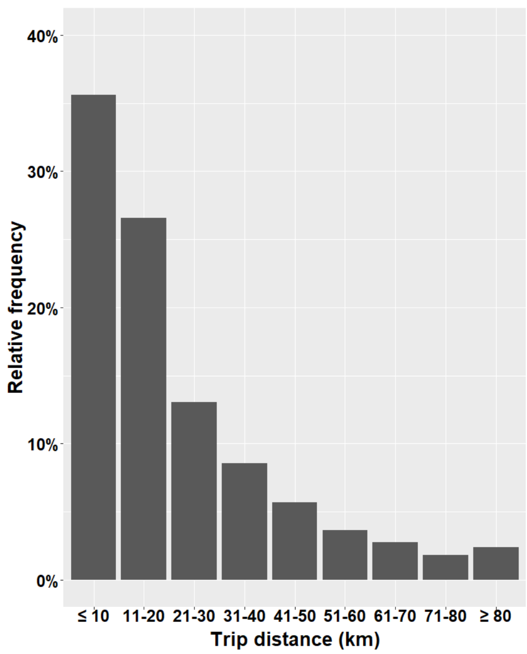


Figure 3.1: Car-sharing system in Regensburg - Distribution of trip distance

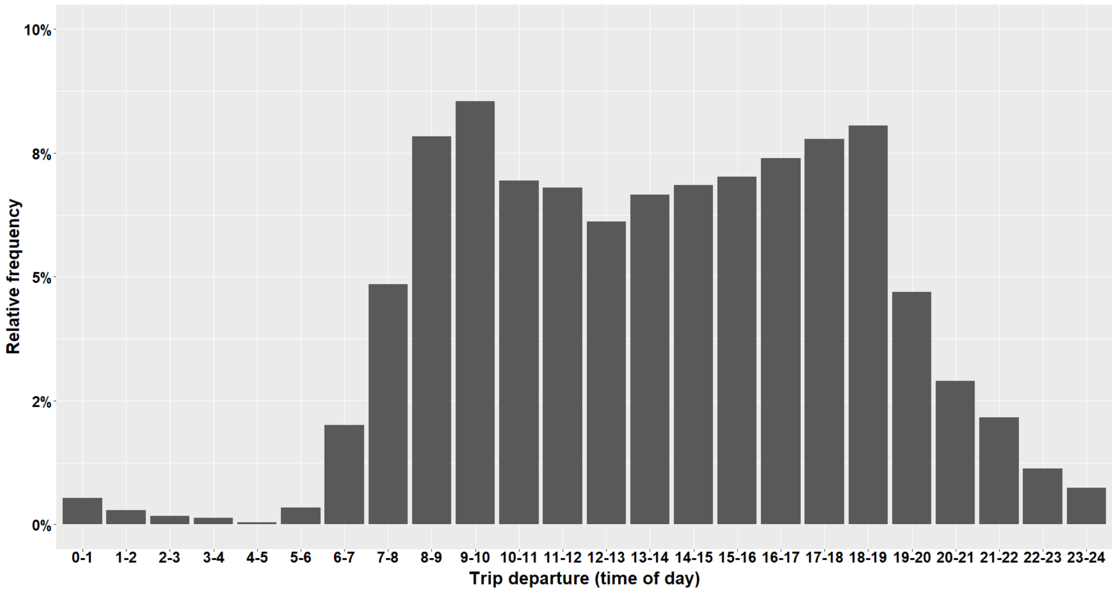


Figure 3.2: Car-sharing system in Regensburg - Distribution of departure times

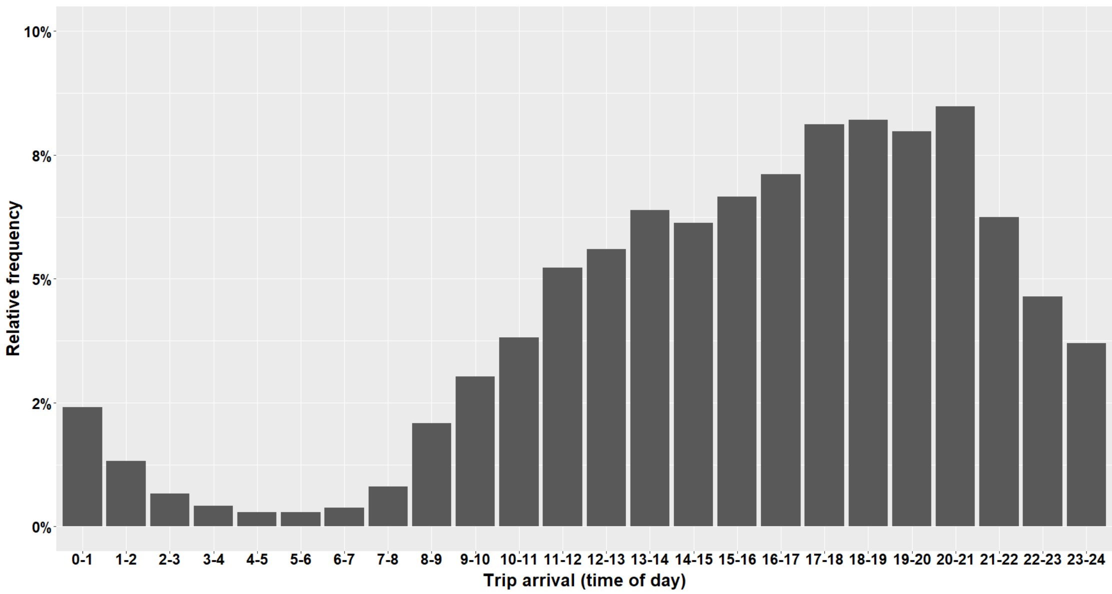


Figure 3.3: Car-sharing system in Regensburg - Distribution of arrival times

Table 3.1: Summary of Regensburg sample characteristics

HH-related variables					
HH monthly income (€)	<900	6.6%	HH Size	1	28.6%
	900-1500	7.8%		2	43.1%
	1500-2000	12.4%		3	12.4%
	2000-2600	11.0%		4	11.3%
	2600-3000	9.1%		5+	4.6%
	3000-3600	12.1%	Yearly mileage for private cars	Min	0
	3600-4600	14.4%		Mean	15,100
	4600-5600	12.5%		Median	11,000
	>5600	14.1%		Max	100,000
HH private cars	0	18.6%	HH bikes	0	13.0%
	1	58.8%		1	23.4%
	2	18.7%		2	27.3%
	3	3.2%		3	13.2%
	4+	0.7%		4+	22.5%
Total trips per day in the household	Min	0			
	Mean	7.4			
	Median	6			
	Max	41			
Individual-specific factors					
Gender	Male	49.7%	Employment	Student	20.5%
	Female	50.3%		Employed (half, full)	47.1%
Mobility restriction	Yes	6.6%		Retired	18.1%
	No	93.4%		Other	14.3%
Age (years)	Min	0	Education	Less than vocational training	37.7%
	Mean	41			
	Median	41		Vocational training	11.6%
	Max	97		University degree	50.7%
PT use frequency	Daily	11.5%	Private car use frequency	Daily	33.6%
	Frequent	18.1%		Frequent	46.5%
	Occasional	36.0%		Occasional	14.0%
	Rare	16.5%		Rare	2.2%
	Never	17.9%		Never	3.7%
Bicycle use frequency	Daily	29.1%	Car license	Yes	93.1%
	Frequent	32.2%			
	Occasional	16.1%		No	6.9%
	Rare	6.9%	PT ticket	Yes	25.2%
	Never	15.7%		No	74.8%
Trips per day (mobility rate)	Min	0	Car-sharing use frequency	Frequent	0%
	Mean	3.3		Occasional	3.2%
	Median	3.0		Rare	3.3%
	Max	13.0		Never	93.5%
Regensburg characteristics					
Average daily demand for the car-sharing service	Min	0	Shared cars per traffic district	Min	1
	Mean	8		Mean	2
	Median	6		Median	1
	Max	30		Max	5

Note:

- Employed - Half: 18 to 34 hr/week, Full: ≥35hr/week
- Use frequency - Frequent: 1 to 4 times per week; Occasional: between 3 times per month and once per quarter; Rare: less common

3.2 Madrid

3.2.1 Details about the datasets

The research sample from the city of Madrid mainly consists of a household travel survey. This was also obtained through EU H2020 project "MOMENTUM". Besides, bike-sharing supply, household income and public parking supply data are also available. While the bike-sharing supply data is from MOMENTUM, the other two data are collected from external sources.

The household survey was carried out by the Madrid regional government between February 2018 and June 2018. The dataset is available online as an open-source dataset and the reader is referred to https://datos.crtm.es for more information. The dataset is designed to understand the daily travel habits and patterns. It contains information, such as household and individual socio-demographic characteristics, along with mobility-related aspects (e.g., mode choice and trip characteristics), for a sample of 85,064 individuals from 58,490 households.

The bike-sharing supply data consists of the station location and the number of docks per station in 2019 and is compiled by the operator of the service, Empresa Municipal de Transportes de Madrid. It is available online at https://opendata.emtmadrid.es. The household income data is available only at the yearly temporal granularity, and furthermore, averaged at the spatial granularity of census tracts. The dataset results from a collaboration between National Statistics Institute of Spain and the Spanish Tax Agency. The data corresponds to 2018 and it can be accessed at https://www.ine.es. The public parking supply data is obtained from the municipality's open data platform (https://www.madrid.es).

3.2.2 Descriptive statistics

The descriptive statistics of the relevant variables is summarised in Table 3.2. Starting with the household related variables, there is a good representation of the different household sizes, with 11% for the smallest household size group and 9% for the largest group. With regards to car-ownership, 18% of the sample have no private car, while the usual major groups (i.e., ownership of one and two cars) account for 44% and 31% of the research sample. There also exists a sizeable amount (7%) with three or more cars. The minimum value for the household yearly income (based on the average per census tract) is €23,510, the maximum is €133,380, and the mean value is €52,560. Observing the statistics for the total number of trips per day, there are households with zero trips per day, whereas the maximum value in the sample is 38. The mean number of trips per day per household is around 4.

Looking at the individual specific variables, the number of females (54%) is higher than the number of males (46%), which is the actual case in the city of Madrid. 44% of the research sample possess a PT pass, while 56% do not. Similarly, 38% of the sample do not own a car driver license, while 62% own one. Concerning the distribution of age, all age groups are sufficiently represented, with a mean value of around 45.

Table 3.2: Summary of Madrid sample characteristics

Household related variables					
HH size	1	11.2%	HH car ownership	0	17.9%
	2	29.5%		1	43.8%
	3	24.6%		2	31.1%
	4	26.1%		3	5.9%
	5 or higher	8.6%		4 or greater	1.3%
Total trips per day in the household	Min	0	HH yearly income (€)	Min	23,510
	Mean	3.8		Mean	52,560
	Median	3		Median	44,571
	Max	38		Max	133,380
Individual specific factors					
Gender	Male	45.9%	Possession of PT pass	Yes	43.8%
	Female	54.1%		No	56.2%
Age (years)	Min	4	Trips per day (mobility rate)	Min	0
	Mean	45.3		Mean	1.7
	Median	48		Median	1.5
	Max	106		Max	15
Education	Less than vocational training	62.3%	Employment	Student	20.6%
				Employed	44.6%
	Vocational degree	9.4%		Retired	20.1%
	University or higher	28.3%		Other	14.7%
Car license	Yes	61.7%	Mobility restriction	Yes	4.8%
	No	38.3%		No	95.2%
Trip characteristics					
Trip distance	Short (≤2 km)	46.8%	Total travel time	Short (≤30 min)	76.7%
	Medium (2 to 5 km)	18.5%		Long (>30 min)	23.3%
	Long (>5 km)	34.7% (21.7% between 5 and 15 km)			
Madrid characteristics					
Population density (inhab./hectare)	Min	0.2	Bike-sharing units per TAZ	Min	0
	Mean	206.5		Mean	12
	Median	203.0		Median	0
	Max	447.5		Max	174
Public parking availability in TAZ	Yes	38.7%			
	No	61.3%			

Note:

- Yearly income: based on the average income value of census tracts

When it comes to education, 62% of the sample have education up to post-secondary education. On the other hand, around 38% of the sample have a vocational or university degree. The survey participants include students (21%), employed professionals (45%) and retired individuals (20%). 15% of the sample belong to 'other' employment category (e.g., unpaid domestic work). Around 5% of the survey respondents have some form of mobility restriction. Observing the number of trips per individual (mobility rate), the mean value is around 2, while the minimum and maximum values are 0 and 15.

With respect to trip characteristics, 47% of the trips recorded fall under short distance range, while 19% belong to medium and 35% to long distance ranges. Within the long distance group (>5 km), 22% belong to the distance range of 5 to 15 km. Finally, in terms of travel time, 77% of the trips are short trips (total travel time $\leq$ 30 minutes) and 23% are long trips (total travel time $>$ 30 minutes). The population density in the transport zones in Madrid ranges between 0.2 and 447.5 inhabitants per hectare and public parking is available in 39% of the transport zones. Finally, the bike-sharing supply per transport zone ranges between 0 and 174 bicycles, with a mean value of 12.

3.3 Leuven

3.3.1 Details about the datasets

The research sample from the city of Leuven consists of household travel survey (Stadsmonitor) and car-sharing supply datasets. These were also obtained through EU H2020 project "MOMENTUM". The Stadsmonitor (City Monitor) survey provides disaggregated socio-demographic information and transport demand data for a sample of 2,669 individuals. This survey was carried out in 2017 in the region of Flanders and the dataset contains details such as socio-demographic characteristics and mobility patterns. The dataset and its details are available at https://gemeente-stadsmonitor.vlaanderen.be.

The car-sharing supply data is available for the years 2017 and 2019. While the 2019 dataset includes the number of available car-sharing vehicles in the 8 districts of Leuven, no district-level data is available for 2017 (the year in which the City Monitor survey was conducted). The 2017 dataset contains only the aggregate number of car-sharing vehicles for the city. Hence, considering the spatial distributions of vehicles in 2019, i.e., the number of car-sharing vehicles per district in relation to the total number of car-sharing vehicles in Leuven, the number of car-sharing vehicles per district in 2017 is determined.

3.3.2 Descriptive statistics

The descriptive statistics of the relevant variables is summarised in Table 3.3. Starting with the household-related variables, there is a good representation of different household sizes, with around 55% of the households having up to two members. Regarding the household income, a range of values is observed, with around 14% of the households having a monthly income lower than €1500 and 26% having more than €4000. When it comes to vehicle-ownership, many of them own one private car (around 54%). Conversely, 80% of households own at least one bike and 5% have at least one cargo bike.

Table 3.3: Summary of Leuven sample characteristics

HH-related variables					
HH monthly income (€)	<1500	14.1%	HH size	1	22.2%
	1500-2500	28.2%		2	32.3%
	2500-4000	32.1%		3	16.6%
	4000-6000	20.0%		4	15.9%
	>6000	5.6%		5+	13.0%
HH private cars	0	20.2%	HH bikes	0	21.1%
	1	54.2%		1	19.2%
	2	21.5%		2	24.1%
	3	3.4%		3	11.1%
	4+	0.4%		4+	24.5%
HH cargo bikes	0	95.0%	HH car-sharing subscriptions	0	95.8%
	1	4.7%		1	3.5%
	2+	0.3%		2+	0.7%
HH PT ticket	0	44.6%			
	1	32.9%			
	2+	22.5%			
Individual-specific factors					
Belgian nationality	Yes	89.3%	Gender	Male	47.1%
	No	10.7%		Female	52.9%
Employment	Student	7.3%	Education	Less than vocational training	15.8%
	Employed	59.4%			
	Retired	23.8%		Vocational training	21.0%
	Other	9.5%		University	63.2%
Age	<25	7.6%	Commute distance to work/study (km)	min	0.1
	25-44	36.2%		mean	17.8
	45-65	31.1%		median	8.0
	65+	25.1%		max	250.0
Drives car to work	always	26.5%	Drives car to leisure activities	always	17.1%
	often	8.9%		often	29.8%
	occasionally	7.9%		occasionally	19.3%
	rarely	12.2%		rarely	7.5%
	never	44.5%		never	26.3%
Commutes by bus to work	always	9.8%	Commutes by bus to leisure activities	always	9.7%
	often	4.5%		often	17.3%
	occasionally	7.9%		occasionally	24.3%
	rarely	14.4%		rarely	28.6%
	never	63.4%		never	20.1%
Commutes by train to work	always	15.9%	Commutes by train to leisure activities	always	4.0%
	often	3.2%		often	11.2%
	occasionally	4.6%		occasionally	32.9%
	rarely	6.4%		rarely	33.0%
	never	69.9%		never	18.9%
Rides bicycle to work	always	35.0%	Rides bicycle to leisure activities	always	27.8%
	often	9.5%		often	25.6%
	occasionally	8.0%		occasionally	14.8%
	rarely	7.9%		rarely	9.1%
	never	39.6%		never	22.7%
Leuven characteristics					
Car-sharing vehicles in district	min	7			
	mean	14			
	median	15			
	max	18			

Looking at the socio-demographic variables of the individuals, similar to Regensburg and Madrid, the share of females is higher. The survey participants include students (around 7%), employed professionals (59%) and retired individuals (24%). Around 10% of the sample belong to the 'other' employment category (e.g., homemaker). Concerning the age distribution, unlike the survey sample in Regensburg and Madrid, the Leuven sample has a categorical variable for age. Nevertheless, all the age groups are sufficiently represented. When it comes to education, around 16% of the sample have an education level lower than vocational training. Conversely, around 21% of the sample have a vocational degree and 63% have a university degree. The share of households with no public transport ticket is 45%, while households with single and multiple public transport tickets account for 33% and 22%, respectively. For both bicycles and PT, a significant number of non-users are found (16% and 18%, respectively).

With regards to the frequency of use of transport modes, when focusing on the trips to work, the highest regular use (i.e, always) is found for bicycle (35%), followed by private car (around 27%). A significant share of the survey participants also use PT (bus and train) regularly for commuting. Conversely, around 40% of the individuals do not use bicycle for commuting and 45% do not use private car. However, a higher share of non-users is found for PT modes (greater than 60%). When focusing on leisure trips, a similar trend is observed. Bicycle (28%) and private car (17%) top the list for regular use compared to PT, although the numbers are less than the values of commuting trips. A significant difference is observed for non-users. Around 20% of the survey participants do not use buses and 19% do not use trains, which is lesser when compared to the non-users of these modes for commuting trips. Finally, the car-sharing supply per traffic district ranges between 7 and 18 vehicles, with a mean value of 14.

3.4 Alexandroupolis - Dataset & descriptive statistics

The research sample from the city of Alexandroupolis is a stated preference survey data. This was obtained through EU H2020 project "IRIS"[2]. The survey was conducted online in 2020. Each survey respondent is provided with six or seven different scenarios (with different travel times and costs), in order to quantify their intention to switch from their existing mode to a bike-sharing service. A subsample of private car users from the aforementioned survey is used in this dissertation.

After cleaning the dataset for missing and inappropriate values, the research sample consists of a total of 55 participants and 385 responses for the mode choice between private car and bike-sharing service. Table 3.4 summarises the descriptive statistics of the research sample. In this research sample, 44% of the respondents are female and 56% are male, with 7% of the households having a monthly income between 0 and 400 Euros, 11% between 401-800 Euros, 27% between 801-1200 Euros, 26% between 1201-1600 Euros, 11% between 1601-2000 Euros and 18% over 2000 Euros per month. The distribution of the participants' age is as follows: 2% of the participants belong to the

[2] https://www.iris-h2020.eu

age group 18-24, 45% belong to the group 25-39, 44% belong to the group 40-54, 7% belong to the group 55-64 and 2% are over 64 years old. Regarding the employment status, 31% of the participants are self-employed, 24% are state employees, 31% are private employees, 5% are unemployed, 2% are students, and 7% belong to the category "other". Overall, a good representation of gender and income is observed. However, students and individuals aged below 25 and above 64 are not adequately represented.

Table 3.4: Summary of the stated preference survey sample from Alexandroupolis

<table>
<tr><td rowspan="2">Gender</td><td>Female</td><td>43.6%</td><td rowspan="5">Age</td><td>18-24</td><td>1.8%</td></tr>
<tr><td>Male</td><td>56.4%</td><td>25-39</td><td>45.5%</td></tr>
<tr><td rowspan="6">Household income (Euros/month)</td><td>0-400</td><td>7.3%</td><td>40-54</td><td>43.6%</td></tr>
<tr><td>401-800</td><td>10.9%</td><td>55-65</td><td>7.3%</td></tr>
<tr><td>801-1200</td><td>27.2%</td><td>>65</td><td>1.8%</td></tr>
<tr><td>1201-1600</td><td>25.5%</td><td rowspan="5">Bike safety perception</td><td>Very safe</td><td>5.5%</td></tr>
<tr><td>1601-2000</td><td>10.9%</td><td>Safe</td><td>23.6%</td></tr>
<tr><td>>2000</td><td>18.2%</td><td>Neutral</td><td>30.9%</td></tr>
<tr><td rowspan="6">Employment status</td><td>Self-employed</td><td>30.9%</td><td>Risky</td><td>21.8%</td></tr>
<tr><td>State employees</td><td>23.6%</td><td>High Risk</td><td>18.2%</td></tr>
<tr><td>Private employees</td><td>30.9%</td><td rowspan="2">No. of leisure trips per week</td><td>Less than 2</td><td>30.9%</td></tr>
<tr><td>Other</td><td>7.3%</td><td>At least 2</td><td>69.1%</td></tr>
<tr><td>Unemployed</td><td>5.5%</td><td rowspan="2">Mode choice</td><td>Car</td><td>46%</td></tr>
<tr><td>Student</td><td>1.8%</td><td>BSS</td><td>54%</td></tr>
</table>

Bike-sharing service is believed to be used (comparatively) more for leisure trips. Hence, the frequency of performing leisure trips was enquired in the survey. 11% of the participants responded that they perform leisure trips every day, 58% two or three times a week, 22% once a week, 7% rarely and 2% never. When asked about how safe the participants think a bike ride is in Alexandroupolis, 18% of the survey respondents stated that it is a high risk, 22% stated that it is risky, 31% were neutral, 24% stated safe and 5% stated that it is very safe. The participants were also asked about how likely they might use the bike-sharing service for commuting trips. To this question, 22% of the participants answered extremely unlikely, 18% stated unlikely, 20% were neutral, 9% stated likely and 13% answered extremely likely. A similar distribution is observed for sports and leisure activities, as well as for the trip to local market.

A further question is related to the implementation of public bicycles in Alexandroupolis, to which 9% of the participants strongly oppose, 9% somewhat oppose, 13% being neutral, 29% somewhat favour and 40% strongly favour. Additionally, the survey participants were asked whether a public bicycle system will help in promoting sustainable urban mobility, and 82% of the respondents answered yes, whilst 18% answered no to the question. The attitude of the research sample shows that the majority of the respondents generally favour the implementation of a bike-sharing service.

3.5 Germany

3.5.1 Details about the dataset

The research sample is from a cargo cycle trial scheme, named "Ich entlaste Städte"[3] [I relieve cities (from environmental burdens)], funded as part of the National Climate Initiative of the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety. Between September 2017 and December 2019, freelancers, private companies, public organisations, and Non-Governmental Organisations (NGOs) across Germany had the opportunity to test a cargo cycle for three months at a very low cost (roughly US $30 monthly). Because of the heterogeneous demand and use patterns, eighteen different cargo cycle models, of five different construction types, have been made available for the participants. During the trial phase, cargo cycle trips have been tracked through a smartphone project application, as well as through a GPS device attached to the cycles. Furthermore, using the total tracked trips, the catchment area of the commercial trips carried out using the cargo cycles are estimated for each participating organisation.

Data from the participating organisations are also collected through a longitudinal survey, conducted before (T0) and at the end (T1) of the trial phase. The data collected from the surveys include the location of the organisation, business sector (Statistisches Bundesamt, 2008), organisation type, main purpose of cargo cycle use, modes substituted during the trial phase, required cargo cycle battery range, details about storage and charging, and change in work process within the organisation during the trail phase. In addition, a set of 23 items about potential drivers and barriers of cargo cycle use, a set of 12 items capturing the attitudes with respect to corporate environmental responsibility and technology, and a set of 6 items corresponding to incentives for cargo cycle purchase are also collected. The items within the three sets are based on five-point Likert scale agreement statements. Within survey T1, the participants stated their intention to purchase a cargo cycle. Subsequent to T1, a follow-up query (T2) is made regarding the actual purchase decision, between three to twelve months after the end of the trial phase.

3.5.2 Descriptive statistics

A summary of the geographic and organisational background of the research sample is presented in this section, along with details on the vehicle types tested by the participating organisations and the characteristics of the trips carried out using the cargo cycles.

3.5.2.1 Geographic and organisational background

The research sample consists of data pertaining to 400 organisations located in 187 different municipalities, spread across all the sixteen states of Germany. 90% of the organ-

[3] https://www.lastenradtest.de

isations do not have any cargo cycle experience prior to the project. Around two-thirds of them are located in a large city (kreisfreie Stadt). A varied organisational background is observed in the sample. Starting from the business sectors, the sample contains organisations from the following eighteen business sectors: 1) Agriculture, forestry and fishing (A); 2) Manufacturing (C); 3) Electricity, gas, steam and air conditioning supply (D); 4) Water supply, sewerage, waste management and remediation activities (E); 5) Construction (F); 6) Wholesale and retail trade, repair of motor vehicles and motorcycles (G); 7) Transportation and storage (H); 8) Accommodation and food service activities (I); 9) Information and communication (J); 10) Financial and insurance activities (K); 11) Real estate activities (L); 12) Professional, scientific and technical activities (M); 13) Administrative and support service activities (N); 14) Public administration and defence (O); 15) Education (P); 16) Human health and social work activities (Q); 17) Arts, entertainment and recreation (R); 18) Provision of other services (S). These business sectors are based on Statistisches Bundesamt (2008), and the letters included inside the brackets will be used to denote the business sectors in the subsequent chapters.

Almost half of the participating organisations are companies, followed by a quarter of freelancers or self-employed individuals. Apart from these two categories, the sample also includes public institutions (around 14%), and NGOs and associations (around 13%). Most of the organisations (81%) follow autocratic fleet decision-making structure (low formalisation and high centralisation), while one-tenth of the sample belong to hierarchic decision-making (high formalisation and centralisation). The rest of the sample fall under either democratic (low formalisation and centralisation) or bureaucratic (high formalisation and low centralisation) decision-making categories. While centralisation refers to the number and independence of decision-makers involved, formalisation refers to the level of rules and procedures guiding the decision process of the fleet purchase and utilisation (Nesbitt & Sperling, 2001). About 72% of the sample belong to the category of micro-enterprises (turnover < € 2 million), while the remainder is evenly distributed among small (turnover € 2 – € 10 million), medium-sized (turnover € 10 – € 50 million) and large enterprises (turnover > € 50 million).

3.5.2.2 Vehicle characteristics

Eighteen different vehicle models are made available for the participating organisations to select. The models can be categorised into five construction types, namely pizza delivery bike, Long John bike, longtail bike, front-load trike and heavy-load trike, as shown in Figure 3.4. All models have a minimum payload capacity of 50 kg (110.2lb.). Excepting two models, the rest of the models have electric assist. Among the models with electric assist, one of the models has electric assist up to 45 km/h (28.0 mph), known as S-Pedelec or fast e-bike. Other models have electric assist up to 25 km/h (15.5 mph), commonly known as Pedelecs or standard e-bikes. Among the five construction types, the Long John bikes are mostly used by the participants (62%), while the longtail bikes and the heavy-load trikes are the least used ones (3.5% and 3.7%, respectively). The reader is referred to Ich entlaste Städte (2020) for more details about the vehicle models.

3.5.2.3 Trip characteristics

Concerning the spatial extent, the catchment area of the commercial trips performed using cargo cycles range from a section of a typical German city district to the size of a medium-sized city, with an average of 26 km^2. The average daily mileage during the trial phase is around 16 km. Around 41% of the participating organisations utilise cargo cycles for service trips, as shown in Figure 3.4. The trip purpose of one-third of the participants fall under the category of goods delivery and pick-up. The battery capacity required for effectively carrying out the commercial trips, as stated by the participants, range from 2 to 200 km (1.2 to 124.2 mi). Around 7% of the participating organisations has tested the cargo cycles during the winter season (between November 1 and March 31).

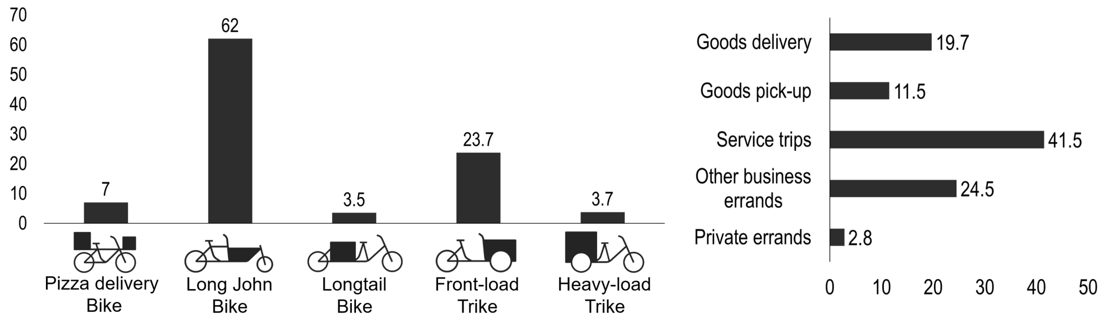


Figure 3.4: Distribution of the cargo cycle research sample in percentage according to the cycle construction type tested (left) and use purpose (right)

Table 3.5 presents the relevant descriptive statistics of the analysed sample. From the table, it can be stated that the dataset contains a wide variety of organisations, with an extensive range of trip characteristics. As shown in the table, only about one-third purchased a cargo cycle, although around half of the sample stated that their intention is to purchase a cargo cycle. This suggests that there is a need to convert intention to actual purchase, when making conclusions based on intentions. A deeper look into the purchase intention and the actual purchase decision values gives the shares shown in Table 3.6.

Table 3.5: Summary of characteristics of the cargo cycle sample from Germany

Located in a large city (Kreisfreie Stadt)	Yes	61.2%	Start-up (share of participating organisations)	Yes	11.5%
CC electric assist (share of participating org.)	No assist	8.8%	Work process change	Negative	4.8%
	Pedelec-25	85.7%		No change	53.0%
	Pedelec-45	5.5%		Positive	42.2%
CC catchment area (km^2)	Min	0.7	Daily mileage during the trial phase (km)	Min	7.9
	Mean	26.3		Mean	15.9
	Median	19.5		Median	15.7
	Max	143		Max	32.7
Decision-making	Autocratic	81.2%	Required battery range (km)	Min	2
	Democratic	4.1%		Mean	33.5
	Hierarchic	9.9%		Median	30
	Bureaucratic	4.8%		Max	200
Organisation type	Self-employed	25.0%	Trial phase season: Winter (share of participating org.)	Yes	6.5%
	Company	47.5%			
	Public institution	14.5%			
	NGOs, associations	13.0%			
Purchase intention	Yes	48.5%	Actual purchase	Yes	32.0%

Note:

- CC: Cargo Cycle

Table 3.6: Shares for cargo cycle purchase intention and actual purchase decision

Intention / **Actual decision**	**Yes**	**No**
Yes	24.3%	7.7%
No	24.3%	43.7%

4 Methodology

Contents

4.1 Intermediate modelling approach

4.1.1 Overview

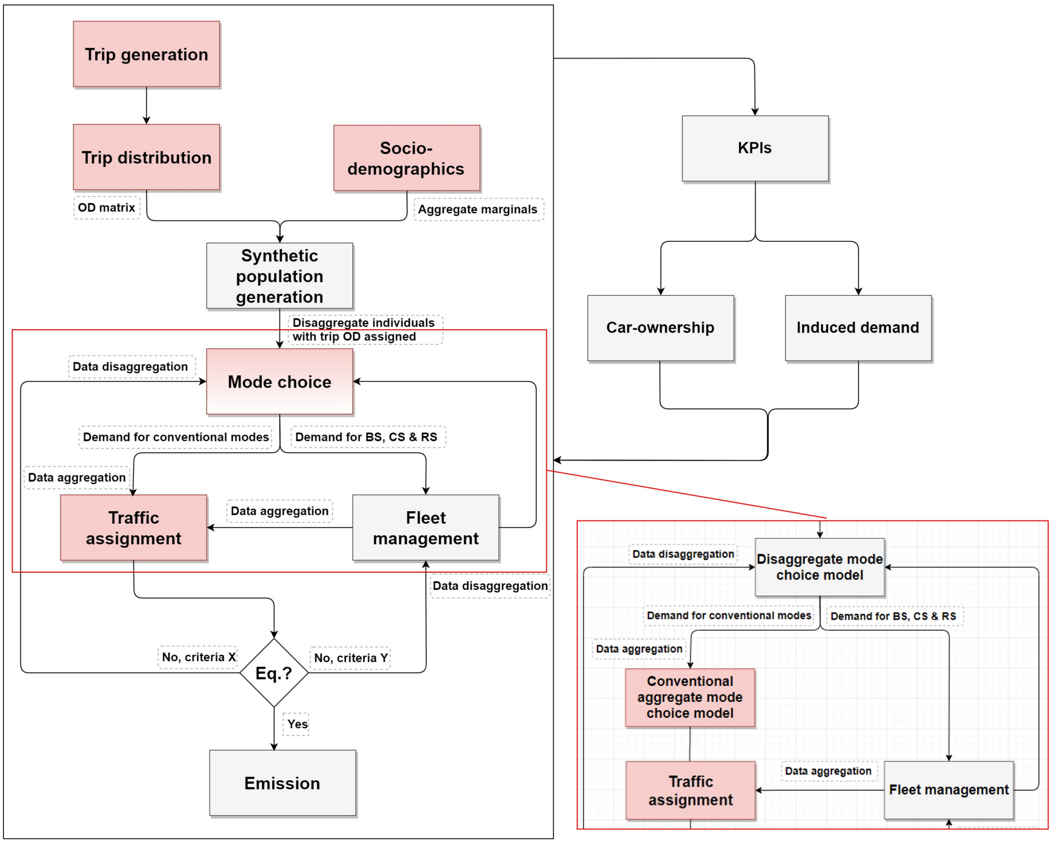
The main objective behind the intermediate modelling approach is to integrate the disaggregate approach of the agent-based models with the traditional strategic four-step approach. The modelling schema is shown in Figure 4.1 and includes the addition of modules for synthetic population generation, disaggregate mode choice and fleet management, along with existing steps in the traditional four-step approach. Furthermore, modules are added for estimation of emissions, car-ownership and induced demand, as such measures are increasingly expected by cities. Based on a survey of planning practitioners (the end users), Te Brommelstroet (2010) state that there is a need to have a shift in the approach from “developing for” to “developing with”. They conclude that the model developers should not only focus on scientific rigour, detail, and comprehensiveness, but also should try to achieve a balance between rigour and relevance, in order to increase the implementation success of advanced models. The intermediate modelling approach has been developed along these lines.

It is to be noted that this dissertation focuses on the design of the framework and the development of models for mode choice and car-ownership. Development of models for other steps that are included in the framework, such as induced demand or the fleet management module, are beyond the scope of this dissertation. Nevertheless, they have been developed by partners of the MOMENTUM project and are briefly summarised in the subsequent sections. Extended descriptions for them, including information on the calibration process and parameters, can be found in H2020 MOMENTUM consortium (2021a) and H2020 MOMENTUM consortium (2021b).

4.1.2 Synthetic population generation

The intermediate modelling approach will continue to use the existing trip generation and trip distribution steps from the traditional four-step approach, as shown in Figure 4.1. Following trip distribution, the OD matrices are disaggregated using socio-demographic data to generate synthetic population. The synthetic population is a key input to agent-based models and microsimulation of urban systems, in order to simulate the behaviour of agents on the transportation network. The objective here is to synthesise a simplified representation of the actual population, from which the preference of an individual to select a new mobility service, as opposed to a traditional transport mode, can be captured.

The process involves generating a set of households and individuals based on sociodemographic attributes, which are usually available in the samples of population (e.g., from travel surveys) and census data, such that they match known distributions of key attributes of the general population. The open source tool PopGen (MARG, 2016) is suggested as the synthetic population synthesizer, which employs the enhanced Iterative Proportional Updating (IPU) algorithm. There could be attributes (especially for the new mobility services) that are not available in both the travel survey and the the census data. The IPU algorithm can not map them in the initial population synthesis. In this case, data-driven approaches are suggested to enrich the synthetic population with additional attributes. For instance, sampling techniques and statistical matching procedures (D'Orazio et al., 2006) can be utilised under certain assumptions.



Note: BS - Bike-Sharing; CS - Car-Sharing; RS - ride-hailing; Red colour shaded boxes indicate the existing components in the traditional four-step approach.

Figure 4.1: Extended four-step modelling approach (The intermediate modelling approach)

4.1.3 Mode choice

Based on the generated synthetic population, the demand for different modes is estimated using a mode choice model. The existing mode choice models of the cities usually include only conventional modes, and hence, an updated model that also includes different shared mobility systems is required. In general, several cities do not have sufficient data to estimate a mode choice model, which includes all conventional modes, as well as the different shared mobility systems. Wherein data is available, the development of a mode choice model for both conventional modes-as-a-whole and the different shared mobility systems could be beneficial, as such a model could be used in other cities. The transferability of the model to other cities is feasible, as it is possible to generalise the demand characteristics of shared mobility systems [e.g., unique profile of users such as younger individuals, possession of Bachelor's degree or higher, and holding of PT passes (Becker et al., 2017; Clewlow, 2016)]. Hence, the proposed framework has been designed to accommodate such a procedure.

The calculation of mode share will be a bilevel procedure. At the upper level, the modal split between conventional modes-as-a-whole and the different shared mobility systems is estimated (mentioned as disaggregate mode choice model in Figure 4.1). The split between the different conventional systems is estimated at the lower level, using the existing mode choice model of the city. Such a separation of mode choices is not unrealistic, as the shared mobility services can be safely assumed to not have a nesting effect with the conventional modes (Li & Kamargianni, 2020). The suggested disaggregate mode choice model is a multinomial logit model, developed as part of this dissertation, with the following mode choices: (i) conventional modes-as-a-whole (base category), (ii) bike-sharing, (iii) ride-hailing and (iv) car-sharing. For the utility specification of this model and the coefficients, the reader is referred to Section 5.1.

4.1.4 Fleet management

Once the modal share at the top level is estimated using the disaggregate mode choice model, the disaggregate demand of the shared systems are fed into a set of fleet management algorithms, which assign vehicles and simulate the operations of the shared vehicles. In the traditional four-step modelling, both the road network and the public transport network are usually exogenous, i.e., the supply components are inputs. However, the higher complexity of shared mobility services, in comparison to the traditional modes (i.e., private car and public transport), necessitates new techniques that are able to generate the supply components within the modelling framework. Besides the supply components, the inclusion of the shared mobility modes requires additional functionalities to simulate these trips.

The fleet management framework in the proposed intermediate approach is composed of the following sub-modules: (i) a set of algorithms that are able to design the characteristics of the shared mobility services, aiming to optimise the general service metrics, and (ii) a tool which is able to simulate such services and calculate actual operational costs, along with fleet- and user-related KPIs. The workflow within the fleet management module, as shown in Figure 4.2, is the following: at first, the disaggregate demand from the mode choice model at the upper level is used for the service optimisation, to generate the supply resources, such as fleet size and location of stops. Then, the fleet simulation is performed to simulate the trips and calculate specific metrics for the supply layout generated through the optimisation. Thus, the first step defines the strategic characteristics of the service (e.g., the desired fleet size and the number of stops) and the latter simulates and assesses the performance of these characteristics in terms of total travel time (including access time, waiting time, in-vehicle travel time and other pertinent costs). These two steps are iterated, until a convergence is reached, wherein the metrics do not change significantly.

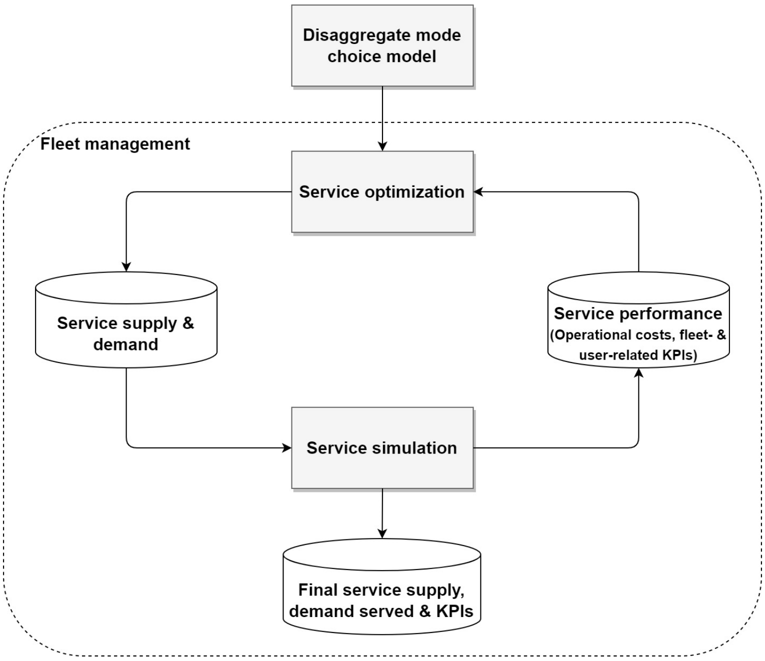


Figure 4.2: Workflow within the fleet management module

With regards to the algorithms for the service optimisation, they can be classified as planning-related and operational-related. For the planning part, linear programming (Bertsimas & Tsitsiklis, 1997), combinatorial optimisation (Nemhauser & Wolsey, 1999) and heuristics (Toth & Vigo, 2014) can be used, while in the operational part, variants of Travelling Salesman Problem, Approximate Dynamic Programming (Simão et al., 2009), and Reinforcement Learning on Markov Decision Processes (Sutton & Barto, 2018) are suggested. For the service simulation, discrete event frameworks could be used. In the MOMENTUM project, such algorithms have been integrated as a plug-in inside the traffic simulation software Aimsun Next (Aimsun, 2021).

4.1.5 Iterative processes and traffic assignment

An initial skim matrix is utilised for the travel times (for the fleet management module) in the first iteration of the modelling framework. If there are any unserved demand (Equation 4.1), they are reassigned to another mode through the disaggregate mode choice model. Once this process is accomplished, the trips to be served by the shared vehicles are aggregated. This will be the OD specific demand corresponding to the shared mobility systems. Similarly, the demand corresponding to the conventional modes-as-a-whole is aggregated and fed into the existing mode choice model. Thus, the OD specific demand corresponding to the individual conventional modes could be obtained.

$$D_s^r - D_s^a = 0 \tag{4.1}$$

where,

D_s^r : Total number of trip requests to be served by shared modes, based on the demand calculated using the disaggregate mode choice model

D_s^a : Total number of trips actually served through shared modes, decided based on the vehicle assignment from the fleet management module

Subsequent to the estimation of the OD specific demands of the conventional modes (from the existing mode choice model) and the shared mobility services (from the fleet management module), they are fed into the existing traffic assignment model. Based on the traffic assignment results, it might be required to iterate the sequence from mode choice or fleet management. Models with feedback between traffic assignment and mode choice steps already exist in literature and it is not something newly introduced in this research. Nevertheless, a criteria for iterating from the mode choice step could be based on the extent of change in travel times (smaller changes might not result in a significant change in modal split), e.g., Equation 4.2. Similarly, to iterate from the fleet management step, the criteria could be based on the feasibility of the shared mobility trips (which depends on the updated travel times from the traffic assignment algorithm), and the need for assigning a different vehicle, for example Equation 4.3.

$$| T_i^n - T_{i-1}^n | < \epsilon, \forall\, n \in \{O, D\} \tag{4.2}$$

$$T_i^n - T_{i-1}^n \leq 0, \forall\, n \in D_s^a \tag{4.3}$$

where,

D_s^a : Trips actually served through shared modes, decided based on the vehicle assignment from the fleet management module

T_i^n : Travel time for a trip n in the current iteration i

4.1.6 Post processing: Emissions

Once an equilibrium is reached, post processing is carried out to calculate emissions. This step is added, since cities are increasingly interested in environmental performance measures. New transportation modes and shared mobility alternatives have the potential to reduce emissions. Some are intrinsically less polluting, while others allow emission reductions through the optimisation of the service. Accurate emission calculations tend to be complex and do not account for the underlying road network, rendering them infeasible and suboptimal for smaller cities. Thus, the spatial-detail benefits of the existing traffic model can be exploited to calculate emissions for pollutants CO, Carbon dioxide (CO_2), NOx, PM and Volatile Organic Compounds (VOC) through a light-weight post-processing step. Specifically, traffic speeds and vehicle-kilometers (vkm) can be extracted on a per-link basis and utilised for emission calculation.

Emission factors (emissions/vkm) vary strongly by vehicle type and age. Moreover, fleet compositions vary among EU member states and evolve over time as new vehicles replace older ones. Using the TML fleet-model [which is linked to COPERT 5 Rodrigues et al. (2020)], a dataset of fleet-average emission factors per (i) pollutant, (ii) EU member state and (iii) year (2016 to 2050) has been created within the MOMENTUM project. These aggregated emission factors are for a fixed speed. However, emissions are speed-dependent: typically both low and high speeds lead to higher emissions due to stop-and-go traffic and larger resistances, respectively.

The COPERT macroscopic emission model can be used to empirically estimate emission under different aggregated speed regimes. These speed regimes reflect an average driving pattern, a drive cycle, which includes acceleration and braking. Further abstraction can be made with respect to the difference in the emission functions per vehicle type. A vehicle fleet average is used to simulate the speed-corrected emission factors. Combining the country- and year-specific speed-corrected emission factors with the traffic model's output, emission estimates can be obtained on a given link, and by aggregation on the entire network.

4.1.7 Post processing: Car-ownership and induced demand

KPIs can be calculated from the aforementioned extensions, along with the estimation of car-ownership and induced demand, which are the two other measures expected by the cities. The model for the car-ownership estimation can be one of the multiple disaggregate multinomial logit models developed as part of this dissertation for household car-ownership. For the utility specification of these models and the coefficients, the reader is referred to Section 5.4.1.

Besides the obvious transportation supply variations that can be caused by new (shared) modes of transport, they also induce changes in demand. A typical four-step model only accounts partially for these changes through mode and route choice, considering the total demand for a given OD pair as independent of changes in the underlying transportation system. Therefore, there is a need to incorporate the total demand changes in the four-step model with minimal framework adaptations. This can be accomplished through a nested logit model, using which change in demand can be calculated with respect to change in utility of the choices in the logit model.

At the upper level of the nested model, the choice to travel or not can be considered, where the share of each choice (i.e., to travel or not) is determined by their utilities. The utility to travel U^t can be estimated based on the expected total utility of the choices in its nest. Typically, the travel modes available in the mode choice model can be considered in the nest and the sum of the utilities of each mode (i.e., the total utility of the available modes) is considered as the utility to travel. The utility of not-to-travel U^{nt} can not be quantified directly (as done for utility to travel, based on utilities of the modes), but this needs to be calibrated. Such a calibration is possible based on the observed demand in the base scenario, and additional quantitative information on demand shifts, e.g., based on case-specific survey or demand elasticity from the literature.

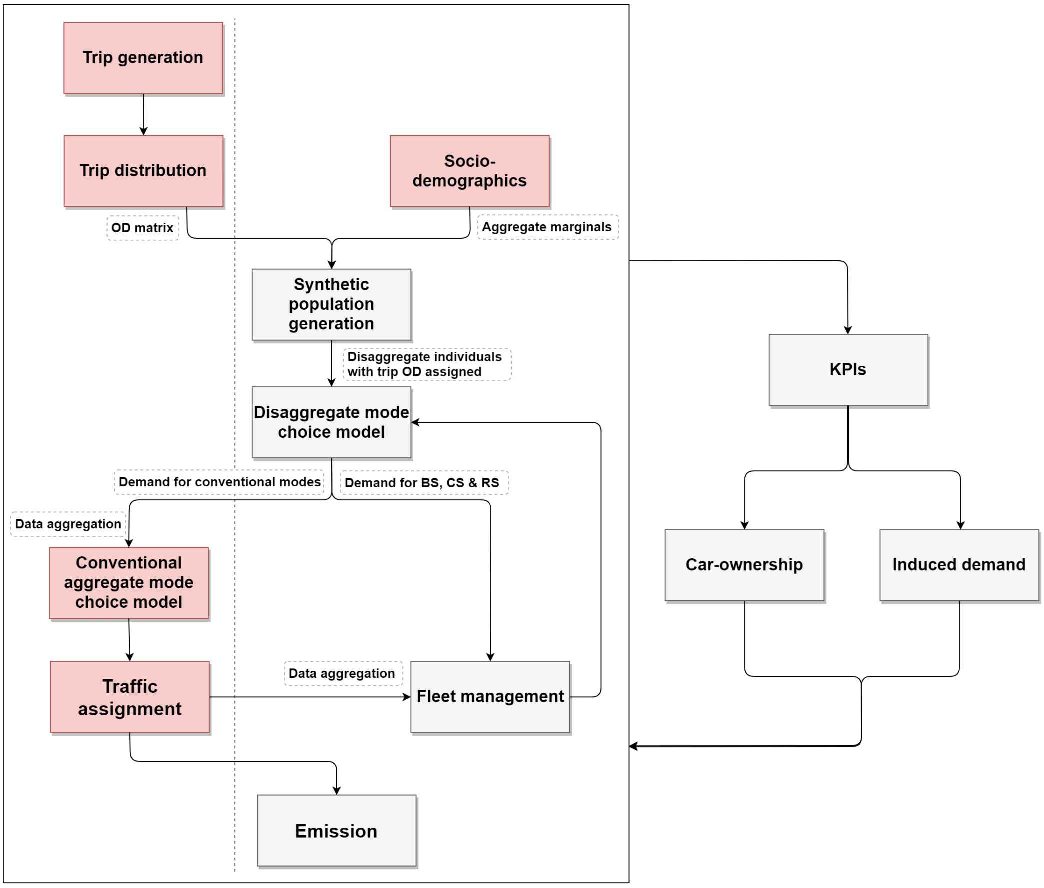
Subsequent to the calculation of car-ownership and induced demand, the entire modelling sequence could be re-run, if necessary and pertinent. Although different equilibrium checks could be introduced, they are avoided in view of the convergence issues and to reduce additional complexity. It is to be noted that the intermediate modelling approach per se is software agnostic and allows the use of equivalent models as alternatives to the extension models suggested in the preceding paragraphs, provided the relevant inputs and outputs are consistent.

4.1.8 Low penetration scenario

The modelling schema presented in Figure 4.1 can be simplified in cases, wherein the penetration of shared mobility services is low enough to not cause substantial change in the existing network travel times. This is the existing scenario in several European cities (e.g., Madrid and Regensburg). The network travel times obtained from a traffic assignment can be considered as fixed in the implementation and evaluation of the disaggregate mode choice model as well as in the fleet management module, which utilise the travel time information. Therefore, the equilibrium check carried out after the traffic assignment step can be neglected. As shown in Figure 4.3, the processing of the existing four steps of the traditional strategic model can be separated from the new additions and a one way interaction (i.e., from the existing steps to the new additions) is sufficient. This means that the cities can run their existing traditional strategic models, obtain the required outputs and run the new additions externally.

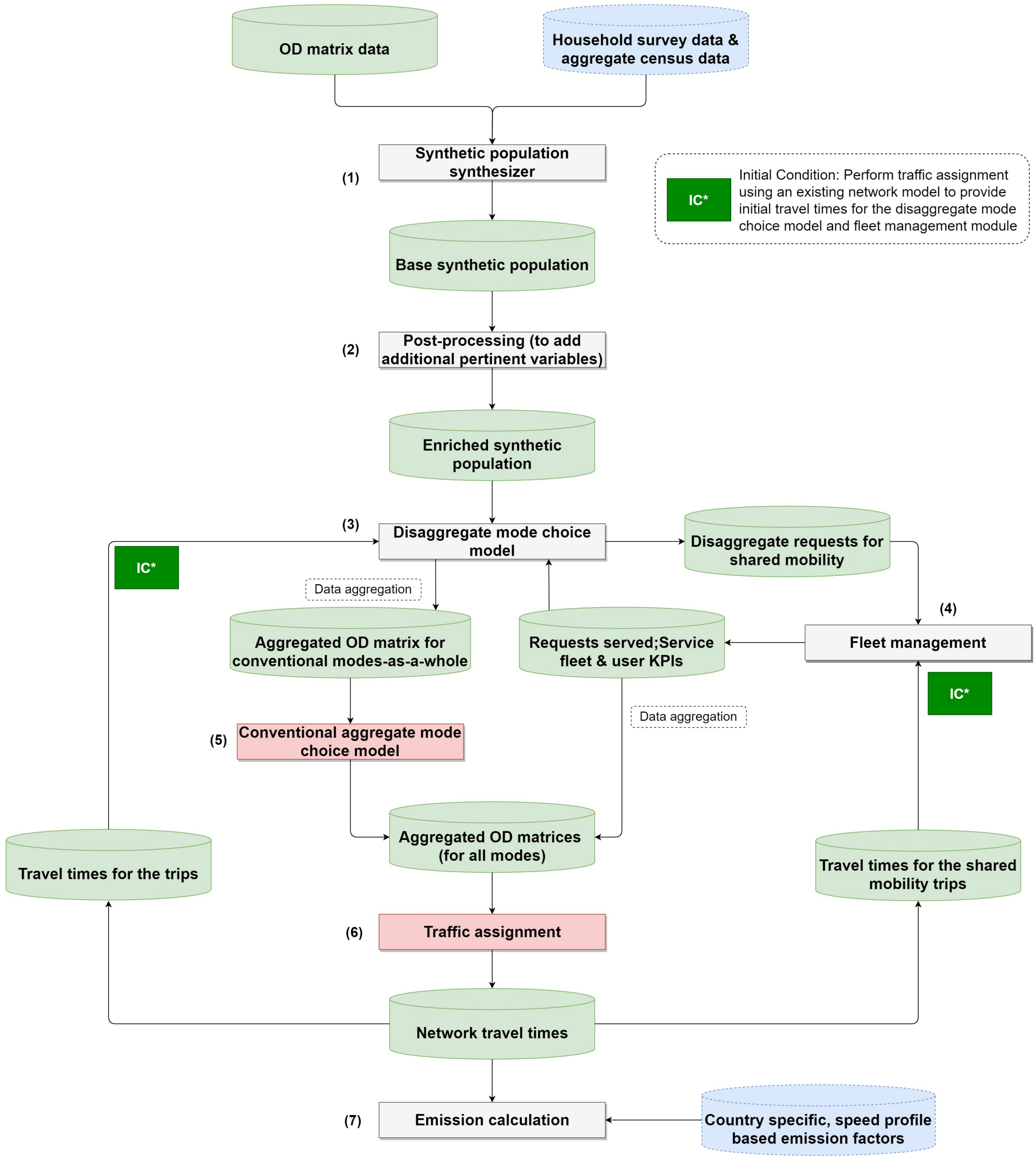
4.1.9 Integration schema

While a generic framework is shown in Figure 4.1, a self-explanatory integration schema with pertinent inputs and outputs, is presented in Figure 4.4. As mentioned earlier, depending on the penetration of the shared mobility services, the modelling framework varies. In Figure 4.4, the integration schema, which consists of the workflow, the interaction between the models and the type of data that is being exchanged, is presented only for the high penetration case, as the modelling framework for the low penetration case is a simplified version of the high penetration case. The schema ensures that the input and output workflow is suitably interfaced and the different components interact with each other properly through information exchange.



Note: BS - Bike-Sharing; CS - Car-Sharing; RS - ride-hailing; Red colour shaded boxes indicate the existing components in the traditional four-step approach.

Figure 4.3: Extended four-step modelling approach for the low penetration case



Note: Only the main extensions from Figure 4.1 (from population generation to emission calculation) are shown. While the car-ownership model takes synthetic population as input, induced demand model takes both synthetic population and the travel time skim matrix as inputs.

Figure 4.4: Integration schema based on the workflow presented in Figure 4.1

4.2 Multi-method demand framework for a small-scale station-based car-sharing service

In traditional transport demand modelling, discrete choice models have been widely used to estimate demand for different transport modes. However, when a car-sharing system is operated at a small-scale, the modal split for the service will be very low, especially at initial stages. For example, in Regensburg, the number of shared vehicles in the car-sharing service is less than 10 and the total demand per day is less than 50 trips. This leads to a situation wherein it is not possible to account the demand for the service through the traditional mode choice models. Furthermore, the samples obtainable for such services through surveys will also be inadequate for estimation of any reasonable choice model.

Alternatively, a linear regression model could be used to calculate the demand for the whole service and then a compositional model can be utilised to apportion the total service demand to individual stations. Users can be assigned to the predicted demand using an use frequency model. Therefore, a data-driven multi-method demand estimation framework has been designed, which can be integrated with the intermediate modelling approach, especially for the case study on Regensburg. Though the framework has been developed aiming at a small-scale station-based car-sharing service, it can be adapted to study, characterise and evaluate many other emerging mobility solutions with different business models, especially during their early stages.

4.2.1 Models

The framework consists of a linear regression, dirichlet regression and a multinomial logit model to estimate the daily trip demand per car-sharing station and determine the frequency of car-sharing use for a synthetic population. The framework is schematised in Figure 4.5. As shown in the figure, a multinomial logit model can be used to determine the use frequency of a car-sharing service. Such a model can be estimated using a household survey containing socio-demographic factors and a variable recording the frequency of car-sharing use of the survey sample.

A linear regression model can be used to calculate the average daily demand for the entire car-sharing service. A multivariate dirichlet regression model can then be used to calculate the average daily demand per station. It is possible to estimate both of these models using a small operator dataset. More details about the model estimation procedure are available in Section 4.3. While the application of linear regression and multinomial logit models are commonly found, the dirichlet regression and the modelling of composition data are comparatively not well-known. Therefore, a brief introduction to them is included in the below paragraphs.

Compositional data are proportions or percentages of multiple categories, which add to one. This unit-sum constraint complicates their analysis (Hijazi & Jernigan, 2009). The unit-sum constrains the sample space of 'C' dependent variables to a 'C-1' dimensional simplex. The regular multivariate covariances and correlations can be misleading for

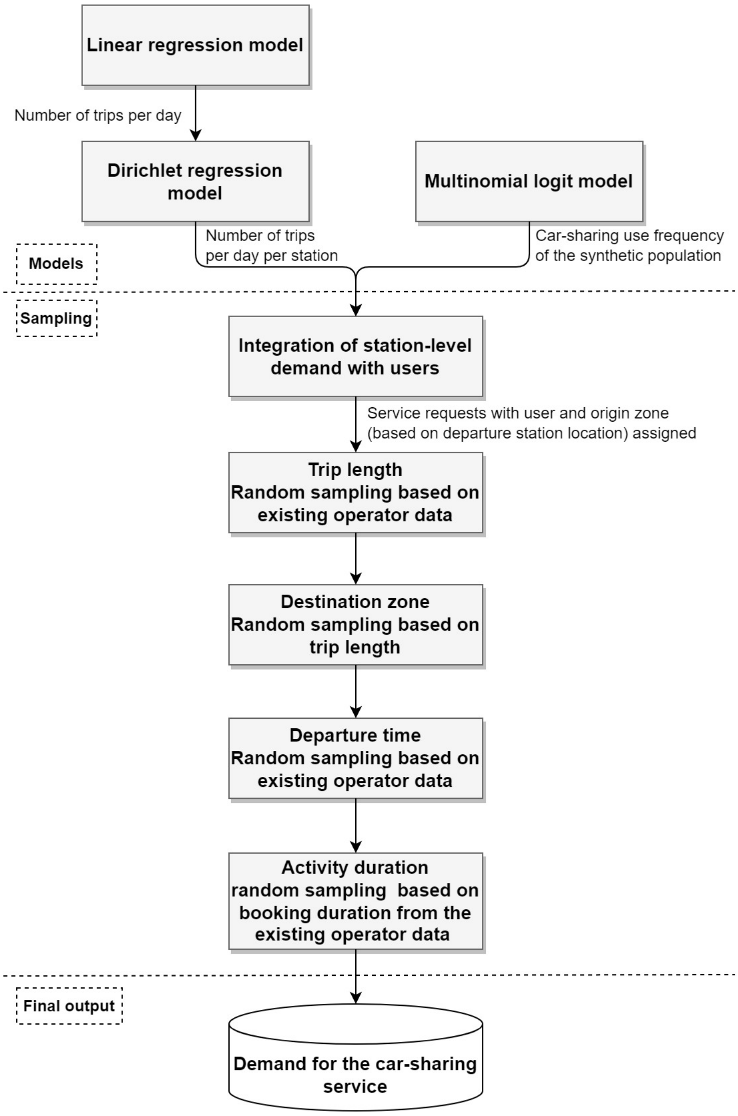


Figure 4.5: Multi-method demand framework for a small-scale station-based car-sharing service

such data and therefore, the traditional multivariate statistical techniques can not be directly used (Hijazi, 2006). Transformations are often applied to overcome this issue.

An established pioneer approach to the statistical analysis of compositional data is the logratio analysis of Aitchison (1982), wherein normality log-ratio transformations are implemented. The transformed variables are then commonly analysed using (multivariate multiple) linear regression models, which have some limitations (Maier, 2014). Such transformations can lead to biased estimates and difficulties in interpretation. The resulting parameters are only interpretable in the transformed space and have no direct meaning. In addition, if heteroscedasticity exists after the transformation, then either the assumption of homoscedasticity in linear models needs to be violated or model terms capturing heteroscedasticity have to incorporated, which further complicate the model (and interpretation).

Subsequent to logratio analysis of Aitchison (1982), Campbell & Mosimann (1987) developed an alternative approach by extending the dirichlet distribution to a class of dirichlet covariate models (i.e., dirichlet regression). The compositional dependent variable is supposed to be dirichlet distributed. The dirichlet regression can be regarded as a generalisation of beta regression models (Ferrari & Cribari-Neto, 2004) for more than two categories. Campbell & Mosimann (1987) show that this class of models can accommodate different covariance structures present in a compositional data.

Dirichlet distribution is a flexible distribution and can accommodate the different shapes in the simplex. It accounts for the -in a linear model- undesirable characteristics of compositional data and performs well in a multivariate generalised linear model-like setting (Maier, 2014). Thus, dirichlet regression techniques model proportions at their original scale, which makes statistical inference more straightforward and produce less biased estimates relative to transformation-based solutions (Douma & Weedon, 2019). Furthermore, it is found to be superior to model compositional data in multiple studies (e.g., Morais et al., 2018; Poudel & Temesgen, 2016).

A comprehensive overview on dirichlet regression models is beyond the scope of this paper and the reader is referred to Douma & Weedon (2019), Hijazi (2003) and Hijazi & Jernigan (2009) for the same. Nevertheless, a quick overview of the pertinent aspects is included here. The multivariate density function of the dirichlet distribution is presented in Equation 4.4. For this distribution, the constraints shown in Equation 4.5 holds. The multinomial beta function in Equation 4.4 is expressed as shown in Equation 4.6.

$$f(y;\alpha) = \frac{1}{B(\alpha)}\left[\prod_{c=1}^{C}(y_c^{\alpha_c-1})\right] \tag{4.4}$$

$$\begin{aligned} &\alpha_c > 0 \ \forall c \\ &y_c = (0,1) \ \forall c \\ &\sum_{c=1}^{C} y_c = 1 \end{aligned} \tag{4.5}$$

$$B(\alpha) = \frac{\prod_{c=1}^{C}\Gamma(\alpha_c)}{\Gamma(\sum_{c=1}^{C}\alpha_c)} \tag{4.6}$$

where,
c represents the categories, whose value ranges between 1 to C
y_c is the share for each of the C categories (dependent variable)
α_c is the model parameter for each of the C categories
$B(\alpha)$ is the multinomial beta function
$\Gamma(.)$ is gamma function

A regression model can be fitted for each of the C values of α_c. An appropriate link function for the corresponding regression model is a log-function (Maier, 2014). Hijazi & Jernigan (2009) has established the maximum likelihood estimation methods for dirichlet regression. The likelihood function, given the covariates, is as presented in Equation 4.7. The asymptotic properties of the estimates have been investigated in Campbell & Mosimann (1987) and Hijazi (2003). Closed form solutions are unavailable, and hence, numerical optimisation techniques are used to maximise the likelihood function. The reader is referred to Maier (2014) for the optimisation procedures.

$$L = \prod_{n=1}^{N}\left[\Gamma\left(\sum_{c=1}^{C}\alpha_c(X_c^n)\right)\prod_{c=1}^{C}\frac{s_{nc}^{\alpha_c(X_c^n)-1}}{\Gamma(\alpha_c(X_c^n))}\right] \tag{4.7}$$

where,
$n = 1, ..., N$ represents the sample
$\Gamma(.)$ is gamma function
c represents the categories, whose value ranges between 1 to C
α_c is the model parameter for each of the C categories
X_c^n represents a set of explanatory variables, associated with the sample, for each of the C categories
s_{nc} is the observed proportion for each of the C categories in the sample

Since the estimation is based on maximum likelihood approach, a likelihood ratio test can be applied for the development of model specification (Equation 4.8). The resulting test statistic is, under the null hypothesis, asymptotically χ^2-distributed with the degrees of freedom equal to the difference in model parameters.

$$LRT = -2log\left(\frac{L_R}{L_{UR}}\right) \sim \chi^2_{K_{UR}-K_R} \tag{4.8}$$

where,
L_R is the likelihood of the restricted model
L_{UR} is the likelihood of the unrestricted model
K represents the number of model parameters n is the sample size

The R^2 measure can be calculated based on Hijazi (2006) and Magee (1990), as shown in Equation 4.9. This equation measures the proportional improvement in the log-likelihood function due to the explanatory variables (i.e., the covariates) in the model, compared to the minimal "constant" model.

$$R^2 = 1 - (L_0/L)^{2/n} \tag{4.9}$$

where,
L_0 is the likelihood of the constant-only model
L is the likelihood of the covariate model
n is the sample size

4.2.2 Sampling procedure

The output of the dirichlet regression model is the demand per station per day and the origin zones for this demand can be assigned based on the TAZ in which the stations are located. Subsequently, the individuals from a synthetic population can be randomly sampled to assign them to the station-level demand, based on the use frequency obtained from the multinomial logit model and the zone of household location. While sampling, a threshold for the distance between the stations and the users can be implemented, if the exact locations of the stations and the individuals are known.

Later, trip lengths are sampled based on a distribution, which is constructed from the travel distance values recorded in the operator dataset. As mentioned in Section 3.1.2, the actual distance recorded in the Regensburg dataset includes the whole round-trip. For calculating the one way trip length, it is assumed that the destination is at a distance equal to half the kilometres recorded in the dataset, since the trips have the same pick-up and return station. This can lead to some bias, but given that there is no other information available, I believe that it is the best approach to characterise the trip distance.

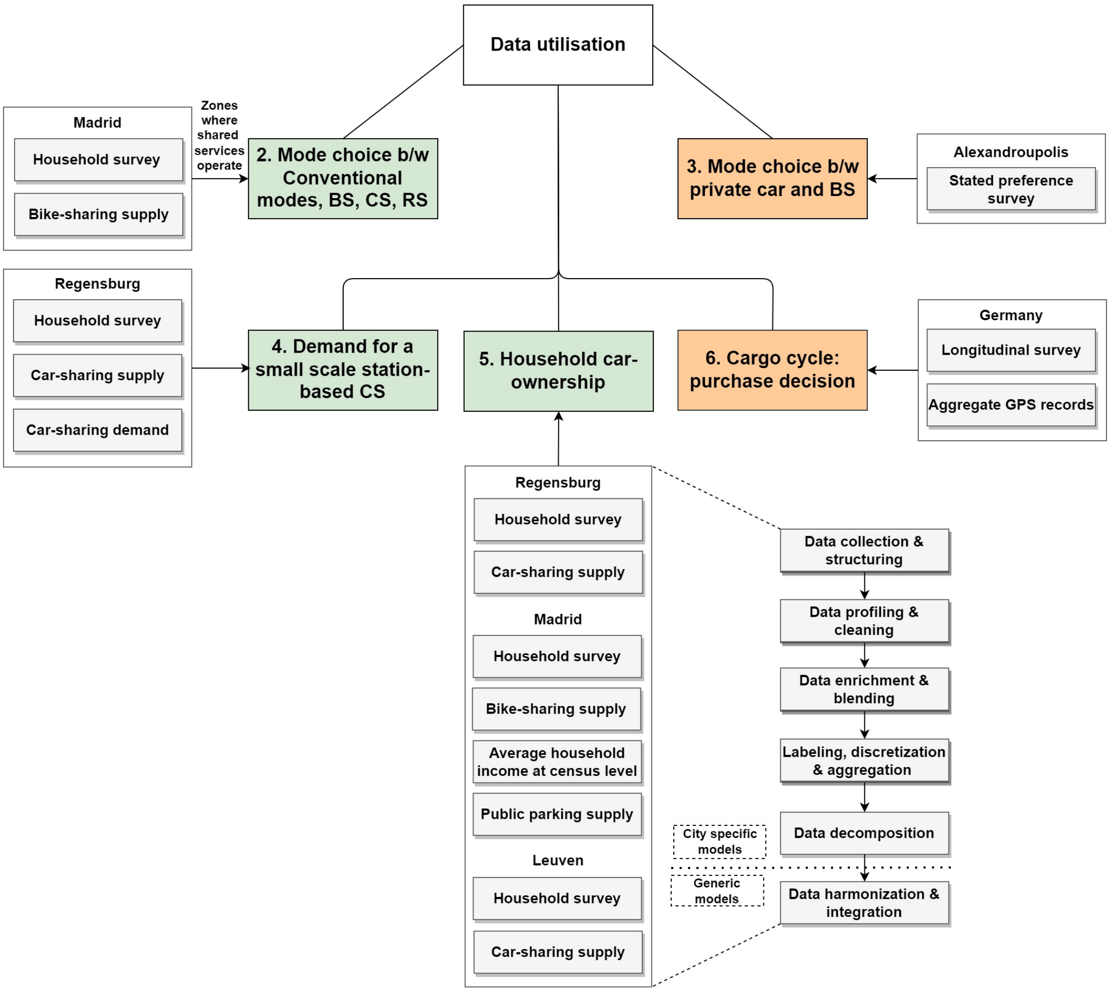
Based on a comparison of the sampled trip lengths and the distances between the TAZs (matching distances or closer to the sampled distances), destination zones for the car-sharing trips are assigned. Similar to trip length, distributions are constructed for departure time and activity duration and a random value is sampled and assigned for the trips. Thus, through the aforementioned procedure, the demand for the onward and return journeys can be constructed, which could then be simulated through a fleet management module.

4.3 Development of the individual models

4.3.1 Data utilisation and processing

In this section, the mapping between the datasets mentioned in Chapter 3 and the standalone models estimated in this dissertation is elucidated. In addition, the data processing steps performed to combine the multiple data sources from multiple cities for the estimation car-ownership models are briefly described. Furthermore, the mapping is summarised in Figure 4.6.

As shown in Figure 4.6, the household survey and the bike-sharing supply datasets from Madrid are used for the estimation of the disaggregate mode choice model, which calculates the modal split between conventional modes-as-a-whole, bike-sharing, car-sharing and ride-hailing. Since the penetration of the shared mobility services are very low (<1%), to reduce the data imbalance issues, a reduced survey sample of 25,463 individuals from 20,916 households (based on the traffic zones where shared mobility services are available) is used. The logit model estimation for the mode choice between private car and bike-sharing is based on the stated preference survey from the city of Alexandroupolis. For the multi-method demand framework for the small-scale car-sharing service, the household survey and the car-sharing operator datasets from Regensburg are utilised.



Note: BS - Bike-sharing; CS - Car-sharing; RS - Ride-hailing; The numbers and the colours represent the research objectives presented in Figure 1.2.

Figure 4.6: Overview of data use and processing

The household car-ownership models are estimated using multiple datasets from multiple cities. Given the use of several datasets, a number of data preparation steps are implemented. A structured sequence of data processing steps is necessary because of the presence of numerous variables from several datasets from multiple cities and to avoid being lost. The initial steps, naturally, include data collection, structuring and profiling. Data structuring involves the storage of the datasets in a homogenised file format. Data profiling is performed to check the completeness of the individual datasets, in terms of outliers, errors and anomalies. Then, data cleaning is performed to rectify the inconsistencies. All these steps are common for all the datasets listed in Chapter 3. The descriptive statistics included there are generated after executing the aforementioned steps.

Specific to the study on car-ownership models, the subsequent step involves the enrichment of the Madrid household survey with income details and parking supply data. In the following step, the shared mobility supply dataset is blended with the household survey dataset of the respective cities. In the Madrid household survey, some of the households do not contain data for all the individuals, while the rest have the data. Therefore, the dataset is labelled to identify these two groups and the one which does not contain data for all the household members are discarded. A reduced sample of 18,593 individuals from 9,163 households is used for the model estimations. This is necessary to ensure proper selection of the household representative and for the accurate aggregation of individual specific variables to produce household level variables.

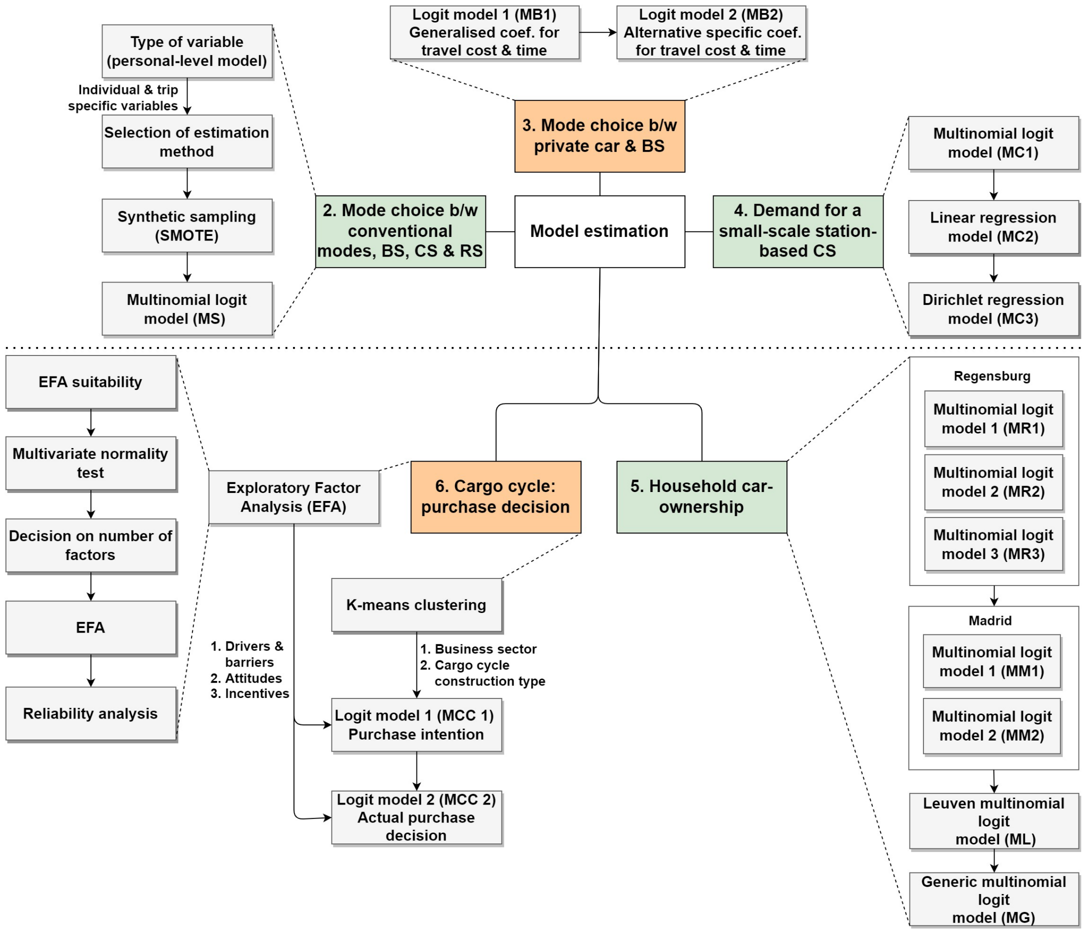
The proceeding step is on data discretisation, i.e., dummies are created based on some of the variables, for example, possession of PT pass and working status. The Regensburg and the Madrid household surveys consist of trip records for each individual and in the next step, this data is aggregated to calculate the mobility rates for the individuals and households. As will be explained in the next section (Section 4.3.2.4), multiple versions of independent variable are tested for the car-ownership models. Therefore, the blended dataset is decomposed into multiple datasets with pertinent information (one for each version of independent variable).

For the estimation of a generic car-ownership model (Section 4.3.2.4), the datasets from the three cities are integrated. As part of the data integration step, the datasets are harmonised to have same formats. For example, the age variable available in continuous format in Madrid and Regensburg are converted to ordinal format (i.e., data binning), as Leuven dataset contains the variable only in the latter format. The aforementioned data preparation structure, especially leading to the estimation of a generic model, can be replicated to study several concepts other than household car-ownership. For example, creation of generic demand models for emerging mobility solutions, such as shared mobility services, based on (survey and operator) data from multiple cities will be of great benefit to operators and policymakers, as well as to the research community.

The logit model estimations for the purchase intention and the actual purchase of cargo cycles are based on the longitudinal survey and the aggregated GPS dataset obtained from the cargo cycle trial scheme conducted in Germany. Finally, based on the experience of working with several datasets from multiple cities, I would like to suggest the future researchers (who want to perform similar research) to design the study objective well in advance and have sufficient time for data preparation, to avoid being lost amidst several datasets. When preparing data, begin with the city with most complexity at first. For example, for the study on household car-ownership, I had to estimate multiple models for Regensburg and hence, several decomposed datasets were to be prepared. Therefore, it is comparatively easier to start with datasets related to Regensburg than with datasets related to Leuven, wherein I had to estimate only one model.

4.3.2 Model estimation procedure

In this section, the estimation sequence for the standalone models are described. The overall estimation framework is outlined in Figure 4.7 and explained in the following sections. All the model estimation procedures were scripted in the R statistical computing software (R Core Team, 2022). The specification for all the models is developed in a stepwise forward fashion, where significant variables are added one after the other. A significance level of 0.1 is used.



Note: BS - Bike-sharing; CS - Car-sharing; RS - Ride-hailing; SMOTE - Synthetic minority over-sampling technique; The numbers and the colours represent the research objectives presented in Figure 1.2.

Figure 4.7: Overview of model estimation sequence

4.3.2.1 Mode choice model between conventional modes-as-a-whole, bike-sharing, car-sharing and ride-hailing

Any household survey, usually, contains details about the trips taken by the respondents. The data that characterise the different available modes (e.g., travel times associated with alternative modes) will not be available. Similar is the case with the current research sample. An option is to construct data for the alternative modes from external data sources. However, to the best of my knowledge, a detailed data source is not available for the shared mobility services, from which the required variables can be generated. Another choice is to synthetically generate the values for the required variables. This involves making several assumptions, which I do not feel warranted making. Hence, it is not possible to estimate a classical multinomial logit mode choice model. Therefore, a personal-level model is developed. Such a model is not newly explored in this dissertation, but rather is already found in the literature (e.g., Anderson & Simkins, 2012; Cheng et al., 2014; Liang et al., 2020). Some studies term such a model as generalised multinomial logit model (e.g., Anderson & Simkins, 2012).

Following the decision on the variable type for the model specification, the choice of estimation method is selected. The penetration of shared mobility services is usually very low in many cities, which will result in very highly imbalanced classes, especially when the conventional modes-as-a-whole is considered instead of the individual conventional modes. In such a scenario, estimation of a multinomial logit model will lead to issues, such as perfect predictions and separation issues (King & Zeng, 2001; Lesaffre & Albert, 1989). An initial analysis in the current case showed the presence of such issues. Therefore, a penalised likelihood estimation approach (Heinze & Schemper, 2002; Kosmidis & Firth, 2021) is tested, with consideration of the choice for shared mobility services as a rare event. This estimation approach, although successfully negated the issues of accurate predictions and separation issues, resulted in other types of issues, such as poor model sensitivity and very high estimation time.

As a consequence, Synthetic Minority Over Sampling Technique (SMOTE) (Chawla et al., 2002) is implemented, by over sampling the minor classes (i.e., shared mobility services) and down sampling the major class (i.e., conventional modes-as-a-whole) to obtain balanced classes, along with the use of conventional maximum likelihood estimation approach. The subsequent step is associated with the development of a multinomial logit model (*MS*) based on the synthetic sample. Models are developed in a stepwise forward fashion, where significant variables are added one after the other (significance level of 0.10). The estimation is carried out using the "mlogit" package (Croissant, 2020) in R. When adding a new variable, the likelihood ratio test is performed to determine the significance in model improvement, along with the comparison of the values of statistical parameters 'Akaike Information Criterion (AIC)' and 'Bayesian Information Criterion (BIC)'.

4.3.2.2 Mode choice between private car and bike-sharing

At first, a binary logit model with generic coefficients for travel cost and time is estimated (*MB1*), and then, another model with alternative specific coefficients is estimated (*MB2*). This is done to ascertain whether the individuals perceive cost and time differently for car and bike-sharing. A binary logit model is selected due to its mathematical simplicity and widespread use in mode choice modelling. The estimation is carried out using the "mlogit" package (Croissant, 2020) in R. The model specification is developed in a stepwise fashion. The decision to keep an independent variable is based on the p-value (significance level of 0.10) of the corresponding variable, log-likelihood test and the statistical parameters 'AIC' and 'BIC'.

4.3.2.3 Demand for a small station-based round-trip car-sharing

The demand calculation is based on a combination of a set of models and a set of sampling procedures, as explained in Section 4.2. The set of models include a multinomial logit (*MC1*), a linear regression (*MC2*) and a multivariate dirichlet regression (*MC3*) models. The dependent variable in the multinomial logit model is the frequency of use of the car-sharing service (Occasional, rare and never). While the dependent variable in the linear regression model is the total demand for the service per day, the dependent variable in the dirichlet model is the demand shares for the individual stations.

R package 'mlogit' (Croissant, 2020) is used for the development of the multinomial logit model. During the stepwise development of the model, when adding a new variable to the model specification, the likelihood ratio test is performed to determine the significance in model improvement, along with the comparison of the values of statistical parameters 'AIC' and 'BIC'. The linear regression model is estimated using the base *lm()* function in R. The dependent variable is constructed by aggregating the individual trips from the operator dataset. Data for a total of 1,108 days are available after aggregation. The improvement in adjusted R^2, AIC and BIC values are used as evaluation criteria for specification development. Furthermore, the residual distribution is checked to ensure the absence of heteroscedasticity.

R package 'DirichletReg' (Maier, 2014) is used for the development of the dirichlet regression model. As done for the average daily demand model (linear regression model), the dependent variable is constructed by aggregating the individual trips corresponding to each station for a whole day. However, unlike in the former model, only those days, during which all the stations are operating, can be considered. Hence, a total of 57 days are used for model estimation. Model evaluation is based on likelihood ratio test, pseudo R^2 measure and the statistical parameters 'AIC' and 'BIC'. It is to be noted that it is infeasible to ascertain the impact of aggregate land-use and socio-demographic factors on the average daily demand, because of the small-scale operation of the service. We believe that this is the usual case for any small-scale service with very low demand and limited number of stations. As such, the novelty behind the development of the regression models lies in the fact that they have minimal variable requirements, which can be obtained (comparatively) in ease.

4.3.2.4 Household car-ownership models

Six different multinomial logit models are developed for the household car-ownership in Regensburg, Madrid and Leuven. Furthermore, a generic model has also been developed by pooling the data from the three cities. The estimations are performed using R package 'mlogit' (Croissant, 2020). The choices included in the dependent variables are 'no car', 'one car' and 'multiple cars'. During the stepwise development of the model, when adding a new variable to the model specification, the likelihood ratio test is performed to determine the significance of the improvement in the log-likelihood value. Moreover, the values of statistical parameters 'AIC' and 'BIC' are compared.

Both in Regensburg and Madrid, the dataset contains details pertaining to all the household members. This leads to a situation wherein one individual from the household has to be chosen as representative for modelling the car-ownership. The usual criterion in the literature is to consider the oldest household member. The same approach has also been followed here (Models *MR1* and *MM1*). In case of multiple individuals with same –oldest– age, a random selection is implemented. Besides the selection of household representative based on age, the Regensburg dataset allows an alternative option: the selection of the representative based on the frequency of the private car use, i.e., the individual with the highest car use frequency is chosen (Model *MR2*). In case of multiple individuals with matching values, the total trip kilometres of the trips reported in the survey is considered and then a random selection is implemented.

Alternative to the estimation of a model based on a household representative, estimation can be performed based on household level variables (e.g., household income) and individual variables aggregated to the household level (e.g., availability of public transport pass in the household). The *MR3* and *MM2* models, shown in Figure 4.7, belong to this category. A model built using data from multiple cities might be more stable/robust for use in other cities, rather than a model which is focused on a single city. Therefore, in order to support cities without adequate resources to estimate a car-ownership model, a generic model (*MG*) has also been developed by combining the data from the three cities (the data corresponding to models *MR1*, *MM1*, and *ML*). Variables are based on those that are commonly found to be significant in the individual city models.

4.3.2.5 Cargo cycle purchase intention and actual purchase decision

At first, LVs are constructed using EFA. These are the variables that are not directly observable. They are inferred from and expressed as a function of other variables (usually called items), which are observable (i.e., directly measurable). Based on the variables obtained through data collection and the LVs constructed through EFA, binary logit models for the intention to purchase cargo cycles and the actual purchase decision are estimated. The R statistical computing software (R Core Team, 2022) is used for both EFA and binary logit model estimation.

EFA is applied to three sets of variables collected during the surveys (refer to section 3.5, i.e., drivers and barriers (LV Set 1), attitudes with respect to corporate environmental responsibility and technology (LV Set 2), and incentive variables (LV Set 3). EFA is utilised primarily to identify the overarching idea behind the three sets of variables (i.e., latent constructs) and secondarily to reduce the data dimensionality. Before carrying out EFA, the suitability of the three sets of variables for EFA is confirmed based on Bartlett's test and Kaiser-Meyer-Olkin index.

The following EFA procedure is implemented: Multi-Variate Normality (MVN) test, tests for determining number of factors, factor extraction, and finally, reliability analysis for the estimated factors. The number of factors for extraction is decided based on Kaiser-Guttman method (eigenvalue > 1), scree plot (elbow point) and parallel analysis.

The final factor model is decided based on the factor model quality, i.e., the number of items per factor, variance explained by the factors, Root Mean Square Error (RMSE) value and Tucker Lewis index. The communality of the individual items is also considered. For the number of items per factor, a minimum value of three is considered, as suggested in Costello & Osborne (2005). However, a 2-item factor is accepted, if the correlation between the two variables is high (> 0.50) and the correlation with the other variables is low.

Non-normality of all the three sets of variables are confirmed by MVN tests, and hence, principal axis factoring is used as the factor extraction method, as suggested in Brown (2015). After testing different rotations, varimax orthogonal rotation is utilised. Following the factor extraction, a reliability analysis (Cronbach alpha test) is performed for each extracted factor. Factor scores are then computed based on the Bartlett method. Subsequent to EFA, the estimation of logit models for purchase intention and actual purchase decision is performed. Both the purchase intention and the actual purchase decision are binary variables, with 1 representing the intention to purchase in the case of former and the actual purchase of a cargo cycle in the case of latter.

Models are developed in a stepwise fashion, where significant variables are added one after the other ((90% confidence interval)). When adding or removing a variable from a model specification, log-likelihood test is performed to determine the significance in model improvement, along with the comparison of the values of statistical parameters 'AIC' and 'BIC'. Variables analysed in the estimation process include the LVs constructed through EFA and the ones available in the original dataset.

When added individually as dummy variables, the variables representing the business sector and cargo cycle construction type (both are categorical variables with multiple levels) are found to be insignificant. Hence, it is decided to reduce the number of categories in each of the these through a clustering analysis. The input value used for clustering is the coefficient value obtained for the dummies, corresponding to each of the categories in a univariate logit model. K-means clustering (Lloyd, 1982) is utilised, and a 2-cluster model [decided based on Silhouette coefficient (Rousseeuw, 1987)] is developed for both the business sector and the construction type. Based on the clusters, a dummy variable is constructed, with the value '0' for one cluster and '1' for the other.

5 Model estimation results

Contents

5.1 Mode choice model between conventional modes-as-a-whole, bike-sharing, car-sharing and ride-hailing

To understand the factors that affect the mode choice between conventional modes-as-a-whole, bike-sharing, car-sharing and ride-hailing, a multinomial logit model (MS) is estimated, as mentioned in Section 4.3.2.1. The utility specification of the final model is shown in Equation 5.1. The estimation results are presented in Table 5.1. The coefficient estimates are in general reasonable in terms of sign and consistent with the prior expectations.

$$\begin{aligned}
Utility(B) = {} & ASC(B) + Age_{20-44}(B) + isMale(B) + \\
& hasUnivOrVocationalDegree(B) + hasPTPass(B) + \\
& HHCarsNum(B) + TripDist_{KM\leq 2}(B) + \\
& TripDist_{KM>2\&\leq 5}(B) + TravelTime_{Mins\leq 30}(B) + \\
& SharedBikesInTheTrafficZone \\
Utility(C) = {} & ASC(C) + Age_{20-44}(C) + isMale(C) + \\
& hasUnivOrVocationalDegree(C) + hasPTPass(C) + \\
& HHCarsNum(C) + TripDist_{KM>2\&\leq 5}(C) + \\
& TripDist_{KM>5\&\leq 15}(C) + TravelTime_{Mins\leq 15}(C) + \\
& TravelTime_{Mins>15\leq 30}(C) \\
Utility(R) = {} & ASC(R) + Age_{20-44}(R) + hasUnivOrVocationalDegree(R) + \\
& hasAnyLicense(R) + hasPTPass(R) + TripDist_{KM>2\&\leq 5(R)} + \\
& TripDist_{KM>5\&\leq 15}(R) + TravelTime_{Mins\leq 15}(R) + \\
& TravelTime_{Mins>15\leq 30}(R) \\
Utility(CM) = {} & 0\ (base\ category)
\end{aligned} \tag{5.1}$$

where, **B:** Bike-sharing; **C:** Car-sharing; **R:** Ride-hailing; **CM:** Conventional modes-as-a-whole; **ASC:** Alternative Specific Constant

Looking at the estimate values, young people belonging to the age group 20 to 44 and individuals with vocational or university degree are more probable to use all three types of shared mobility services. While males have a higher likelihood to use bike-sharing and car-sharing, a significant difference between males and females is not observed for ride-hailing. On the other hand, the possession of (any) license has a negative influence on the use of ride-hailing. Besides the possession of a license, owning a PT pass also has a negative impact for ride-hailing, although it improves the odds of using bike-sharing and car-sharing, with a stronger influence on bike-sharing. Looking at the number of household cars, households with higher number of cars are less probable to use bike-sharing. In contrast, a positive impact is seen for car-sharing.

Table 5.1: Estimation results for Model *MS*

Group	Variable	Estimate	S.E.
Who	Age_{20-44}(B)	1.11 (***)	0.04
	Age_{20-44}(C)	1.07 (***)	0.04
	Age_{20-44}(R)	0.80 (***)	0.04
	isMale(B)	1.44 (***)	0.03
	isMale(C)	1.27 (***)	0.03
	hasUnivOrVocationalDegree(B & R)	0.92 (***)	0.03
	hasUnivOrVocationalDegree(C)	1.48 (***)	0.04
	hasAnyLicense(R)	-0.19 (***)	0.04
	hasPTPass(B)	1.13 (***)	0.04
	hasPTPass(C)	0.89 (***)	0.04
	hasPTPass(R)	-0.27 (***)	0.03
	HHCarsNum(B)	-0.69 (***)	0.02
	HHCarsNum(C)	0.45 (***)	0.02
When	$\text{TripDistance}_{KM\leq 2}$(B)	1.45 (***)	0.06
	$\text{TripDistance}_{KM>2\&\leq 5}$(B)	2.18 (***)	0.06
	$\text{TripDistancet}_{KM>2And\leq 5}$(R)	1.47 (***)	0.04
	$\text{TripDistance}_{KM>2And\leq 5}$(C) & $\text{TripDistance}_{KM>5and\leq 15}$(R)	1.77 (***)	0.03
	$\text{TripDistance}_{KM>5And\leq 15}$(C)	2.02 (***)	0.05
	$\text{TotalTravelTime}_{Mins\leq 15}$(C)	2.04 (***)	0.06
	$\text{TotalTravelTime}_{Mins\leq 15}$(R) & $\text{TotalTravelTime}_{Mins>15And\leq 30}$(C)	1.35 (***)	0.04
	$\text{TotalTravelTime}_{Mins>15And\leq 30}$(R) & $\text{TotalTravelTime}_{Mins\leq 30}$(B)	0.87 (***)	0.04
	SharedBikesInTheTrafficZone[1](B)	1.36 (***)	0.04
–	ASC(B)	-4.57 (***)	0.11
	ASC(C)	-5.85 (***)	0.11
	ASC(R)	-2.47 (***)	0.06

Summary statistics

Log-likelihood:	-35216.21
McFadden R^2:	0.22
AIC:	70482.42
BIC:	70545.21

Note:
- B: Bike-Sharing; C: Car-Sharing; R: Ride-hailing; HH: Household; ASC: Alternative Specific Constant
- ***p <0.001
- Conventional modes-as-a-whole is the base alternative
- [1]The number of shared bikes is represented in terms of hundreds

With regards to trip characteristics (i.e., when a shared mobility service will be used), bike-sharing systems are more likely to be used for trips with distances up to 5 km, with significantly higher probability for the range 2 to 5 km. However, car-sharing and ride-hailing systems are expected to be used for a longer distance range of 2 to 15 km, with a higher probability for the range 5 to 15 km. Concerning trip travel times, there is a lower probability to use the three shared mobility services for travel times beyond 30 minutes. When it comes to supply of shared mobility services, with an increase in the number of shared bikes in the traffic zone, there is a higher probability to use the bike-sharing service. With respect to car-sharing and ride-hailing, relevant supply data is not available, and hence, they are missing in the mode choice model.

I acknowledge the importance of the influence of travel cost on mode choice. Unfortunately, the household survey does not contain any cost related data. To overcome this issue, synthetic travel cost could be estimated using information such as published PT and shared mobility system fares. However, this involves making several assumptions about the costs of travel, which I do not feel warranted making.

5.2 Mode choice between private car and bike-sharing

A binary logit model with generic coefficients for travel cost and time is estimated at first, the result of which is shown in the left side of Table 5.2. On the right side of the table, the estimation results for a model with alternative specific coefficients is shown. The likelihood ratio test shows that the latter model is better than the former. This result conveys that the individuals perceive cost and time differently for car and bike-sharing. Furthermore, although the time variable for the choice 'car' has a negative coefficient, it is found to be insignificant, and hence, removed from the final model specification. This conveys the fact that, when comparing a car with bike-sharing, the car users are not significantly influenced by the time that they would require to travel by car. However, they are sensitive to bike-sharing travel time. The model with alternative specific coefficients is considered as the best model (utility specification shown in Equation 5.2) and further exploration of the coefficients will be based on that.

Based on the coefficients shown in Table 5.2, it can be concluded that the respondents of the survey are almost twice as sensitive to the cost of the bike-sharing as they are to the private car. Similarly, respondents are sensitive to the bike-sharing travel time, but not to the car travel time. It can also be seen that the negative perception of bike safety reduces the probability of using a bike-sharing service, whilst the opposite is true if an individual feels that biking is safe, although the former has lesser impact. On the positive side, individuals, who make leisure trips for at least twice a week, have a significantly higher odds of using the bike-sharing system. Likewise, state employed car users are more likely to shift to bike-sharing, when the system is introduced. However, having a household income of less than €1200 Euros per month reduces the odds of using the bike-sharing service. Looking at the gender aspect, males are more probable to use the service.

$$\begin{aligned} Utility(Car) &= Cost(Car) \\ Utility(BS) &= ASC(BS) + Cost(BS) + Time(BS) + \\ &\quad Perception(Bike\ is\ not\ safe)(BS) + \\ &\quad Perception(Bike\ is\ safe)(BS) + Leisure\ trips \geq\ 2/week(BS) + \\ &\quad Household\ income < €1200/month(BS) + \\ &\quad Employed\ by\ state(BS) + isMale(BS) \end{aligned} \tag{5.2}$$

where, **BS:** Bike-sharing; **ASC:** Alternative Specific Constant

Table 5.2: Estimation results for Models *MB1* and *MB2*

Generic coefficient (*MB1*)			**Alternative specific coefficient (*MB12*)**		
Variable	**Estimate**	**S.E.**	**Variable**	**Estimate**	**S.E.**
Cost	-0.026 (***)	0.004	Cost(BS)	-0.032 (***)	0.005
			Cost(Car)	-0.018 (**)	0.006
Time	-0.035 (*)	0.017	Time(BS)	-0.184 (**)	0.060
Perception - bike is not safe(BS)	-0.707 (*)	0.292	Perception - bike is not safe(BS)	-0.726 (*)	0.296
Perception - bike is safe(BS)	1.093 (**)	0.343	Perception - bike is safe(BS)	1.111 (**)	0.346
Leisure trips $\geq$ 2/week(BS)	1.250 (***)	0.285	Leisure trips $\geq$ 2/week(BS)	1.277(***)	0.289
HH income < €1200/month(BS)	-0.653 (*)	0.260	HH income < €1200 /month(BS)	-0.665 (*)	0.263
Employed by state(BS)	0.965 (**)	0.318	Employed by state(BS)	0.985 (**)	0.320
isMale(BS)	0.533 (*)	0.254	isMale(BS)	0.544 (*)	0.256
ASC(BS)	-1.249 (**)	0.40	ASC(BS)	1.68 (.)	0.97
Summary statistics			**Summary statistics**		
Log-likelihood	-204.74		Log-likelihood	-201.87	
McFadden R^2	0.23		McFadden R^2	0.24	
AIC	427.48		AIC	423.75	
BIC	463.06		BIC	463.27	
Cross-validation accuracy	72.1%		Cross-validation accuracy	72.4%	

Note:
- BS: Bike-sharing; ASC: Alternative Specific Constant; HH: Household
- (.) - p <0.1; (*) - p <0.05; (**) - p <0.01; (***) - p <0.001
- Car is the base alternative. For the perception variable, neutral is kept as the base category.
- ‘Time:car’ has a negative coefficient, however, it is found to be insignificant.

5.3 Demand for a small-scale station-based car-sharing service

In this section, the final specification of the three models included in the data-driven demand framework is presented, along with the coefficients of the variables in this specification.

5.3.1 Frequency of use of the car-sharing service

To understand the factors that influence the use frequency of the car-sharing service (occasional, rare and never), a multinomial logit model is estimated. The utility specification of the final model is shown in Equation 5.3. The estimation results are presented in Table 5.3. The coefficient estimates are in general reasonable in terms of sign and consistent with the prior expectations.

$$\begin{aligned}
Utility(O) = {} & ASC(O) + Age(O) + Employment_{Student}(O) + \\
& Employment_{Full}(O) + Employment_{Half}(O) + \\
& BicycleUse_{Frequent}(O) + PTUse_{Frequent}(O) + \\
& SharedCarsInTheDistrict(O) \\
Utility(R) = {} & ASC(R) + Age(R) + Employment_{Student}(R) + \\
& Employment_{Full}(R) + Employment_{Half}(R) + \\
& hasUniversityDegree(R) + HHLowIncome(R) + \\
& HHBicyclesNum(R) + HHCarsNum(R) + \\
& BicycleUse_{Occasional}(R) + PrivateCarUse_{Rare}(R) + \\
& isPTAndCarUser(R) + \\
& SharedCarsInTheDistrict(R) \\
Utility(N) = {} & 0 \; (base\ category)
\end{aligned} \tag{5.3}$$

where, **O:** Occasional; **R:** Rare; **N:** Never; **ASC:** Alternative Specific Constant: **HH:** Household

Looking at the estimates shown in Table 5.3, the frequency of use of the car-sharing service is influenced by the following factors: age, employment, education, household income, number of household bikes and cars, frequency of use of conventional modes (bicycle, PT and private car) and the number of shared cars in the district. With regards to their influence, with increasing age, there is a decreasing probability to use the car-sharing system. However, students, fully employed persons ($\geq$ 35 hr/week) and individuals with half employment (between 18 to 34 hr/week) are more likely to use the service. Similarly, people with university degree are more probable to use the service, and low income population (<€ 1500/month) is more probable to be a rare user.

With regards to household vehicle ownership, bicycles are found to have a positive influence on the rare use of the service. However, a negative impact is observed for private car ownership. With regards to this negative effect, given the small-scale of operation, the service may not still be sufficient, to stimulate people to shift to the car-sharing service. Concerning the frequency of use of conventional modes, there is a higher probability to use the car-sharing service, if an individual is a bicycle user (both bicycle use frequency groups 'Frequent' and 'Occasional'). Similarly, PT use is also found to complement car-sharing use. Furthermore, individuals, who use their private cars rarely, are more probable to use the car-sharing system. In addition, when an individual uses both PT and private car for at least once a week, a lower probability to use the service is observed. Finally,the higher is the number of car-sharing vehicles in a district, the greater is the likelihood to use the system. Thus, the introduction of new car-sharing vehicles will have a positive effect.

Table 5.3: Estimation results for Model *MC1*

Group	Variable	Estimate	S.E.
Socio-demographic characteristics	Age(both O & R)	-0.04 (***)	0.01
	$\text{Employment}_{\text{Student}}$(O)	1.56 (***)	0.46
	$\text{Employment}_{\text{Student}}$(R)	2.05 (***)	0.38
	$\text{Employment}_{\text{Full}}$(O)	1.14 (*)	0.45
	$\text{Employment}_{\text{Full}}$(R)	1.68 (***)	0.37
	$\text{Employment}_{\text{Half}}$(both O & R)	1.63 (***)	0.39
	hasUniversityDegree(both O & R)	0.61 (**)	0.23
	HHLowIncome(R)	0.72 (.)	0.37
Mobility patterns	HHBicyclesNum(R)	0.17 (**)	0.05
	HHCarsNum(both O & R)	-0.33 (*)	0.14
	$\text{BicycleUse}_{\text{Frequent}}$(O)	1.55 (***)	0.39
	$\text{BicycleUse}_{\text{Occasional}}$(R)	0.54 (*)	0.24
	$\text{PTUse}_{\text{Frequent}}$(O)	1.01 (**)	0.37
	$\text{PTUse}_{\text{Occasional}}$(R)	0.50 (*)	0.22
	$\text{PrivateCarUse}_{\text{Rare}}$(R)	0.68 (*)	0.33
	isPTAndCarUser(R)	-0.71 (*)	0.35
Transport supply	SharedCarsInTheDistrict(O)	0.24 (**)	0.09
	SharedCarsInTheDistrict(R)	0.14 (*)	0.06
_	ASC(O)	-5.24 (***)	0.57
	ASC(R)	-4.21 (***)	0.48

Summary statistics
Log-likelihood: -516.92
McFadden R^2: 0.17
AIC: 1073.85
BIC: 1186.70

Note:
- O: Occasional; R: Rare; HH: Household; ASC: Alternative Specific Constant
- (.) - p <0.1; (*) - p <0.05; (**) - p <0.01; (***) - p <0.001
- The category 'Never' is the base alternative

5.3.2 Total demand per day for the service

A linear regression model is estimated to calculate the daily demand for the whole car-sharing system. The specification of the final model is shown in Equation 5.4. The estimation results are presented in Table 5.4. The estimation results show that, on an average, the demand increases by around 1.82 trips for every new station introduced (with 1 or 2 vehicles). This effect is also complemented by the positive influence of the vehicle count observed in the use frequency model. These positive impacts indicate that it is appropriate for the city of Regensburg to expand their car-sharing service. On a different note, the demand peaks on Friday and during the months March to May. Nevertheless, there is also a higher demand during February and July, compared to other months. On a different note, demand decreases on Saturdays and Sundays, reaching the lowest demand on Sundays.

$$\begin{aligned} AverageDailyDemand = {} & Intercept + StationCount + isFriday + isSaturday + \\ & isSunday + isInFebruary + \\ & isInMarchOrAprilOrMay + isInJuly \end{aligned} \tag{5.4}$$

Table 5.4: Estimation results for Model *MC2*

Variable	**Estimate**	**S.E.**
StationCount	1.82 (***)	0.03
isFriday	0.56 (*)	0.22
isSaturday	-0.46 (*)	0.22
isSunday	-2.58 (***)	0.22
isFebruary	1.23 (***)	0.29
isInMarch/April/May	1.52 (***)	0.18
isJuly	0.79 (**)	0.27
Intercept	0.91 (***)	0.17
Summary statistics		
Adjusted R^2: 0.75		
AIC: 5139.35		
BIC: 5184.44		

Note: (*) - $p < 0.05$; (**) - $p < 0.01$; (***) - $p < 0.001$

5.3.3 Station level demand per day

A dirichlet regression model is estimated to distribute the average daily demand to the car-sharing stations (currently eight stations are present in the city of Regensburg), i.e., this model finds the shares for individual stations. The specification of the final model is shown in Equation 5.5.

The estimation results are presented in Table 5.5. The estimation results show that, as the average daily demand increases, certain stations attract more customers, e.g., there is a higher share for Candis, when the demand increases. With regards to demand shares for stations during different days of a week, Candis has a lower share on Mondays, while a higher share on Saturdays. Stadtamhof receives a greater share on Tuesdays, Fridays and Sundays, the value being the highest on Sundays. Burgweinting also receives a greater share on Sundays, with a share higher than Stadtamhof. Landratsamt and Petersweg receive a larger share on Wednesdays, with latter attracting more demand than the former. Finally, the demand for the station at Dachauplatz decreases on Fridays.

$$\begin{aligned}
DemandShare(B) &= Intercept(B) + log[AverageDailyDemand](B) + \\
&\quad isSunday(B) \\
DemandShare(C) &= Intercept(C) + log[AverageDailyDemand](C) + \\
&\quad isMonday(C) + isSaturday(C) \\
DemandShare(D) &= Intercept(D) + log[AverageDailyDemand](D) + \\
&\quad isFriday(D) \\
DemandShare(K) &= Intercept(K) + log[AverageDailyDemand](K) \\
DemandShare(R) &= Intercept(R) + log[AverageDailyDemand](R) + \\
&\quad isWednesday(R) \\
DemandShare(P) &= Intercept(P) + log[AverageDailyDemand](P) + \\
&\quad isWednesday(P) \\
DemandShare(S) &= Intercept(S) + log[AverageDailyDemand](S) + \\
&\quad isSunday(S) \\
DemandShare(T) &= Intercept(T) + log[AverageDailyDemand](T)
\end{aligned} \tag{5.5}$$

where, **B:** Burgweinting; **C:** Candis; **D:** Dachauplatz; **K:** Koenigswiesen; **L:** Landratsamt; **P:** Petersweg; **S:** Stadtamhof; **T:** Techbase

Table 5.5: Estimation results for Model MC3

Variable	Estimate	S.E.
AverageDailyDemand(B)	2.85 (***)	0.59
AverageDailyDemand(C)	3.10 (***)	0.38
AverageDailyDemand(D)	2.07 (***)	0.38
AverageDailyDemand(K)	2.37 (***)	0.41
AverageDailyDemand(R)	1.97 (***)	0.32
AverageDailyDemand(P)	2.77 (***)	0.36
AverageDailyDemand(S)	1.96 (***)	0.43
AverageDailyDemand(T)	3.06 (***)	0.41
isMonday(C)	-0.46 (.)	0.25
isTuesday(S)	0.40 (.)	0.22
isWednesday(R)	0.38 (.)	0.22
isWednesday(P)	0.51 (**)	0.18
isFriday(D)	-0.35 (.)	0.21
isFriday(S)	0.33 (.)	0.20
isSaturday(C)	0.49 (*)	0.21
isSunday(B)	0.79 (*)	0.37
isSunday (S)	0.51 (.)	0.29
Intercept(B)	-7.84 (***)	1.65
Intercept(C)	-7.84 (***)	1.06
Intercept(D)	-4.36 (***)	1.05
Intercept(K)	-6.01 (***)	1.13
Intercept(L)	-4.73 (***)	0.89
Intercept(P)	-6.39 (***)	1.01
Intercept(S)	-4.43 (***)	1.20
Intercept(T)	-7.92 (***)	1.15

Summary statistics

Log-likelihood: 612.80

Pseudo R^2: 0.90

AIC: -1176

BIC: -1125

Note:

- **B**: Burgweinting; **C**: Candis; **D**: Dachauplatz; **K**: Koenigswiesen; **L**: Landratsamt; **P**: Petersweg; **S**: Stadtamhof; **T**: Techbase
- (.) - p <0.1; (*) - p <0.05; (**) - p <0.01; (***) - p <0.001

5.4 Household car-ownership models

The estimation results of the multinomial logit models for household car-ownership in Regensburg, Madrid and Leuven are presented at first, and then the results for a generic model, based on the pooled data from the three cities, are described. Table 5.6 summarises the availability of the different variables in the three cities and their significance in the estimated models. It is to be noted that the presence of a variable in multiple models does not necessarily imply the same direction of effect, matching coefficient value, or similar variable type (continuous vs categorical). For such details, the reader is suggested to check the subsequent tables summarising the estimation results.

Table 5.6: Availability of variables from Regensburg, Madrid & Leuven for the estimation of car-ownership models

Group	**Variable**	**Madrid**		**Regensburg**			**Leuven**	**Generic**
		MM1	**MM2**	**MR1**	**MR2**	**MR3**	**ML**	**MG**
Socio-demographic characteristics	Household size	✓	✓	✓	✓	✓	✓	✓
	Income	✓	✓	✓	✓	✓	✓	✓
	Working status	✓	✓	✗	✗	✗	✗	✓
	Student status	✓	✓	✗	✗	✗	✗	✗
	Education	✓	✓	✗	✗	✗	✗	✗
	Nationality	✓	✓	—	—	—	✓	—
	Gender	✓	✓	✗	✗	✗	✗	✗
	Age	✓	✓	✓	✓	✓	✓	✓
	Mobility restrictions	✓	✓	✗	✗	✗	—	—
Urban characteristics	Density	✓	✓	—	—	—	—	—
Transport supply	Public parking supply	✓	✓	—	—	—	—	—
	Car-Sharing supply	—	—	—	—	—	✓	—
	Bike-Sharing supply	✓	✓	—	—	—	–	✓
Mobility patterns	Total trips	✓	✓	✓	✓	✓	—	—
	Availability bikes	—	—	✗	✗	✗	✗	—
	Availability moped	—	—	✓	✓	✗	✗	—
	Availability cargo bike	—	—	—	—	—	✓	—
	Driving licenses	✓	✓	✓	✓	✓	—	—
	PT pass	✓	✓	✓	✓	✓	✗	✓
	PT use frequency	—	—	✓	✓	✓	✓	—
	Car use frequency	—	—	✓	✓	✓	✓	—
	Bike use frequency	—	—	✗	✓	✓	✓	—
	Car-Sharing use freq.	—	—	✗	✗	✓	—	—

Notes:

- MR1: Model Regensburg 1; individual variables of the household representative (oldest member)
- MR2: Model Regensburg 2; individual variables of the household representative (member with highest car use)
- MR3: Model Regensburg 3; individual variables aggregated to the household level
- MM1: Model Madrid 1; individual variables of the household representative (oldest member)
- MM2: Model Madrid 2; individual variables aggregated to the household level
- ✓: Available and significant; ✗: Available but insignificant; —: Not available.

5.4.1 Household car-ownership in Regensburg

Based on the data availability, the focus of the disaggregate car-ownership model in Regensburg is on socio-demographic characteristics and mobility patterns. As described in Section 4.3.2.4, three different models (*MR1*, *MR2* and *MR3*) are estimated for Regensburg. The utility specification of the estimated models are shown in Equations 5.6 - 5.8. The estimation results are presented in Table 5.7. The coefficient estimates are in general reasonable in terms of sign and consistent with the prior expectations.

Model MR1

$$\begin{aligned}
Utility(0\ car) &= 0\ (base\ alternative)\\
Utility(1\ car) &= log(HouseholdSize) + log(Income) + Age_{\text{ up to 67}} + hasMoped +\\
&\quad DailyCarUse + FrequentCarUse + ShareCarLicense_{\text{ up to 50\%}}\\
&\quad + TripsPerPerson + DummyPTPass + DailyPTUse + ASC\\
Utility(2+cars) &= log(HouseholdSize) + log(Income) + Age_{\text{ up to 67}} +\\
&\quad hasMoped + DailyCarUse + FrequentCarUse +\\
&\quad ShareCarLicense_{\text{ up to 50\%}} + ShareCarLicense_{\text{ beyond 50\%}} +\\
&\quad TripsPerPerson + DummyPTPass + DailyPTUse + ASC
\end{aligned} \tag{5.6}$$

Model MR2

$$\begin{aligned}
Utility(0\ car) &= 0\ (base\ alternative)\\
Utility(1\ car) &= log(HouseholdSize) + log(Income) + Age_{\text{ up to 67}} + hasMoped +\\
&\quad DailyCarUse + FrequentCarUse + ShareCarLicense_{\text{ up to 50\%}} +\\
&\quad TripsPerPerson + DummyPTPass + DailyPTUse + ASC\\
Utility(2+cars) &= log(HouseholdSize) + log(Income) + Age_{\text{ up to 67}} +\\
&\quad DailyBikeUse + hasMoped + DailyCarUse + FrequentCarUse +\\
&\quad ShareCarLicense_{\text{ up to 50\%}} + ShareCarLicense_{\text{ beyond 50\%}} +\\
&\quad TripsPerPerson + DummyPTPass + DailyPTUse + ASC
\end{aligned} \tag{5.7}$$

Model MR3

$$\begin{aligned}
Utility(0\ car) &= 0\ (base\ alternative)\\
Utility(1\ car) &= log(HouseholdSize) + log(Income) + AverageAge_{\text{ up to 67}} +\\
&\quad ShareDailyCarUsers + ShareFrequentCarUsers +\\
&\quad ShareCarLicense_{\text{ up to 50\%}} + TripsPerHousehold +\\
&\quad SharePTPass + ShareDailyPTUsers +\\
&\quad DummyCarSharingUse + ASC\\
Utility(2+cars) &= log(HouseholdSize) + log(Income) + AverageAge_{\text{ up to 67}} +\\
&\quad ShareDailyBikeUsers + ShareDailyCarUsers +\\
&\quad ShareFrequentCarUsers + ShareCarLicense_{\text{ up to 50\%}} +\\
&\quad ShareCarLicense_{\text{ beyond 50\%}} + TripsPerHousehold +\\
&\quad SharePTPass + ShareDailyPTUsers +\\
&\quad DummyCarSharingUse + ASC
\end{aligned} \tag{5.8}$$

Table 5.7: Estimation results for Models *MR1*, *MR2* and *MR3*

		MR1		**MR2**		**MR3**	
Group	**Variable**	**Estimate**	**S.E.**	**Estimate**	**S.E.**	**Estimate**	**S.E.**
Socio-demographic characteristics	log(HouseholdSize) (1)	2.25 (***)	0.37	1.83 (***)	0.36	2.93 (***)	0.43
	log(HouseholdSize) (2+)	6.33 (***)	0.60	5.89 (***)	0.59	7.37 (***)	0.64
	log(Income) (1)	0.59 (*)	0.28	0.59 (*)	0.29	0.43 (.)	0.26
	log(Income) (2+)	2.07 (***)	0.43	2.06 (***)	0.44	1.79 (***)	0.42
	$\text{Age}_{\text{up to 67}}$ (1 & 2+)	0.02 (.)	0.01	0.01 (.)	0.01		
	$\text{AverageAge}_{\text{up to 67}}$ (1 & 2+)					0.02 (.)	0.01
Mobility patterns	DailyBikeUse (2+)			-0.70 (*)	0.30		
	ShareDailyBikeUsers (2+)					-0.87 (*)	0.36
	hasMoped (1 & 2+)	-1.06 (*)	0.51	-1.12 (*)	0.52		
	DailyCarUse (1)	3.70 (***)	0.41	4.14 (***)	0.42		
	DailyCarUse (2+)	5.02 (***)	0.54	4.28 (***)	0.60		
	FrequentCarUse (1)	3.24 (***)	0.34	3.65 (***)	0.37		
	FrequentCarUse (2+)	3.74 (***)	0.49	2.38 (***)	0.58		
	ShareDailyCarUsers (1)					3.51 (***)	0.42
	ShareDailyCarUsers (2+)					5.43 (***)	0.65
	ShareFreqCarUsers (1)					3.13 (***)	0.35
	ShareFreqCarUsers (2+)					3.79 (***)	0.58
	$\text{ShareCarLicense}_{\text{up to 50\%}}$ (1)	0.11 (***)	0.03	0.12 (***)	0.03	0.10 (***)	0.02
	$\text{ShareCarLicense}_{\text{up to 50\%}}$ (2+)	0.18 (***)	0.05	0.18 (***)	0.05	0.17 (***)	0.05
	$\text{ShareCarLicense}_{\text{beyond 50\%}}$ (2+)	0.06 (***)	0.01	0.06 (***)	0.01	0.06 (***)	0.01
	TripsPerPerson (1 & 2+)	-0.21 (***)	0.06	-0.21 (***)	0.06		
	TripsPerHousehold (1 & 2+)					-0.10 (***)	0.03
	DummyPTPass (1)	-1.06 (**)	0.34	-0.98 (**)	0.35		
	DummyPTPass (2+)	-1.31 (***)	0.39	-1.42 (***)	0.41		
	SharePTPass (1)					-0.87 (*)	0.39
	SharePTPass (2+)					-1.08 (*)	0.52
	DailyPTUse (1 & 2+)	-0.92 (*)	0.43	-1.07 (*)	0.44		
	ShareDailyPTUsers(1 & 2+)					-1.09 (*)	0.47
	DummyCarSharingUse (1 & 2+)					-0.40 (*)	0.19
-	ASC (1)	-7.60 (***)	1.75	-8.47 (***)	1.80	-7.30 (***)	1.36
	ASC (2+)	-21.25 (***)	2.87	-20.57 (***)	2.90	-21.50 (***)	2.72
Summary statistics	Log-Likelihood:	-452.94		-432.70		-485.62	
	McFadden R^2:	0.47		0.50		0.47	
	AIC:	943.88		905.39		1,011.23	
	BIC:	1,035.00		1,001.42		1,108.55	

Note:

- ASC: Alternative-Specific Constant
- (.) - p <0.1; (*) - p <0.05; (**) - p <0.01; (***) - p <0.001
- **(1)**: One car per household; **(2+)**: Multiple cars per household; no household car is the base category
- MR1: model with individual variables of the household representative (oldest member)
- MR2: model with individual variables of the household representative (highest car use)
- MR3: model with individual variables aggregated to the household level
- DummyCarSharingUse: at least a household member uses car-sharing once or more per quarter
- DummyPTPass: at least one public transport pass is available in the household.
- The variables prefixed with ‘Share’ are in decimal format, except the license variable, which is in percentage format.
- Income: ordinal variable

Looking at the estimates shown in Table 5.7, starting with the socio-demographic characteristics, household size is found to have a positive impact on private car-ownership. Furthermore, this positive impact has a logarithmic effect, showing that the marginal utility decreases as the household size increases. Household income also has a similar influence. Age has a piecewise effect, with a positive impact till the age of 67 (usually the retirement age) and then the utility stabilises (i.e., there exists no further increase in the utility after the age of 67). It is to be noted that, for Model *MR3* (which is based on aggregated household data), the average age of the household members is used and still, the piecewise effect holds.

Moving on to the variables related to the mobility patterns, daily bike use can result in a lower probability of owning multiple cars. Interestingly, this effect is not observed in Model *MR1*, but in Models *MR2* and *MR3*. This shows that a model based on the highest car use or a model with aggregate household variables are suitable to ascertain such effects (i.e., the oldest individual is not representative for the daily bicycle use). With regards to household moped-ownership, this variable has a significant negative impact in models *MR1* and *MR2*. The impact is insignificant in the model *MR3* (although the variable has a negative coefficient) and the reason is not yet clear. As expected, daily and frequent car use increase the probability of car-ownership.

Possession of a license is necessary to drive a car. Therefore, it is not appropriate to consider the possession of license for a representative individual in the models. Nevertheless, an interesting case is to consider the proportion of household members owning a license. An increase in the probability of car-ownership is observed as this share increases. A detailed analysis reveals the existence of a piecewise impact, with different effects up to and beyond 50% share. Till the 50% share, a significant coefficient is observed for both the ownership of single and multiple cars, with a higher magnitude for the latter. Beyond the 50% share, the coefficient for single car-ownership is insignificant. Furthermore, the marginal utility is lower for the multiple car-ownership, when compared to the coefficient corresponding to the license share till the 50%.

Considering the mobility rates of individuals, i.e., the number of trips per person per day, a decrease in the likelihood of owning a private car is observed. The subsequent variable to explore is the possession of a PT pass, the estimate of which conveys that it negatively impacts private car-ownership. Similarly, the daily use of PT also has a negative influence. Finally, if at least one household member uses the car-sharing service, the probability of owning a car decreases. However, the car-sharing use of the household representative does not have a significant impact (and thus, the car-sharing use is not seen in Models *MR1* and *MR2*). In Regensburg, the car-sharing service is currently operated on a small-scale and thus, only when all the household members are considered, a significant estimate can be observed.

5.4.2 Household car-ownership in Madrid

Based on the data availability, the focus of the disaggregate car-ownership model in Madrid is on socio-demographic characteristics, urban characteristics, transport supply, and mobility patterns. As described in Section 4.3.2.4, two different models (*MM1* and

MR2) are estimated for Madrid. The utility specification of the estimated models are shown in Equations 5.9 and 5.10. The estimation results are presented in Table 5.8. The coefficient estimates are in general reasonable in terms of sign and consistent with the prior expectations.

Model MM1

$$\begin{aligned}
Utility(0\ car) &= 0\ (base\ alternative)\\
Utility(1\ car) &= log(HouseholdSize) + log(Income) + Worker +\\
&\quad StudentWorker + Student + Education_{\text{ post-sec.}} +\\
&\quad Education_{\text{ higher}} + SpanishNationality + Male + Age_{\text{ up to 67}} +\\
&\quad MobilityRestricted + Density + DummyPublicParkingSupply +\\
&\quad BSBikesInTheDistrict + TripsPerPerson +\\
&\quad ShareCarLicense_{\text{ up to 50\%}} + ShareCarLicense_{\text{ beyond 50\%}} +\\
&\quad DummyPTPass + ASC \qquad (5.9)\\
Utility(2+cars) &= log(HouseholdSize) + log(Income) + Worker +\\
&\quad StudentWorker + Student + Education_{\text{ post-sec.}} +\\
&\quad Education_{\text{ higher}} + SpanishNationality + Male + Age_{\text{ up to 67}} +\\
&\quad MobilityRestricted + Density + BSBikesInTheDistrict +\\
&\quad TripsPerPerson + ShareCarLicense_{\text{ up to 50\%}} +\\
&\quad ShareCarLicense_{\text{ beyond 50\%}} + DummyPTPass + ASC
\end{aligned}$$

Model MM2

$$\begin{aligned}
Utility(0\ car) &= 0\ (base\ alternative)\\
Utility(1\ car) &= log(HouseholdSize) + log(Income) +\\
&\quad ShareWorkersStudentWorkers + ShareEducation_{\text{ post-sec.}} +\\
&\quad ShareEducation_{\text{ higher}} + ShareSpanishNationality +\\
&\quad ShareMale + AverageAge_{\text{ up to 67}} + AverageAge_{\text{ beyond 67}} +\\
&\quad ShareMobRestricted + Density +\\
&\quad DummyPublicParkingSupply + BSBikesInTheDistrict +\\
&\quad TotalTripsHousehold + ShareCarLicense_{\text{ up to 50\%}} +\\
&\quad ShareCarLicense_{\text{ beyond 50\%}} + ShareMembersWithPTPass +\\
&\quad ASC \qquad (5.10)\\
Utility(2+cars) &= log(HouseholdSize) + log(Income) +\\
&\quad ShareWorkersStudentWorkers + ShareEducation_{\text{ post-sec.}} +\\
&\quad ShareEducation_{\text{ higher}} + ShareSpanishNationality +\\
&\quad ShareMale + AverageAge_{\text{ up to 67}} + AverageAge_{\text{ beyond 67}} +\\
&\quad ShareMobRestricted + Density + BSBikesInTheDistrict +\\
&\quad TotalTripsHousehold + ShareCarLicense_{\text{ up to 50\%}} +\\
&\quad ShareCarLicense_{\text{ beyond 50\%}} + ShareMembersWithPTPass +\\
&\quad ASC
\end{aligned}$$

Looking at the estimates shown in Table 5.8, starting with the socio-demographic characteristics, the private car-ownership in Madrid is influenced by the household size, income, employment, education, Spanish nationality, gender, age, and mobility restriction. Household size is found to have a positive impact on private car-ownership. Furthermore, this positive impact has a logarithmic effect, showing that the marginal utility decreases as the household size increases. Household income also has a similar influence. When it comes to employment, workers and students-who-work are more likely to own private cars. Model *MM1* shows that students who do not work are less likely to own a car, although the estimate for the counterpart in Model *MM2* is insignificant. Post-secondary education qualification and possession of a vocational or university degree also increases the odds of private car-ownership. The impact of the former (i.e, post-secondary education) is same for both single and multiple car-ownership.

Individuals with local citizenship are more likely to own private cars. Gender also has a significant influence, with a higher car-ownership probability for males. On the other hand, individuals with mobility restrictions are less probable to own a private car. Age has a piecewise effect, with a positive impact till the age of 67 (usually the retirement age) and then there is no further increase in the utility after the age of 67. It is to be noted that, for Model *MM2* (which is based on aggregated household data), the average age of the household members is used and still, the piecewise effect holds. When it comes to urban characteristics, the population density, has a negative coefficient as expected, especially a higher value for owning multiple cars.

Concerning transport supply-related variables, the presence of public parking in the transport analysis zone can increase ownership of single car. However, a significant influence is not found for the ownership of multiple cars. The other transport supply-related variable explored in this study, bike-sharing supply, negatively influences the ownership of private cars. Moving on to the mobility pattern-related variables, an increase in the likelihood of owning a private car is observed with increasing mobility rates. This is in contrast to the effect observed for Regensburg. Regarding driving license possession, as mentioned in Section 5.4.1, it is not possible to consider the license possession of the household representative. Alternatively, the share of household members owning a license can be considered. An increase in the probability of car-ownership is observed for this variable, along with the presence of a piecewise effect. Finally, the estimate for the possession of PT pass has a negative value, implying a reduction in the likelihood to own a car.

Table 5.8: Estimation results for Models *MM1* and *MM2*

		MM1		**MM2**	
Group	**Variable**	**Estimate**	**S.E.**	**Estimate**	**S.E.**
	log(HouseholdSize) (1)	2.09 (***)	0.10	1.84 (***)	0.12
	log(HouseholdSize) (2+)	5.82 (***)	0.16	5.17 (***)	0.18
	log(Income) (1)	0.52 (***)	0.10	0.60 (***)	0.10
	log(Income) (2+)	1.03 (***)	0.14	1.28 (***)	0.14
	Worker (1)	0.59 (***)	0.09		
	Worker (2+)	0.74 (***)	0.12		
	StudentWorker (1 & 2+)	0.94 (**)	0.34		
	Student (1 & 2+)	-0.57 (*)	0.28		
	ShareWorkersStudentWorkers (1)			0.45 (***)	0.10
	ShareWorkersStudentWorkers (2+)			0.80 (***)	0.17
	Education$_{\text{post-sec.}}$ (1 & 2+)	0.49 (**)	0.17		
	Education$_{\text{higher}}$ (1)	0.25 (**)	0.08		
	Education$_{\text{higher}}$ (2+)	0.60 (***)	0.11		
	ShareEducation$_{\text{post-sec.}}$ (1 & 2+)			0.53 (**)	0.20
Socio-demographic characteristics	ShareEducation$_{\text{higher}}$ (1 & 2+)			0.15 (.)	0.09
	SpanishNationality (1)	1.05 (***)	0.14		
	SpanishNationality (2+)	1.66 (***)	0.25		
	ShareSpanishNationality (1)			1.39 (***)	0.16
	ShareSpanishNationality (2+)			2.45 (***)	0.32
	Male (1)	0.35 (***)	0.07		
	Male (2+)	0.45 (***)	0.10		
	ShareMale (1)			0.49 (***)	0.09
	ShareMale (2+)			1.05 (***)	0.19
	Age$_{\text{up to 67}}$ (1 & 2+)	0.03 (***)	4 x 10^{-3}		
	AverageAge$_{\text{up to 67}}$ (1 & 2+)			0.02 (***)	3.2 x 10^{-3}
	AverageAge$_{\text{beyond 67}}$ (1)			-0.04 (***)	0.01
	AverageAge$_{\text{beyond 67}}$ (2+)			-0.06 (**)	0.02
	MobilityRestricted (1 & 2+)	-0.26 (*)	0.12		
	ShareMobRestricted (1)			-0.35 (*)	0.15
	ShareMobRestricted (2+)			-0.79 (*)	0.39
Urban characteristics	Density (1)	-3 x 10^{-3} (***)	3 x 10^{-4}	-2.5 x 10^{-3} (***)	3.2 x 10^{-4}
	Density (2+)	5.0 x 10^{-3} (***)	5.0 x 10^{-4}	-4.6 x 10^{-3} (***)	-5.0 x 10^{-4}
Transport supply	DummyPublicParkingSupply (1)	0.14 (*)	0.06	0.14 (*)	0.06
	BSBikesInTheDistrict[1] (1)	-0.97 (***)	0.13	-1.05 (***)	0.13
	BSBikesInTheDistrict[1] (2+)	-2.12 (***)	0.22	-2.22 (***)	0.22
	TripsPerPerson (1)	0.08 (**)	0.02		
	TripsPerPerson (2+)	0.23 (***)	0.04		
	TotalTripsHousehold (1)			0.06 (***)	0.01
	TotalTripsHousehold (2+)			0.11 (***)	0.02
	ShareCarLicenses$_{\text{up to 50\%}}$ (1)	0.07 (***)	2.6 x 10^{-3}	0.07 (***)	2.6 x 10^{-3}
Mobility patterns	ShareCarLicenses$_{\text{up to 50\%}}$ (2+)	0.15 (***)	8 x 10^{-3}	0.15 (***)	8.1 x 10^{-3}
	ShareCarLicenses$_{\text{beyond 50\%}}$ (1)	0.02 (***)	2.4 x 10^{-3}	0.02 (***)	2.4 x 10^{-3}
	ShareCarLicenses$_{\text{beyond 50\%}}$ (2+)	0.05 (***)	3.3 x 10^{-3}	0.05 (***)	3.4 x 10^{-3}
	DummyPTPass (1)	-0.71 (***)	0.07		
	DummyPTPass (2+)	-1.39 (***)	0.11		
	ShareMembersWithPTPass (1)			-0.74 (***)	0.08
	ShareMembersWithPTPass (2+)			-1.74 (***)	0.13
-	ASC (1)	-10.08 (***)	0.84	-10.73 (***)	0.85
	ASC (2+)	-24.10 (***)	1.25	-26.17 (***)	1.27
Summary statistics	Log-Likelihood:		-4,824.55		-4,786.92
	McFadden R^2:		0.47		0.47
	AIC:		9,713.09		9,637.84
	BIC:		9,940.74		9,865.50

Note:

- ASC: Alternative-Specific Constant
- (.) - p <0.1; (*) - p <0.05; (**) - p <0.01; (***) - p <0.001; no household car is the base category
- **(1)**: One car per household; **(2+)**: Multiple cars per household; no household car is the base category
- MM1: individual variables of the household representative (oldest member)
- MM2: individual variables aggregated to the household level
- $\text{Education}_{\text{higher}}$: vocational training or university level.
- DummyPTPass: at least one Public Transport pass is available in the household
- Income: Ordinal variable, based on the average income value of a transport analysis zone.
- [1]The number of shared bikes is represented in terms of hundreds
- The variables prefixed with 'Share' are in decimal format, except the license variable, which is in percentage format

5.4.3 Household car-ownership in Leuven

Based on the data availability, the focus of the disaggregate car-ownership model in Leuven is on socio-demographic characteristics, transport supply, and mobility patterns. The utility specification of the final model is shown in Equation 5.11. The estimation results are presented in Table 5.9. The coefficient estimates are in general reasonable in terms of sign and consistent with the prior expectations.

$$
\begin{aligned}
Utility(0\ cars) &= 0\ (base\ alternative)\\
Utility(1\ car) &= log(HouseholdSize)\ +\ log(Income)\ +\ BelgianNationality +\\
&\quad Age\ +\ CSCarsInTheDistrict +\\
&\quad InteractionCSSubscription\&SharedCars +\\
&\quad hasCargoBike\ +\ neverTravelsByBusToWork +\\
&\quad alwaysOrOftenDrivesCarToWork +\\
&\quad rarelyTravelsByBusForLeisure +\\
&\quad neverTravelsByBusForLeisure +\\
&\quad alwaysRidesBikeForLeisure +\\
&\quad rarelyTravelsByTrainForLeisure +\\
&\quad neverTravelsByTrainForLeisure\ + ASC \qquad (5.11)\\
Utility(2+cars) &= log(HouseholdSize)\ +\ log(Income)\ +\ BelgianNationality +\\
&\quad Age\ +\ CSCarsInTheDistrict +\\
&\quad InteractionCSSubscription\&SharedCars +\\
&\quad hasCargoBike\ +\ neverTravelsByBusToWork +\\
&\quad alwaysOrOftenDrivesCarToWork +\\
&\quad rarelyTravelsByBusForLeisure +\\
&\quad neverTravelsByBusForLeisure +\\
&\quad alwaysRidesBikeForLeisure +\\
&\quad rarelyTravelsByTrainForLeisure +\\
&\quad neverTravelsByTrainForLeisure\ + ASC
\end{aligned}
$$

Table 5.9: Estimation results for Model *ML*

Group	Variable	Estimate	S.E.
Socio-demographic characteristics	log(HouseholdSize) (1)	1.25 (***)	0.26
	log(HouseholdSize) (2+)	2.56 (***)	0.32
	log(Income) (1)	1.53 (***)	0.30
	log(Income) (2+)	3.09 (***)	0.37
	BelgianNationality (1 & 2+)	2.53 (***)	0.37
	Age (1 & 2+)	0.23 (*)	0.10
Transport supply	CSCarsInTheDistrict (1)	-0.06 (*)	0.03
	CSCarsInTheDistrict (2+)	-0.10 (**)	0.04
	InteractionCSSubscription&SharedCars (1 & 2+)	-0.13 (***)	0.02
Mobility patterns	hasCargoBike (1)	-1.04 (*)	0.46
	hasCargoBike (2+)	-2.56 (***)	0.54
	neverTravelsByBusToWork (1 & 2+)	0.57 (**)	0.27
	alwaysOrOftenDrivesCarToWork (1)	3.84 (***)	0.70
	alwaysOrOftenDrivesCarToWork (2+)	5.07 (***)	0.72
	rarelyTravelsByBusForLeisure (1 & 2+)	0.77 (***)	0.29
	neverTravelsByBusForLeisure (1 & 2+)	1.61 (***)	0.52
	alwaysRidesBikeForLeisure (1 & 2+)	-0.72 (***)	0.27
	rarelyTravelsByTrainForLeisure (1)	0.73 (**)	0.28
	rarelyTravelsByTrainForLeisure (2+)	1.28 (***)	0.32
	neverTravelsByTrainForLeisure (1)	1.50 (*)	0.60
	neverTravelsByTrainForLeisure (2+)	2.44 (***)	0.64
-	ASC (1)	-14.75 (***)	2.34
	ASC (2+)	-29.87 (***)	2.94

Summary statistics
Log-likelihood: -694.05
McFadden R^2: 0.36
AIC: 1,434.09
BIC: 1,548.70

Note:
- ASC: Alternative-Specific Constant; CS: Car-sharing
- (.) - p <0.1; (*) - p <0.05; (**) - p <0.01; (***) - p <0.001
- **(1)**: One car per household; **(2+)**: Multiple household cars; no household car is the base category
- Income and Age: Ordinal variables
- CSSubscription: At least one car-sharing subscription in the household

Looking at the estimates shown in Table 5.9, starting with the socio-demographic characteristics, the private car-ownership in Leuven is influenced by the following factors: household size, income, Belgian nationality, and age. As is the case in the other two cities, household size and income are found to have a positive logarithmic effect on private car-ownership. Individuals with local citizenship are more likely to own private cars. Similar to the models of Regensburg and Madrid, age has a positive impact on car-ownership. It is not possible to explore the presence of a piecewise effect for age, as age is available only in the form of an ordinal variable in Leuven.

Concerning transport supply-related variables, with increasing car-sharing supply, there is a decrease in the probability of owning private cars. This effect is further intensified for those individuals who have a car-sharing subscription. Moving on to the mobility pattern-related variables, a decrease in the likelihood to own a private car is observed when a cargo bike is available in the household. When it comes to the mode used for commuting, as expected, an increase in the odds of private car-ownership is found for individuals who frequently use car. Likewise, a positive estimate is also observed when buses are never used for commuting. For leisure trips, a similar effect can be noted for the use of buses and trains, although the magnitude of the estimate for the commuting trips is lower. Finally, the use of bikes for all the leisure trips results in a decreased probability of household car-ownership.

5.4.4 Generic household car-ownership model

A generic model is estimated in order to support cities, which do not have adequate resources to estimate a car-ownership model. The utility specification of the final model is shown in Equation 5.12. The estimation results are presented in Table 5.10. The coefficient estimates are in general reasonable in terms of sign and consistent with the prior expectations.

$$
\begin{aligned}
Utility(0\ cars) &= 0\ (base\ alternative)\\
Utility(1\ car) &= log(HouseholdSize)\ +\ log(Income)\ +\ log(Age)\ +\\
&\quad DummyWorkers\ +\ hasPTPass\ +\ BikeSharingAvailable\ +\\
&\quad TotalBikesBikeSharing\ +\ ASC\ +\ City_{\text{ Regensburg}}\ +\ City_{\text{ Leuven}}\\
Utility(2+cars) &= log(HouseholdSize)\ +\ log(Income)\ +\ log(Age)\ +\\
&\quad DummyWorkers\ +\ hasPTPass\ +\ BikeSharingAvailable\ +\\
&\quad TotalBikesBikeSharing\ +\ ASC\ +\ City_{\text{ Regensburg}}\ +\ City_{\text{ Leuven}}
\end{aligned}
\tag{5.12}
$$

The estimation results show some of the common patterns identified in the three cities, i.e., household size and income have a positive logarithmic impact. A positive effect is also observed for age. In addition, the presence of a worker in the household also increases the probability of household car-ownership. However, the possession of a PT pass reduces the probability. With regards to the bike-sharing supply, the introduction of the system per se can have a negative influence on the household car-ownership. Furthermore, this influence is strengthened when the size of the bike-sharing fleet is increased. Finally, the dummies constructed for Regensburg and Leuven to capture the city-specific impacts and reduce the bias in the estimates of the other variables have positive estimates. This shows that the two cities have a higher average household car-ownership.

Table 5.10: Estimation results for Model *MG*

Group	**Variable**	**Estimate**	**S.E.**
Socio-demographic characteristics	log(HouseholdSize) (1)	1.17 (***)	0.05
	log(HouseholdSize) (2+)	2.94 (***)	0.08
	log(Income) (1)	1.16 (***)	0.07
	log(Income) (2+)	2.66 (***)	0.12
	log(Age) (1)	0.37 (***)	0.08
	log(Age) (2+)	0.84 (***)	0.13
	DummyWorkers (1)	0.68 (***)	0.06
	DummyWorkers (2+)	1.31 (***)	0.09
	hasPTPass (1)	-0.75 (***)	0.05
	hasPTPass (2)	-1.29 (***)	0.07
Transport supply	BikeSharingAvailable (1)	-0.29 (***)	0.08
	BikeSharingAvailable (2+)	-0.89 (***)	0.15
	TotalBikesBikeSharing[1] (1)	-0.45 (**)	0.14
	TotalBikesBikeSharing[1] (2+)	-1.10 (***)	0.28
-	ASC (1)	-2.86 (***)	0.20
	ASC (2+)	-9.11 (***)	0.34
	$\text{City}_{\text{Regensburg}}$ (1 & 2+) or $\text{City}_{\text{Leuven}}$ (1)	1.29 (***)	0.07
	$\text{City}_{\text{Leuven}}$ (2+)	1.40 (***)	0.10

Summary statistics
Log-Likelihood: -9,795.27
McFadden R^2: 0.21
AIC: 19,626.53
BIC: 19,959.88

Note:
- ASC: Alternative-Specific Constant
- (.) - p <0.1; (*) - p <0.05; (**) - p <0.01; (***) - p <0.001
- **(1)**: One car per household; **(2+)**: Multiple cars per household; no household car is the base category
- DummyWorkers: indicates whether there is at least one worker in the household
- Both in Regensburg and Leuven, there is no significant bike-sharing service, and hence, the bike-sharing supply is considered to be zero
- Income and Age: Ordinal variables
- [1]The number of shared bikes is represented in terms of hundreds

5.5 Cargo cycle purchase intention and actual purchase decision

The results of EFA and estimation of the logit models for the intention to purchase cargo cycles and actual purchase decision are presented in this section.

5.5.1 Exploratory factor analysis

For variables related to drivers and barriers (LV Set 1) from T1 survey, four factors are extracted, explaining a cumulative variance of 45%. These four factors are not only selected based on the statistical measures mentioned in Section 4.3.2.5, but also with a consideration of the findings in the existing literature (Thoma & Gruber, 2020). Looking at the first factor, the variables under it are related to operational benefits, and hence, it has been named as perception of operation benefits (F-OB). On the other hand, the second factor is connected with risks and concerns, and therefore, is called perception of risks and operational concerns (F-OC). The third and the fourth ones are associated with soft and cost benefits, and are labelled as perception of soft benefits (F-SB) and cost benefits (F-CB). The outcome of the factor analysis is presented in Table 5.11. As indicated in Section 4.3.2.5, Cronbach alpha value is not applicable to a factor with less than three items and correlation is considered for such a case. The two items in the fourth factor (F-CB) have a high correlation of 0.60. Their correlations with the other variables in the set are less than 0.5. Hence, F-CB with 2 items is acceptable.

For the attitude variables (LV Set 2), two factors are obtained, as shown in Table 5.12, explaining a cumulative variance of 40%. By looking at the latent meaning that these variables may have, the factors are interpreted as interest towards sustainability transformation in transport (F-ST) and interest towards technology and innovation (F-TI). Finally, two factors are constructed from the incentive variables (LV Set 3), explaining a cumulative variance of 67%. The constructed factors, shown in Table 5.13, are importance of deterioration of conditions for combustion-engine vehicles (F-DC) and importance of purchase cost of cargo cycles (F-PC). The two items in the second factor have a high correlation of 0.63. Their correlations with the other incentive variables are less than 0.5. Hence, F-PC with 2 items is acceptable.

Table 5.11: Factor analysis results for the LV set 1 (Drivers and barriers)

Loadings	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**
Possible to access areas that are closed to CVs	0.66			
CCs are faster than CVs for my case	0.56			
CCs offer greater flexibility concerning parking or loading/unloading	0.80			
Travel time can be reliably planned	0.59			
Payload could be damaged during transport		0.59		
Using CCs in mixed traffic is dangerous		0.67		
Riding CCs requires experience		0.61		
Cycling infrastructure is inadequate		0.46		
Implementation of CCs requires organisational effort		0.60		
There is no established service network for CCs		0.50		
CCs could get stolen		0.47		
Employees enjoy using CCs			0.63	
CCs help to reach corporate environmental goals.			0.51	
CCs improve the health of the employees			0.73	
CCs promote the image of the organisation			0.54	
CCs are cheaper than CVs (purchase cost)				0.76
CCs have lower maintenance costs than CVs				0.48
SSL	2.30	2.27	1.84	1.12
Proportion variance	0.14	0.13	0.11	0.07
Cumulative Variance	0.14	0.27	0.38	0.45
Cronbach alpha	0.72	0.71	0.65	-
Factor interpretation: Perception of	Operational Benefits (F-OB)	Risks & Operational Concerns (F-OC)	Soft Benefits (F-SB)	Cost benefits (F-CB)

Note:

- SSL: Sum of Square of Loadings; CVs: Conventional Vehicles (Diesel/petrol operated cars, vans and trucks); CCs: Cargo Cycles
- Loadings lower than 0.4 are not shown
- Although F-CB has only a proportion variance value of 0.07, the decision to keep it is based on other criteria such as RMSE and Tucker Lewis index.

Table 5.12: Factor analysis results for the LV set 2 (Attitudes)

Loadings	**Factor 1**	**Factor 2**
Willing to invest into climate protection	0.56	
Policymakers should restrict CV traffic	0.73	
All stakeholders of society should fight global warming	0.57	
Economy is more important than environment	-0.52	
CCs are a temporary phenomenon	-0.58	
CCs can be used by all as an alternative to the car	0.51	
CCs will generally prevail in my industry	0.40	
Following technological progress is important		0.77
We use new technologies, even if they are expensive		0.75
We are pro innovation organisation		0.62
SSL	2.29	1.72
Proportion variance	0.23	0.17
Cumulative Variance	0.23	0.40
Cronbach alpha	0.69	0.72
Factor interpretation: Interest towards	Sustainability Transformation in Transport (F-ST)	Technology and Innovation (F-TI)

Note:
- SSL: Sum of Square of Loadings; CVs: Conventional Vehicles (Diesel/petrol operated cars, vans and trucks); CCs: Cargo Cycles
- Loadings lower than 0.4 are not shown

Table 5.13: Factor analysis results for the LV set 3 (Incentives)

Loadings	**Factor 1**	**Factor 2**
Interest towards cargo cycles will increase if		
Parking cost for CVs increases	0.80	
Fuel (diesel/petrol) becomes more expensive	0.83	
More access restrictions for CVs are implemented	0.83	
Purchase cost incentive is provided for CCs		0.79
Purchase cost of CCs is reduced		0.78
SSL	2.05	1.31
Proportion variance	0.41	0.26
Cumulative Variance	0.41	0.67
Cronbach alpha	0.89	-
Factor interpretation: Importance of	Deterioration of Conditions for CVs (F-DC)	Purchase Cost of CCs (F-PC)

Note:
- SSL: Sum of Square of Loadings; CVs: Conventional Vehicles (Diesel/petrol operated cars, vans and trucks); CCs: Cargo Cycles
- Loadings lower than 0.4 are not shown

5.5.2 Factors affecting the purchase intention and the actual purchase of cargo cycles

To understand the factors that affect the purchase intention and the actual purchase decision, two different binary logit models are estimated. The model specifications and the estimation results are shown in Table 5.14. The coefficient estimates are in general reasonable in terms of sign and consistent with the prior expectations. The negative negative alternative specific constant values for both purchase intention and actual purchase decision are considered to be indicative of the general negative tendency towards cargo cycles.

Concerning purchase intention, a larger catchment area covered for the commercial trips, using cargo cycles during the trial phase, could have a negative influence. In contrast, higher daily mileage during the trial phase results in a positive impact on the purchase intention. Winter testing period also has a significant positive impact. Estimates for the LVs F-OB and F-SB (i.e., perception of operational and soft benefits from LV Set 1) are highly significant and positive. A positive estimate is also obtained for F-TI (i.e., interest towards technology and innovation from LV Set 2). On the other hand, F-OC (i.e., perception of risks and operational concerns from LV Set 1) has a negative estimate.

With regards to the actual purchase decision, a negative impact is also obtained for the catchment area of the commercial trips, and a positive impact for the daily mileage carried out during the trial phase, winter testing period, F-OB (i.e., operational benefits) and F-SB (i.e., soft benefits). However, F-OC (i.e., operational concerns) and F-TI (i.e., interest towards technology and innovation) are insignificant for the actual purchase decision. Nevertheless, there are other significant variables that have a positive impact. The most significant among them is the dummy variable constructed for the business sector (using cluster analysis as mentioned in Section 4.3.2.5). Similarly, the dummy variable constructed for the cargo cycle construction type is also found to significantly impact the actual purchase decision, when interacted with the variable accounting for the substitution of commercial light vehicle trips. The variable accounting for the percentage of car trips substituted during the trial phase also has a positive influence, although without any interaction. Finally, F-DC (i.e., deterioration of conditions for conventional vehicles) and F-CB (i.e., cost benefits) are also decisive for the actual purchase decision.

The research sample has payload data only for 55% of the organisations. Hence, it is not possible to test the influence of the payload adequately. However, a binary model with the reduced sample show that the payload does not have a significant influence on the actual purchase decision. This is in line with Gruber et al. (2013), wherein the bike and car messengers state that the payload capacity of cargo cycles is sufficient. Similarly, a dummy constructed for the effect of electric assist (i.e., a cargo cycle with electric assist vs a cargo cycle with no assist) is found to be insignificant.

Table 5.14: Estimation results for Models *MCC1* and *MCC2*

Purchase Intention (Model *MCC1*)			**Actual Purchase Decision (Model *MCC2*)**		
Variable	**Estimate**	**S.E.**	**Variable**	**Estimate**	**S.E.**
ASC	**-0.36 (.)**	**0.19**	**ASC**	**-1.81 (***)**	**0.31**
catchmentArea (**km^2**)	**-0.01 (.)**	**0.01**	**catchmentArea** (**km^2**)	**-0.01 (.)**	**0.01**
dailyMileage (**km**)	**0.11 (**)**	**0.04**	**dailyMileage** (**km**)	**0.11 (**)**	**0.04**
winterTesting (D)	**0.98 (*)**	**0.48**	**winterTesting (D)**	**0.74 (.)**	**0.45**
operationalBenefits (L)	**0.42 (***)**	**0.11**	**operationalBenefits (L)**	**0.29 (*)**	**0.12**
softBenefits (L)	**0.37 (***)**	**0.10**	**softBenefits (L)**	**0.36 (**)**	**0.11**
operationalConcerns (L)	-0.24 (*)	0.10	costBenefits (L)	0.23 (.)	0.12
technologyInnovation (L)	0.20 (.)	0.10	deteriorationOfConditions (L)	0.34 (**)	0.11
			carSubstitution (P)	0.67 (*)	0.32
			lightVehicleSubstitution (P)	1.79 (.)	1.09
			businessSector (D)	0.84 (***)	0.24
Summary statistics			**Summary statistics**		
Log-likelihood:	-240.39		Log-likelihood:	-213.10	
McFadden R^2:	0.10		McFadden R^2:	0.12	
AIC:	496.78		AIC:	448.20	
BIC:	528.40		BIC:	491.69	

Note:
- D: Dummy variable; L: Latent variable (Section 5.5.1); P: Percentage in decimal format
- (.) - p <0.1; (*) - p <0.05; (**) - p <0.01; (***) - p <0.001
- The category 'No' is the base alternative
- Variables that are common to both purchase intention and actual purchase decision are made bold

6 Case study on Regensburg

Contents

6.1 Case study background

Regensburg is a German city located at the northernmost point of the Danube river, about an hour's drive from Munich. The historically and culturally significant city is not only a UNESCO world heritage site and an international tourist destination, but it has also developed in the last decades to become one of the major economic centres in Germany and a prosperous commercial and industrial centre (since 2000, Regensburg ranks among the top 15 German business locations). The city has a total area of 80.7 km2, with 18 districts, hosting around 168,000 inhabitants. The city receives 660,000 visitors per year. It is also known for its universities with 32,000 students and is home to many nationalities (16.6% of the population has foreign origins).

Regensburg is connected to the rail network in the direction of Munich, Nuremberg and Vienna with long-haul high-speed trains. There is also a network of local trains, which connects the rural dominated hinterland of Regensburg with the city. The PT system within the city consists of a bus fleet of 131 vehicles, with 600 bus stops and 5.5 million vehicle kilometres travelled per year. In order to grant an integrated fare for the city and surrounding municipalities, as well as for railways and buses, there exists a transport organisation named Regensburger Verkehrsverbund (RVV). Regensburg had around 185 electric charging stations per 100,000 inhabitants in 2021 and is still increasing the number continuously. Since 2016, Regensburg has subsidised the purchase of electric vehicles, cargo pedelecs and e-scooters by citizens.

With regards to road network, Regensburg is located at the crossing of two highways in north-south (A93) and east-west (A3) direction. The total road network within the city is approximately 414 km. Accompanying cycle paths have been built on the main roads. In the old town (around 1.1 km^2 area), approximately 0.2 km^2 is designated as a pedestrian zone. This pedestrian zone is open to cyclists. Around the old town, there is a green belt exclusively for pedestrians and cyclists, with a length of around 3 km. The city began converting roads meant for car traffic into cycle paths in 2019 and is now encouraging cycling by adding more cycle lanes. Besides, the city is planning to introduce dedicated bus lanes in around 70 links, through which the PT buses run.

Car ownership in the city is 759 vehicles per 1,000 inhabitants. The total number of trips per person per day (mobility rate) is 3.3. An autonomous shuttle (Emilia) is being tested as a feeder/collector service to the existing PT system, in a 1.3 kilometre circuit in a industrial park. The service lies within a single TAZ, and henceforth, it will be called the shuttle zone. The shuttle has a capacity of 6 people and runs with a headway of 10 minutes and average speed of 15 kmph. A small-scale car-sharing system (round-trip station-based) is active in the city since 2016, with 8 stations and 1 to 2 vehicles per station. A one-way station-based bike-sharing system is planned to be initiated with around 500 bicycles. Based on the interests of the city, the objectives of the case study are set as follows:

- Can the implementation of dedicated bus lanes result in mode shift to PT and emission reduction? Air quality is an increasing concern and is considered one of the main priorities of the city council, together with the preservation and regeneration of the city centre. Therefore, mode shift to PT and emission reductions are given an emphasis.

- Can the autonomous shuttle service complement conventional PT services? Vehicle automation opens the room to innovative transport supply schemes and the city is keen on utilising this innovation to reinforce the existing PT services.

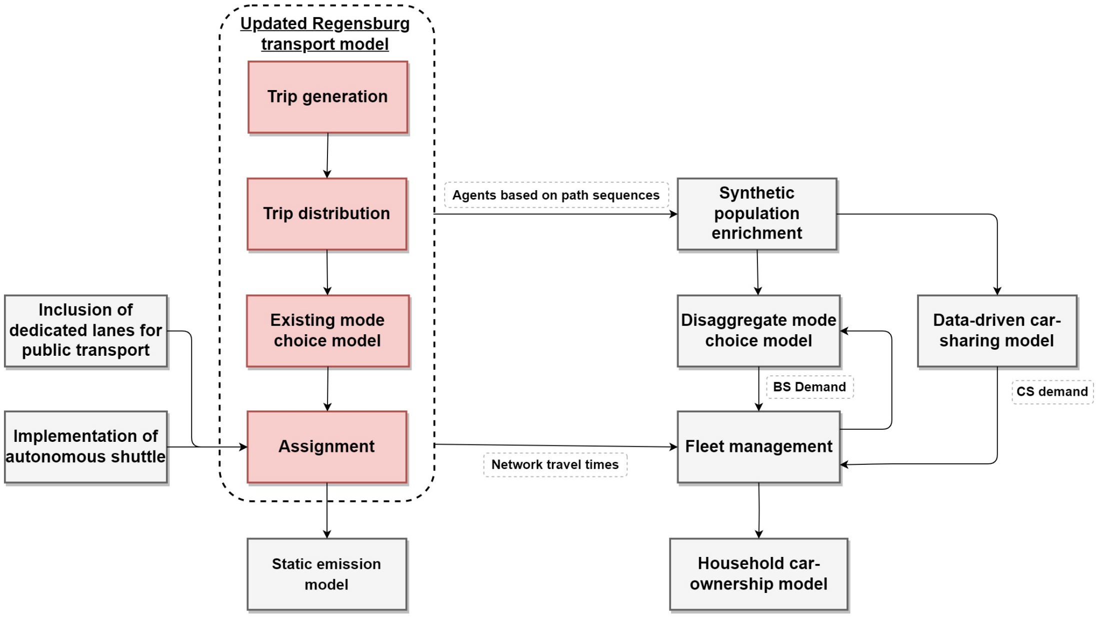
- To what extent the shared mobility services have an impact on car ownership? The reduction of car ownership is a major discussion in the Regensburg city council. Hence, the impact on car ownership is seen as a crucial element. At first, the combined impact of the planned bike-sharing and the existing car-sharing systems is analysed (Scenario SM). Then, a scenario analysis is conducted to ascertain the impact of bike-sharing fleet size on car-ownership. The scenarios are constructed by varying the planned fleet size by -40% (SB1), -20% (SB2), +20% (SB3) and +40% (SB4). Similarly, a scenario analysis is also conducted for the car-sharing service. Unlike the bike-sharing service, the car-sharing service is very small and it is only possible to construct scenarios by increasing the fleet size. Considering that the city council is interested only in a gradual expansion of the service, the scenarios are constructed by increasing the number vehicle per stations by 1 (SC1), 2 (SC2), 3 (SC3) and 4 (SC4).

6.2 Modelling approach for the case study

The city currently uses a conventional four-step model, implemented in PTV Visum (PTV Group, 2021), which follows an aggregated static modelling approach. This Visum model follows a timetable based approach for PT assignment. Therefore, a base scenario model is created initially, by loading the PT buses into the actual network, to take into consideration the impact of congestion on bus movements. Since multiple implementations are involved in the case study, an incremental approach is then followed. The bus lanes and the autonomous shuttle are included through modifications in the existing Visum model, and hence, they are analysed at first. The dedicated bus lanes are included in the base scenario and the updated model is called the bus lane scenario. Over this bus lane scenario, autonomous shuttle is implemented, which is called the autonomous shuttle scenario. Finally, the shared mobility services are integrated to this scenario based on the intermediate modelling approach, as shown in Figure 6.1. The updated framework is called the shared mobility scenario (SM).

6.2.1 Existing aggregate four-step transport model

The demand generation in the existing Regensburg model is based on a specialised tour-based approach called VISEM. This approach is a modified version to the traditional four-step model. Within this approach, the trip distribution and mode choice processes are implemented as a combined step and further this combined step is inter-locked with trip generation step.



Note: BS - Bike-Sharing; CS - Car-Sharing; Red colour shaded boxes indicate the existing components in the traditional four-step approach.

Figure 6.1: Adapted intermediate modelling approach for the Regensburg case study

Modes simulated within the model include private cars, trucks, PT, pedestrians and bicyclists. City buses, regional buses, regional rail system, and walking for first- and last-mile of PT trips are included under PT mode. Commercial trips are defined externally and attributes for the same are user-defined. For PT, the network loading component is purely timetable based. For pedestrians and cyclists, there is no network loading component. Data for the road network is from NAVTEQ (currently known as HERE).

6.2.2 Adaptation for mixed lane use

In the existing Regensburg model, the volume of PT vehicles is not integrated in the volume delay function, which describes the congestion in a link. To integrate PT volumes in the volume delay function, the first step introduced is the modification of the "Base Volume" in the assignment procedure. According to the PTV VISUM manual, the "Base Volume" is used to consider the volume of vehicles loaded into the network, before the private vehicle assignment. The traffic assignment step has been modified to allow the extraction of base volume from a link attribute. In the current case, this link attribute will be based on the scheduled PT vehicle trips. Through this modification, the modelling of the influence of PT volumes on the private vehicles is addressed. Nonetheless, the barrier to the influence of the private vehicles on PT travel times is still unaddressed.

As mentioned earlier, the original Regensburg model uses a timetable-based approach for the assignment of the PT vehicles. As a consequence, the travel time in the lines of

PT is dependent on the established speed for the transport mode. Thus, the travel times of PT is independent of the volume of traffic in the transport network. To introduce the influence of private vehicles on the travel times of PT, the special function “Set run and dwell times” in Visum is used. This PTV Visum functionality enables the transfer of link travel times to the PT lines. After implementing this second modification in the original Regensburg model, the PT travel times are calculated with the consideration of link travel times. With the aforementioned modifications for the simulation of a mixed traffic, the demand modelling procedures are affected. Consequently, the model outputs does not represent the real traffic in Regensburg. Thus, a recalibration of the model is performed.

For the recalibration, the OD matrices from the original Regensburg model are used. The recalibration procedure adjusts the trip length distribution for private vehicles to coincide with the OD matrix of the original model. To evaluate the quality of the calibration process, two aspects are considered. The new modifications influence the combined trip distribution and mode choice step. Thus, both the trip distribution and modal split values are analysed after calibration. In order to quantify the trip distribution, the GEH statistic is used (Equation 6.1). Moreover, the acceptance criterium is to find a GEH value less than 5 in 85% of the OD pairs (Highway Agency, 1996). In the current case, the resulting GEH calculations show that 99% of the OD pairs have a GEH value of less than 5. Consequently, the model can be considered calibrated with respect to trip distribution.

$$GEH = \sqrt{\frac{2(O_i - M_i)^2}{(O_i + M_i)}} \tag{6.1}$$

where,
O_i is the observed OD matrices
M_i represents the modelled OD matrices

The second aspect to validate the calibration procedure is the modal split from the model. In the original Regensburg model, the modal share are 9.97% and 90.03% for PT and private modes, respectively. After the calibration of the mixed traffic model, the corresponding modal shares are 8.16% and 91.84%. The difference is less than 2%, which suggests that the calibration is sufficient.

6.2.3 Inclusion of dedicated bus lanes

After setting up the base scenario, the subsequent step is to include the dedicated bus lanes in the network. The first step is to introduce such infrastructure in the network. Within this regard, a User-Defined Attribute (UDA) is enabled to distinguish the links with dedicated bus lanes. This attribute is defined as “IsSegregated”, which takes the value (0) when there is no segregation for the bus lane and the value (1) when the link has a dedicated bus lane. Initially, all the links in the network are defined with “IsSegregated=0”. In the original Regensburg model, the lane level capacities are not defined, but rather the capacity is defined only for a complete link (single direction). However, the implementation of the bus lane requires capacity values at the lane level. Therefore, an auxiliary UDA "CapacityPerLane" is created to quantify the capacity of every lane per link. Equation 6.2 represents the formula used to calculate the value for the attribute.

$$c_i = \frac{C_i}{N_i} \tag{6.2}$$

where,
c_i is the capacity per lane in link i
C_i is the total capacity of link i
N_i is the number of lanes in link i

In order to assign the bus lanes, the relevant PT line routes are selected using the filter function. The filter function identifies every link that is used by the desired line routes. The "IsSegregated" UDA for these links is set to the value of 1 and the capacity for the private vehicles are modified as shown in Equation 6.3. This modification is performed using the "multi-edit" function. In the dedicated bus lanes, free-flow travel times are considered for PT vehicles. For the links with mixed lanes, the travel time for PT is assigned based on the traffic assignment results.

$$C_i^p = c_i(N-1) \tag{6.3}$$

where,
C_i^p is the link capacity available for private vehicles in link i
c_i is the capacity per lane in link i
N_i is the number of lanes in link i

To compute the emission levels for pollutants CO, CO_2, NOx, PM and VOC, a COPERT macroscopic emission model (Ntziachristos et al., 2020) is utilised. This model is used to empirically estimate emission under different aggregated speed regimes. A dataset of fleet-average emission factors per pollutant created for Germany (Rodrigues et al., 2020) is used as a basis for this model. The link speeds and volumes are extracted from Visum and combined with the emission factors to obtain emissions on a given link and by aggregation on the entire network. Since different modes are simulated in the Visum model, each mode with their own speed from the traffic assignment algorithm, there is a necessity to calculate an average speed in each link. In this case, the weighted mean is calculated based on the Passenger Car Equivalent (PCE) units of each mode. Based on Pajecki et al. (2019), it is assumed that both buses and trucks have a PCE of 2.

6.2.4 Implementation of autonomous shuttle

In general, the evaluation of an autonomous shuttle service, which is implemented within a single traffic zone, requires a microscopic modelling approach. Nevertheless, in order to incorporate this service into the macroscopic model at hand, a more simplified approach is considered, especially taking into account the fact that the shuttle service focuses only on the first- and last-mile of PT trips. In transport models, the first- and last-mile are usually reflected through the use of zone connectors. Thus, the effect of the shuttle can be introduced based on how it will improve the connector time for the PT trips. The connector travel time in the original Regensburg model is defined based on walking speed. It is expected that the introduction of the shuttle service will result in an improvement in the connector travel time, since the shuttle line is planned for an average operational speed of 15 km/h, while the average walking speed is 4 km/h. Nevertheless, another factor that will influence the travel time, when using the shuttle service, is the average waiting time of the mover line ($\bar{W}$). Thus, the connector travel time is updated as shown in Equation 6.4.

$$T_j = \frac{\frac{L_j}{v_w} + \left(\frac{L_j}{v_a} + \bar{W}\right)}{2} \tag{6.4}$$

where,
T_j is the travel time in connector j
L_j is the length of connector j
v_w is the walking speed (4 km/h)
v_a is the speed of the autonomous shuttle service (15 km/h)
$\bar{W}$ is the average waiting time for the shuttle service

The unknown parameter in the above equation is the average waiting time. Amin-Naseri & Baradaran (2015) describe that the theoretical average waiting time for a scheduled service is half of the headway. However, other exiting literature indicate that this theoretical waiting time is an overestimation of the actual value for similar services (Nygaard & Tørset, 2016). This statement is also supported by Amin-Naseri & Baradaran (2015), who conclude in their literature review that the theoretical average time is overestimated by a factor of 14.43%, when compared to the actual values. Considering these aspects, the average waiting time for the autonomous shuttle is calculated based on Equation 6.5 from O'Flaherty & Mancan (1970), which results in a value of 3.19 minutes.

$$\bar{W} = 1.79 + 0.14h \tag{6.5}$$

where,
$\bar{W}$ is the average waiting time for the shuttle service in minutes
h is the shuttle service headway in minutes (e.g., 10 minutes in the current case)

6.2.5 Integration of shared mobility services

The model corresponding to the autonomous shuttle scenario will be used as a basis for developing the (modified) intermediate modelling framework for evaluating shared mobility services. The existing round-trip station-based car-sharing service in Regensburg is operated at a small scale (less than 10 vehicles) and gradual expansion is planned. Currently, the planned expansion is not large-scale and therefore, it can be considered that this system will not have a substantial impact on the existing travel times in the city. Similarly, the one-way bike-sharing service can also be considered to not (substantially) impact the existing travel times in the next 4-5 years, as the system is yet to commence and the expect modal share is very low (around 0.2%). Therefore, static travel times from the VISUM model can be used for the modelling of the shared mobility services. Due to this assumption, an iterative interaction with the traffic assignment step is not required, which leads to the low penetration case of the intermediate modelling approach (refer to Section 4.1.8 for more information).

The adapted intermediate modelling approach is shown in Figure 6.1. As stated earlier, the Regensburg model consists of a specialised demand generation procedure called VISEM. It models activity chains based on different person groups and their trips. This enables modelling of tours for every agent discretely, with some assumptions. Thus, a base synthetic population is directly generated based on the VISEM outputs. Then, this base synthetic population is enriched with additional variables using random forest models. Subsequently, the disaggregate mode choice model (Section 4.3.2.1) is used to calculated the demand for the bike-sharing system, followed by the application of the data-driven demand model (Section 4.2) for the estimation of demand for the car-sharing service. The shared mobility demand is simulated using Aimsun Ride (Aimsun, 2021). Finally, household car-ownership is determined using the generic disaggregate car-ownership model (Section 4.3.2.4).

6.2.5.1 Generation of synthetic population based on path sequences

The VISEM model used in Regensburg allows the export of path sequences. A “path sequence” represents each tour of an agent (PTV Group, 2021). Each path sequence consists of a series of “path sequence items”. This element represents each segment of a tour and indicates the origin, the destination and the mode used. Another relevant term is the “path sequence set”. This term corresponds to a structure, which seeks to group all path sequences, based on the information of the agent that executes the tour. In the case of the Regensburg VISEM model, the path sequence sets are defined by the activity chains and the different person groups. A total of 843 path sequence sets are found in the model.

For the calculation of path sequences, the time interval of the demand time series should either be constant or same for all the activity pairs of a person group. In the Regensburg model, the activity pair “Work-Home (W-H)” is in a different format from the other activity pairs. The activity pair W-H is defined in a time frame from 6:00 -19:00 with no hourly distribution. In contrast, the time series of the remaining activity pairs are defined on an hourly basis. In order to overcome this discrepancy, a time series has been generated for W-H activity pair, using the Mobilitaet in Deutschland data (Nobis & Kuhnimhof, 2018). Finally, to extract the required data from the model, the Python COM interface available in Visum is utilised.

6.2.5.2 Enrichment of the synthetic population

A number of socio-demographic variables are required for the synthetic population, for use in the subsequent steps. However, not all the pertinent variables are available for the agents extracted from the VISEM procedure. Some of the individual and household specific variables are to be added to the agents through an external procedure. Thus, the base synthetic population is enriched and such an enrichment process is called statistical matching (Leulescu & Agafitei, 2013). The matching procedure involves donor and recipient datasets, which share a set of common variables called mutual attributes (Hörl & Balac, 2021). The donor dataset has a set of unique attributes called the target attributes, which are not present in the recipient dataset. Based on the values of the mutual and the target attributes, a model has to be estimated to establish the relationship between the two set of attributes in the donor sample. Subsequently, the model can be used to construct the target attributes in the recipient database.

Traditionally, statistical matching is based on hot deck methods, regression based methods, mixed methods, and multiple imputation methods [the reader is referred to Leulescu & Agafitei (2013) for more information]. Nonetheless, authors, such as D'Orazio (2019), have tried to overcome the shortcomings of the traditional statistical matching methods by using alternative methodologies. D'Orazio (2019) concludes that statistical and machine learning methods are more time efficient than the traditional methods. In the current study, this process involves the development of a multivariate random forest model, exploiting its ability to model conditional probabilities to predict the missing attributes of the target population. The household survey dataset mentioned in Section 3.1.1.1 is used as the donor dataset. Conversely, the recipient sample is the base synthetic population generated from the VISEM model. The mutual attributes between the two datasets include the activity at the trip destination, trip mode, travel distance and time, occupation, and car availability. The target attributes are the following: gender, education (whether holds a vocation training or higher degree), employment (working or not), possession of PT pass, age, household size, household income (low, medium or high) and number of household cars.

The multivariate random forest model is constructed using the Scikit-learn package in Python (Pedregosa et al., 2011). A 5-fold cross validation approach is implemented to assess the performance of the model and avoid overfitting. The parameter of maximum tree depth is used to tune the random forests in the model, since they influence the overfitting behaviour of the model (Schonlau & Zou, 2020). The parameter value has been iterated from 1 to 40 elements per splits and evaluated against the precision and recall scores (F1-Score). Based on the parameter tuning, the final random forest model has 1000 trees, with a maximum depth of 18. This model yields an F1-Score of 82%, guaranteeing that it is suitable for the population enrichment. Subsequent to the estimation of the random forest model, the missing attributes in the recipient dataset are generated, thereby resulting in an enriched synthetic population.

Although the statistical matching prcoedure enriched the synthetic agents from VISEM, it does not overcome a major limitation for fleet simulation, i.e., the demand aggregated to the level of traffic zones. Thus, a random coordinate sampler is used. Each agent from VISEM has two types of trip chains as: Home-Activity-Home (Type 1) or Home-Activity 1-Activity 2-Home (Type 2). Moreover, each activity of the trip chain has an associated TAZ with it. In addition, each trip between a set of activities in the chain has a recorded travel distance based on the VISUM simulation. Given the fact that all trip chains are home based, the first step of disaggregation is to sample a random point (within the TAZ where the household is located) and assign it as a home location.

The location of Activity 1 is sampled as a random point, which satisfies (i) the recorded travel distance between Home and Activity 1 and (ii) the TAZ of Activity 1. For the trip chain Type 2, the algorithm has to fulfil the distance condition between the Activity 1 and Activity 2, as well as between the Activity 2 and Home. An exact matching for the leg between Activity 2 and Home leads to an exorbitant computation time and thus, the coordinates are sampled with the following criteria: the difference between the distance based on the sampled coordinate and the actual recorded distance in the dataset should be within 10%. This threshold is chosen based on the computational time in a PC with 16GB RAM and 6 cores.

6.2.5.3 Demand estimation for the shared mobility services

Followed by this step, the disaggregate mode choice model (Section 4.3.2.1) is run to calculate the demand for the bike-sharing service. It is assumed that the minimum age for using the bike-sharing service is 16 years and the trip origin should be located within 300 metres from the station location. The alternative specific constant of the mode choice model is calibrated to an expected demand of 0.2% (based on the internal estimations by Regensburg city council). Fishman (2016) conducted a review on bike-sharing services and found out that the bike-sharing schemes across the world attract between 0.3 trips per bike per day and 7 trips per bike per day. The expected demand of 0.2% in Regensburg translates to roughly 2.06 trips per bike per day. This value is reasonable, when compared to the values found for similar cities.

The model specification is shown in Equation 6.6. Besides the variables specified in the equation, in order to consider non-availability of a sharing vehicle, a dummy variable with very high negative coefficient (-100) is added to the utility specification of the bike-sharing system. Thus, if no sharing vehicle is available to serve a trip request, the utility becomes highly negative, thereby restraining the allocation of a sharing mode for that trip. For calculating the demand for the car-sharing service, the data-driven framework (Section 4.2) is adapted and used.

$$
\begin{aligned}
&Utility(CM) = 0\ (base\ category)\\
&\quad Utility(B) = -7.25[ASC(B)] + 1.11[Age_{20-44}(B)] + 1.44[isMale(B)]+\\
&\qquad\qquad 0.92[hasUnivOrVocationalDegree(B)] + 1.13[hasPTPass(B)]-\\
&\qquad\qquad 0.69[HHCarsNum(B)] + 1.45[TripDist_{KM\leq 2}(B)]+\\
&\qquad\qquad 2.18[TripDist_{KM>2\&\leq 5}(B)] + 0.87[TravelTime_{Mins\leq 30}(B)]+\\
&\qquad\qquad 1.36[TotalSharedBikesInHundreds]
\end{aligned}
\tag{6.6}
$$

where, **B:** Bike-sharing; **CM:** Conventional modes-as-a-whole; **ASC:** Alternative Specific Constant

6.2.5.4 Fleet management module

The fleet operations are simulated using Aimsun Ride simulation platform (Aimsun, 2021). It is a commercial tool to deploy and test various scenarios related to new shared mobility applications. At first, the road network from the Visum model is imported into Aimsun Ride. The station locations and the fleet size are predefined. Subsequently, the demand (service requests) for the bike-sharing service is fed and vehicle assignment (vehicle in the nearest station) is performed.

The operational algorithm in the platform decides whether an offer is accepted or not. Subsequently, the accepted trip requests are simulated. The trip plan for each user (i.e., how to travel from an origin to a destination) is derived based on the available paths in the network and their corresponding travel times. Travel times are based on the traffic assignment results from the VISUM model. If any of the requests is rejected, due to vehicle unavailability or walking constraints, the disaggregate mode choice model is re-run for those requests, till no rejection is observed. The bike-sharing vehicles are relocated only during nights and hence, a relocation algorithm is not implemented. After the simulation is over, the platform outputs the necessary KPIs, e.g., user waiting times, travel times and travelled distance for the fleet. Similar to the bike-sharing service, the car-sharing service is also simulated in Aimsun Ride. However, for this round-trip service, the return journeys are also need to be simulated. The return journeys are simulated based on the departure and travel time of the onward journeys and the activity duration.

6.2.5.5 Car-ownership model

The household car-ownership calculation is based on the generic disaggregate car ownership model (Section 4.3.2.4). In the utility specification of this model, income is defined as an ordinal variable. However, in the current dataset, the income is available as a categorical variable (i.e., low, medium and high income). Therefore, the generic model has been re-estimated with income as a categorical variable. Furthermore, the generic model does not have car-sharing supply in the model specification. Hence, the coefficient for car-sharing supply (at the district level) in the Leuven car-ownership model is adopted. In the proceeding step, the alternative specific constants in the new model specification is calibrated. The SrV household survey (refer to Section 6.2.5.2 for more details) is used for the calibration process. The final model specification is shown in Equation 6.7.

$$
\begin{aligned}
Utility(0\ car) &= 0\ (base\ category)\\
Utility(1\ car) &= -4.02 + 0.72[HouseholdSize] - 1.42[IsLowIncome]-\\
&\quad 0.69[IsMediumIncome] + 0.42[Age]+\\
&\quad 0.72[DummyWorkers] - 0.77[hasPTPass]-\\
&\quad 0.20[TotalSharedCars] - 0.18[BikeSharingAvailable]-\\
&\quad 0.50[TotalSharedBikesInHundreds] - 0.20[ASC]+\\
&\quad 1.03[City_{\text{ Regensburg}}] \qquad (6.7)\\
Utility(2+\ cars) &= -12.41 + 2.99[HouseholdSize)] - 3.25[IsLowIncome]-\\
&\quad 1.41[IsMediumIncomee] + 0.84[Age]+\\
&\quad 1.42[DummyWorkers] - 1.32[hasPTPass]-\\
&\quad 0.35[TotalSharedCars] - 0.69[BikeSharingAvailable]-\\
&\quad 1.10[TotalSharedBikesInHundreds] - 0.34[ASC]+\\
&\quad 1.03[City_{\text{ Regensburg}}]
\end{aligned}
$$

where, where, **ASC:** Alternative Specific Constant

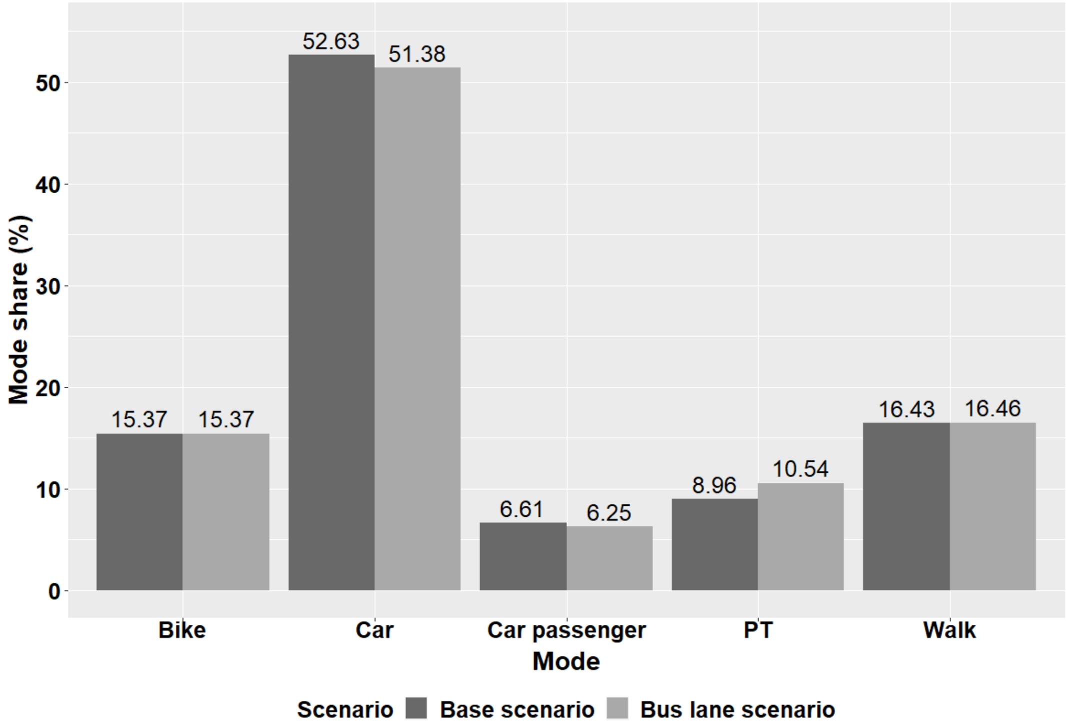
6.3 Case study results

The case study on Regensburg focuses on the evaluation of dedicated bus lanes, autonomous shuttles and shared mobility services (bike-sharing and car-sharing). This section elucidates the evaluation results.

6.3.1 Dedicated bus lanes

In order to analyse the impact of dedicated bus lanes, the following KPIs are considered: modal split, emissions and service efficiency of the bus lines. The resulting modal split due to the introduction of dedicated bus lanes is shown in Figure 6.2. As it can be observed, the modal share for PT increases by 1.58 percentage points (corresponds to 17.6% increase from the base scenario). Moreover, the private car share is diminished by 1.25 percentage points. This indicates that the implementation of dedicated bus lanes encourages the use of PT, disincentivizing directly the private car trips. The second assessment of the bus lane implementation is their environmental impacts. The values of the 24-hour emissions are shown in Figure 6.3.

Based on the results shown in Figure 6.3, it is evident that the introduction of bus lanes causes a significant decrease in transport-related emissions, varying from 3.25% to 6.65%. This reduction in emissions can be attributed to decrease in the private traffic volumes and congestion in the city. In particular, a network section that significantly illustrates this effect is the Nordgaustrasse. One of the most common measures to evaluate congestion levels is the Volume/Capacity ratio, which compares the service volume with the capacity of a road segment. The value for this ratio in Nordgausstrasse has reduced by 5.8%. The reduction of vehicle traffic in the network combined with the reduction in network congestion has lead to the reduction of traffic emissions in the city.



Note: The 1.58 percentage points change in modal share for PT corresponds to 17.6% increase from the base scenario.

Figure 6.2: Modal split for the base and bus lane scenario

The final assessment of the bus lane implementation is the impact on average trip run time. This measure is the average time associated with a PT vehicle trip to travel through the planned route, considering both the total travel time between planned stops and the dwelling time at the stops. The implementation of the dedicated bus lanes in Regensburg will amount to a average trip run time reduction of 8.6%. In summary, the dedicated bus lane implementation in Regensburg results in positive impacts. Evidence of that is the increased modal share for public transport, which is closely related to the decrease of private car trips in the city. Moreover, the dedicated infrastructure promotes a more efficient bus line in the city, by decreasing the average service time, and thus, increasing the overall quality of the PT of the city. Finally, the other prominent advantage of the dedicated bus lanes is the decrease in traffic-related emissions in the city, which range between 3% - 6% according to the different pollutants tested.

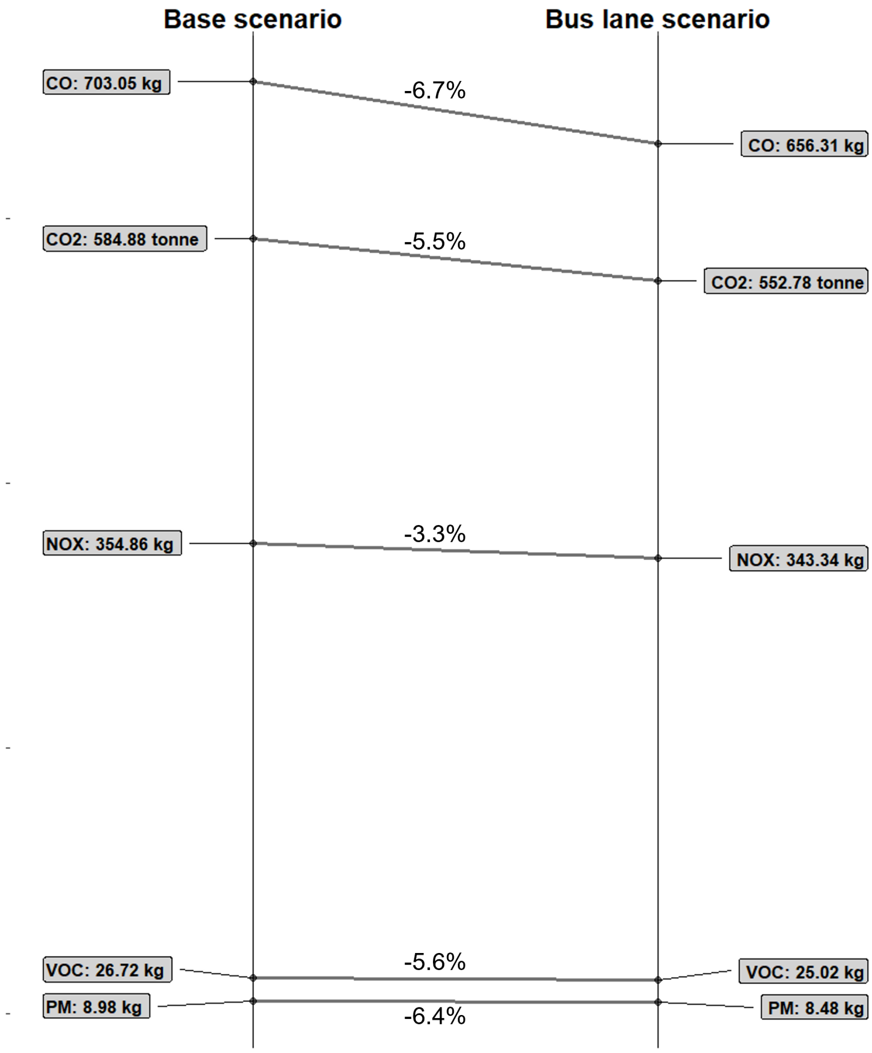


Figure 6.3: Emission values for the base and bus lane scenario

6.3.2 Autonomous shuttle

The impact of the autonomous shuttle is evaluated based on its effect on modal split. The first metric to be analysed is the modal share changes at the level of Regensburg city. No significant change is found, which is expected as the shuttle service serves only the first- and last-mile of the PT for a small area within a single traffic zone. However, when we take a specific look at the trips in the relevant traffic zone (i.e., the shuttle zone), the potential of the service is clear at a local level. As it can be seen in Figure 6.4, the impact of the shuttle line is significant at creating additional PT trips within, from and to the zone (around 5% increase). This is due to the reduction in the average PT travel time, which makes the zone more attractive. Thus, the shuttle service complements the existing PT service. Due to the small-scale operation of the shuttle service, there is no significant change in the network travel times and the emission levels.

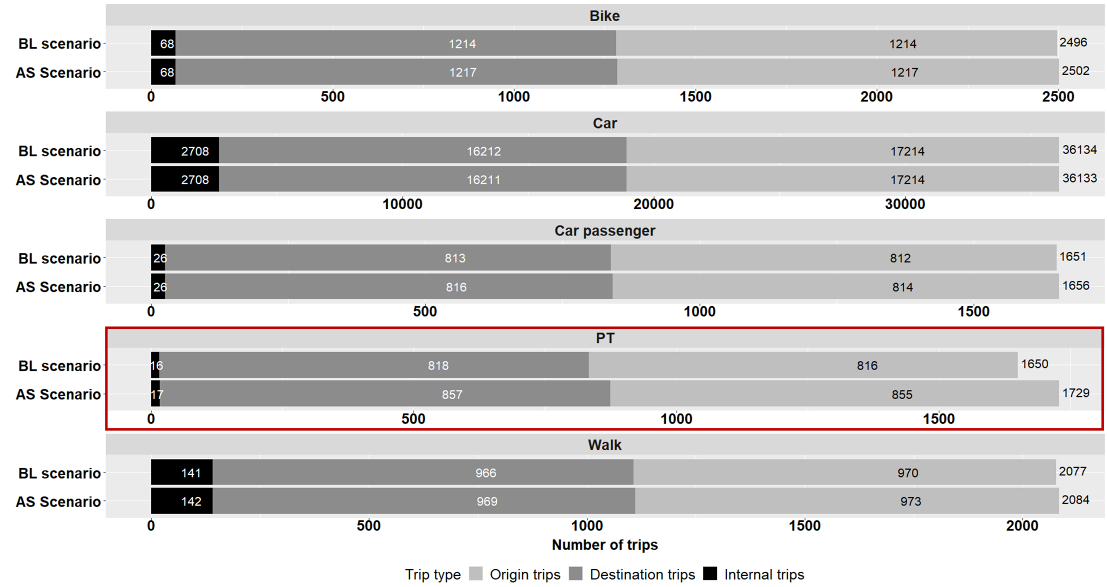


Figure 6.4: Impact of autonomous shuttle in the zone of implementation

6.3.3 Shared mobility services

Starting with the mode choice results related to the bike-sharing service, although the calibration for the expected demand of 0.2% result in a high negative alternative specific constant, there are combinations of attributes that result in positive utility (e.g., males with vocational or university degree, possessing PT pass and belonging to age group 20 to 44). Looking at the mode shift pattern, about 41% of the bike-sharing users were previously using PT, while only 15% were previously using car mode. This reveals that PT usage is reduced more than car usage, which is not a positive sign. Therefore, there is a necessity for a proper integration between the bike-sharing service and the PT system. Furthermore, complementary policies, which acts as push measures, are in absolute need for reducing the demand for private cars. The positive impact of push measures, such as vehicle access restrictions and higher parking cost, has already been confirmed in Narayanan et al. (2022d).

The trip distances range between 0.5 and 8.9 kilometres, with an average of 3.1 kilometres. The average travel time is around 7 minutes, with a maximum value of around 27 minutes. From the perspective of the operator, the number of trips served by a shared bike ranges between 0 to 6, with an average of around 2. The shared bikes have an average total ridden distance of 6 kilometres per day and an average service time of 14 minutes per day. The most used bike is ridden for 52 minutes per day and the maximum service distance is 15.7 kilometres. A deeper look into the vehicle usage shows that 15.7% of the shared vehicles remain idle throughout the day. In conclusion, the bike-sharing system planned for Regensburg handles the expected demand of the city. However, the shared bike utilisation rate shows that the service can be optimised further to reduce the percentage of idle vehicles.

The results from the multi-method approach for calculating the demand for the car-sharing service show that the system serves 18 trips, with an average of 1.8 trips per vehicle per day. The number of trips per car-sharing station is shown in Figure 6.5. The trip distances range between 4.5 and 77.7 kilometres, with an average of 20.1 kilometres. The average travel time is around 18 minutes, with a maximum value of around 58 minutes. From the perspective of the operator, the number of trips served by a shared car ranges between 1 to 3. The shared cars have an average total driven distance of 72 kilometres per day and a average service time of 64 minutes per day. The most used car is driven for 138 minutes per day and the maximum service distance is 184 kilometres. Compared to the bike-sharing service, naturally, the car-sharing service is used for longer distances. Similarly, given the special business model of the car-sharing service in Regensburg, they are driven longer than the general driven distance observed in literature.

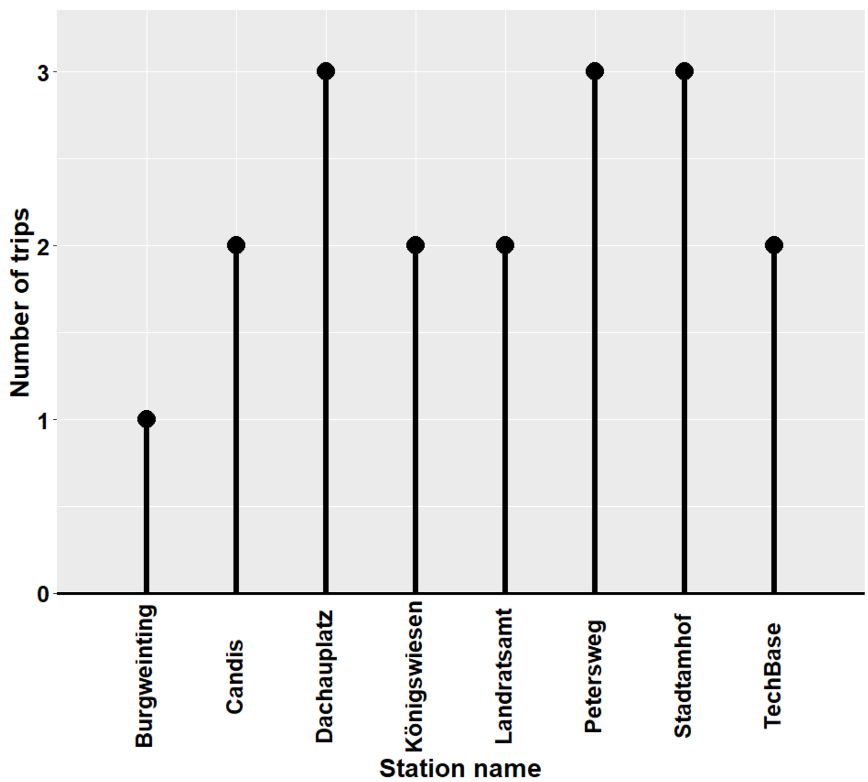


Figure 6.5: Demand per station for the car-sharing system

Given the small-scale operation of the car-sharing service and a demand of around 0.2% for the bike-sharing service, a major reduction in car-ownership cannot be expected. Nevertheless, as shown in Figure 6.6, the introduction of the shared mobility services has the potential to reduce the private car-ownership, with 2.5% reduction in single car ownership and around 2.29% shift from multiple to single car-ownership. A scenario analysis is conducted by varying the fleet size of the bike-sharing and the car-sharing services, as mentioned in Section 6.2. When the fleet size for the bike-sharing service is increased, a number of single car-households give up their car. However, a higher shift from multiple car-ownership to single car-ownership (than the shift from single car-ownership to no household car) is observed, resulting in the net impact shown in Figure 6.7. Interestingly, the net impact of decreasing the fleet size for the bike-sharing service follows an equal switching behaviour between the categories 'no household car' and 'multiple household cars'. However, increasing the fleet size leads to a larger net reduction in multiple car-ownership. Thus, the actual bike-sharing fleet size planned in Regensburg appears to be a threshold for a switching mechanism, which requires further study in future.

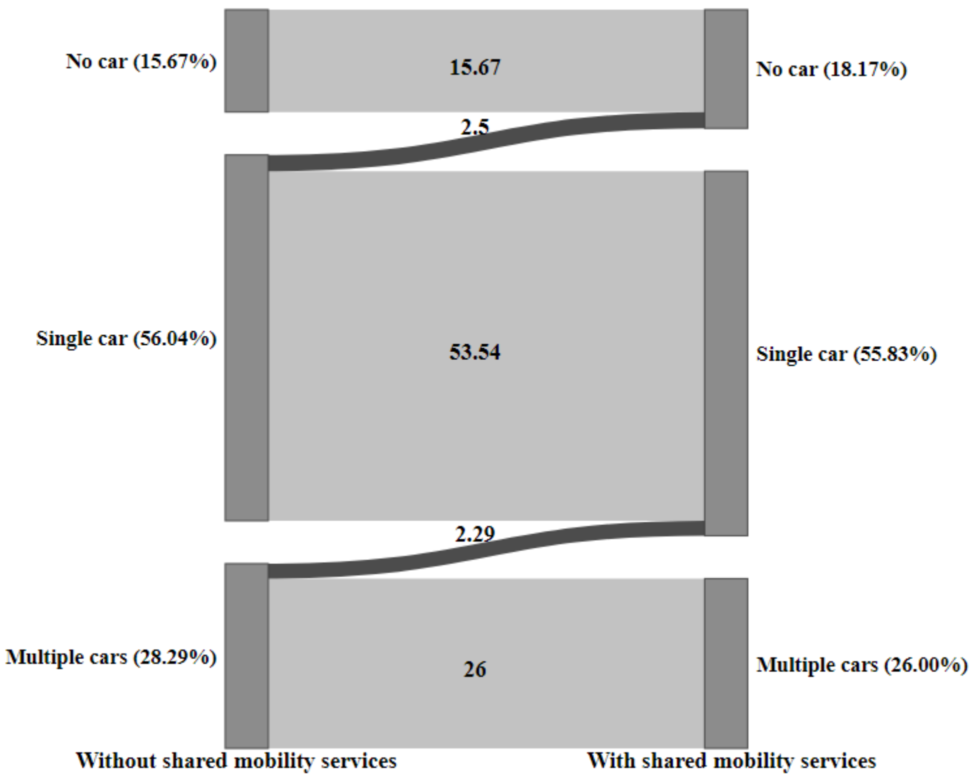
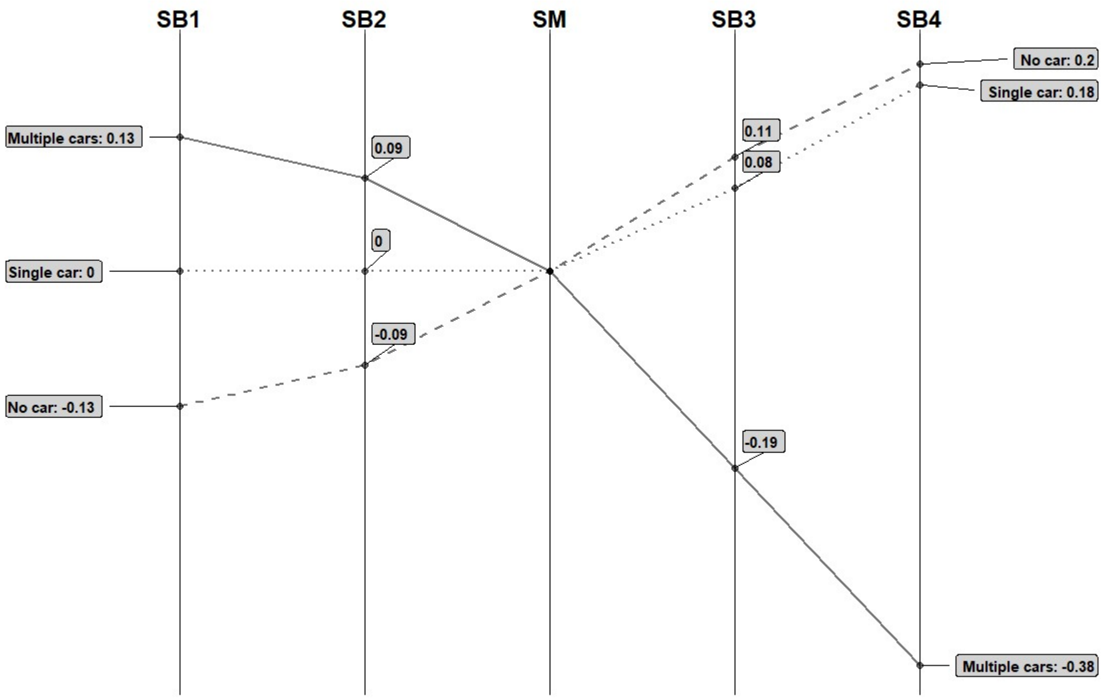


Figure 6.6: Impact of shared mobility services on household car-ownership

As mentioned in Section 6.2, unlike the bike-sharing service, the car-sharing service is very small. Hence, it is only possible to construct scenarios by increasing the fleet size.

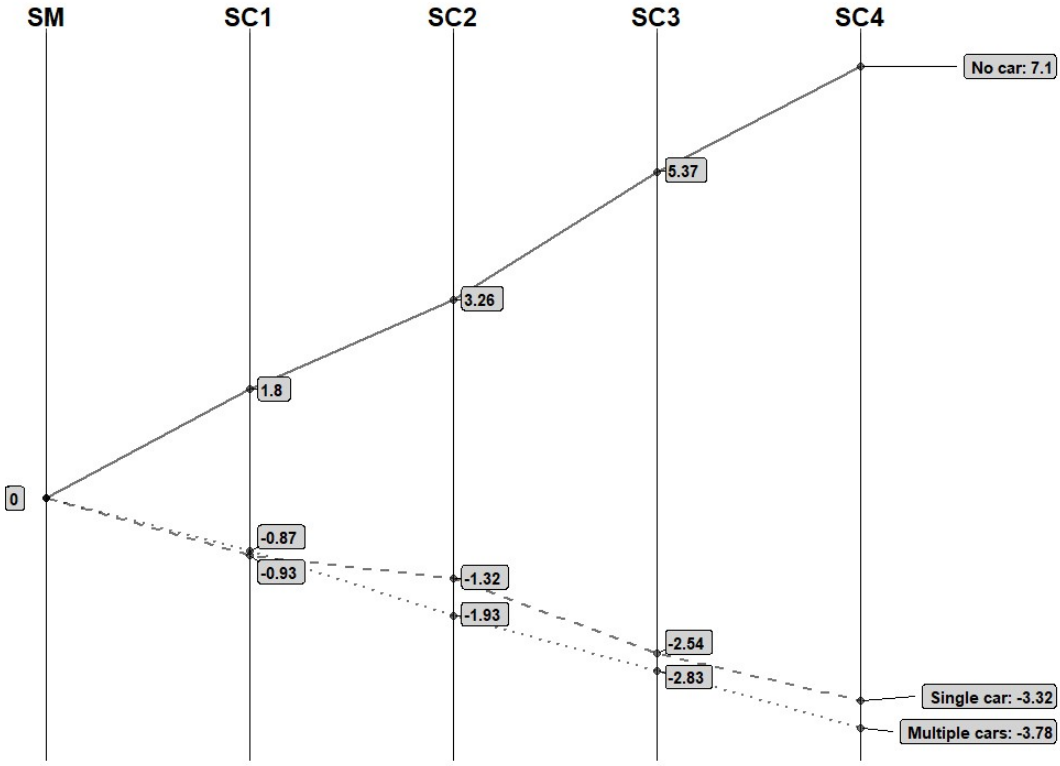
Looking at Figure 6.8, an increase in the car-sharing fleet size will result in a significant reduction in the car-ownership levels. Furthermore, comparing Figures 6.7 and 6.8, it is evident that smaller increases in car-sharing fleet size can have a substantial impact and the car-sharing service has a higher potential to reduce household car-ownership, than the bike-sharing service. This result is also supported by the mode shift pattern associated with the bike-sharing service, i.e., the major shift is from PT. Therefore, the bike-sharing service and the PT system have to be well integrated. This integrated system may have a better potential to reduce car-ownership, than the bike-sharing service on its own.

When increasing the fleet size of the bike-sharing service, a larger reduction in car-ownership is seen among households that own multiple cars. Nevertheless, for the case of the car-sharing service, a larger reduction is observed among households that own single cars. We believe that these households own a private car for occasional trips and having access to the car-sharing service, they may feel that owning a car is no more required. All these show that the bike-sharing and the car-sharing services have to be designed with a focus to serve different demand segments, supporting the notion of combining these services in the form of a MaaS platform to cater to a wider set of individuals.



Note: The figure shows the change in car-ownership levels with respect to the actual shared mobility scenario (SM), in terms of percentage points. At higher fleet sizes, there is a net increase in single car-ownership. This is due to the higher shift from multiple car-ownership to single car-ownership, than the shift from single car-ownership to no household car. The scenarios are constructed by varying the planned fleet size (Scenario SM) by -40% (SB1), -20% (SB2), +20% (SB3) and +40% (SB4).

Figure 6.7: Impact of bike-sharing fleet size on household car-ownership



Note: The figure shows the change in car-ownership levels with respect to the actual shared mobility scenario (SM), in terms of percentage points. Unlike the bike-sharing service, the car-sharing service is very small and it is only possible to construct scenarios by increasing the fleet size. Considering that the Regensburg city council is interested only in a gradual expansion of the service, the scenarios are constructed by increasing the number of vehicles per stations (in Scenario SM) by 1 (SC1), 2 (SC2), 3 (SC3) and 4 (SC4).

Figure 6.8: Impact of car-sharing fleet size on household car-ownership

7 Insights derived

Contents

7.1 Demand for shared mobility services

This section focuses on the insights obtained from the estimation results related to demand for shared mobility services, presented in Sections 5.1, 5.2 and 5.3. The letters inside the bracket, in the headings of the subsequent sections, represent the model(s) based on which the discussion is made in the respective sections.

7.1.1 Commonality and disparity (MS)

This section elucidates the common and differing characteristics of the three shared mobility services included in the disaggregate mode choice model (i.e., bike-sharing, car-sharing and ride-hailing), presented in Section 5.1. Most of the influencing factors identified are common (not necessarily having the same coefficient values) to the three services, showing that the shared mobility services have several overlapping user and use characteristics. As shown in Figure 7.1, these common factors include age group, education, possession of PT pass, trip distance and travel time. Besides these factors, gender and private car availability influence both bike-sharing and car-sharing.

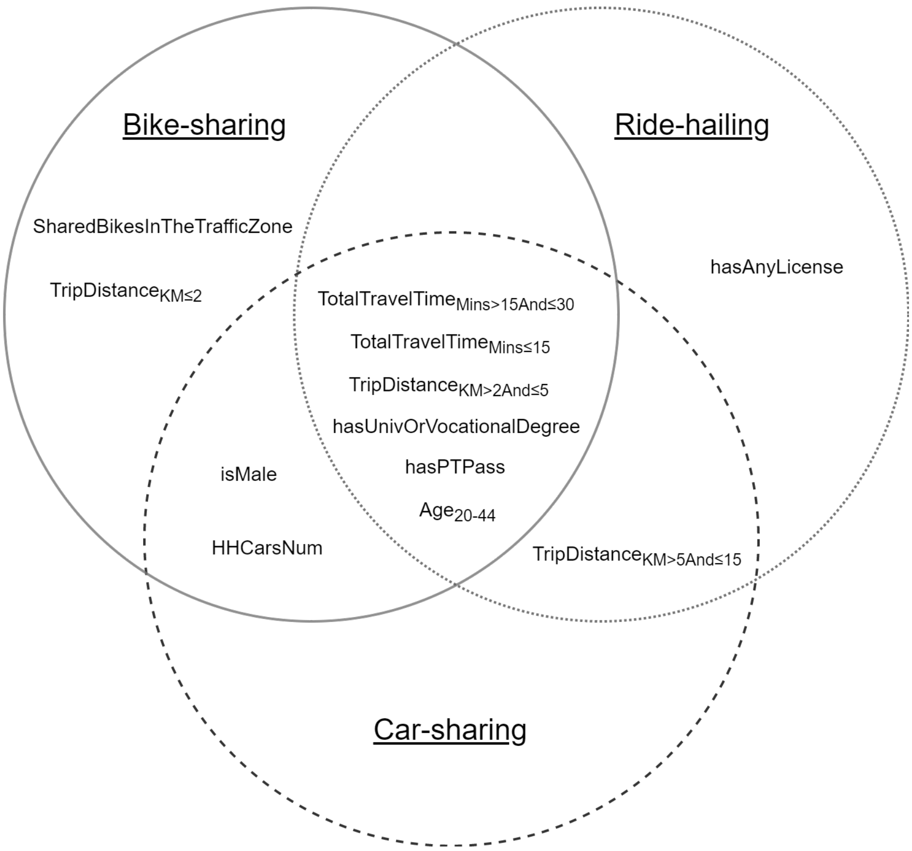


Figure 7.1: Significant variables influencing the mode choice of bike-sharing, car-sharing and ride-hailing service

7.1.2 Travel behaviour and other relevant insights

7.1.2.1 Age and education related aspects (MS, MC1)

The estimation results of Model *MS* show that individuals belonging to the age group 20 to 44 are more probable to use all the three kinds of shared mobility services. The decreased probability for the older group is in line with the estimation results of Model *MC1*, which focuses on the frequency of use of a small-scale round-trip station-based car-sharing service. Although young persons, in general, are expected to use the shared mobility services more, individuals younger than 20 usually have no or less income, and hence, the financial status can be the natural issue for them to use the shared mobility services. To attract this group towards bike-sharing and ride-hailing services, subsidies can be designed to motivate them. The effect of such subsidies might be especially pronounced for ride-hailing, as individuals without any license are more prone to use the service. The intention is not to shift individuals from PT, but to improve transport equity wherein PT service is weak. For car-sharing, given the requirement of license, it is not possible to target this user group.

Concerning the older age group, the reason for lower probability of use can be due to their lower tech-savviness and their attachment to the business-as-usual case (i.e., they are old to change their habitual behaviour of using conventional modes). To increase the penetration among this age group, educational campaigns to improve tech-savviness can be designed. Such campaigns are also recommended in Lavieri & Bhat (2019), to make ride-hailing services more accessible for older individuals. In addition, free-ride promotions (e.g., Shen et al., 2018b) can be introduced.

To alter the habitual behaviour, nudging (Thaler & Sunstein, 2008) may also be beneficial. There is an increasing interest in the application of behavioural economics to transport, especially in the field of promoting alternatives to private car use (e.g., Anagnostopoulou et al., 2020; Avineri, 2012; Franssens et al., 2021; Gardner, 2019; Kristal & Whillans, 2020; Namazu et al., 2018b). Personalised interventions based on persuasive technologies (Anagnostopoulou et al., 2020) that (digitally) nudge users towards sustainable transportation habits can be formulated. It is to be remembered that nudging should be used as part of bigger initiatives (e.g., congestion charges, vehicle access restrictions and parking bans) to improve the effects, rather than as a replacement for other interventions. If not, there may not be an achievement of the intended result (Avineri, 2012; Kristal & Whillans, 2020). Combination of nudging with gamification strategies can also result in a positive impact.

Both Models *MS* and *MC1* show that individuals with higher education level (e.g., with a university degree) have a higher probability to use shared mobility services. The reason could be the better awareness of technology and the use benefits of the shared services. Therefore, technology and social awareness campaigns could be beneficial to attract individuals with lower education.

7.1.2.2 Gender related aspects (MS)

For females, although they are more concerned (than males) about environmental-friendly mobility, the rejection of innovative technology (due to their pragmatic approach towards mobility) can be a reason for lower probability to use the shared mobility services (Kawgan-Kagan, 2020). Considering this aspect, nudging and campaigns can be applied to influence their attitude. Besides the aforementioned reason, the lower use by females could be a result of not considering the gender differences in the planning and operational design. The mobility pattern of women is usually different to that of men (e.g., women are involved in longer trip chains than men), and hence, women have specific requirements for their daily mobility. Therefore, measures should focus on gender inherent obstacles.

Service operators usually collect data, such as the vehicle type and information on the route, but not the gender of the user or the purpose of the journey. Such data, along with studies based on them to capture the heterogeneous needs, are critical for adapting the services to different target groups like women. Measures, such as provision of child seats, ensuring planning reliability and guaranteeing vehicle availability within shorter distances, are of higher importance for female travellers. Given the typical longer chaining nature of the trips by female travellers, interim parking at various stops can make the trip cost expensive. Therefore, financial incentives, such as special rates for families or caregivers around daycare centres, can be beneficial. To summarise, a better understanding of and operational design based on typical mobility patterns of women, their trip requirements and the resulting mobility limitations may pave the way for shared mobility services as an alternative to conventional modes (especially private car) for women, thereby ensuring transport equity.

7.1.2.3 Vehicle ownership (MS, MC1) and the use of conventional modes (MC1)

The positive relationship between car-sharing and household car-ownership in Model *MS*, implies that the private car users can be shifted to car-sharing, i.e., people owning a higher number of private cars may be prone to give up their secondary and tertiary cars and shift to car-sharing services. Nevertheless, the negative relationship observed in Model *MC1*, for the frequency of use of car-sharing, may appear contradictory. However, it should be remembered that the system focused in Model *MC1* is a small-scale service, which is at its early stages. Thus, due to the small-scale of operation, the service may not still be sufficient to stimulate people with higher number of cars, to shift to the car-sharing service. This notion is supported by the positive influence of rare use of private cars, showing that the private car owners, who use their vehicles rarely (for rare essential trips), are slowly moving towards the car-sharing service. Thus, with an adequate growth of the small-scale system to a large-scale service, more car users may begin using the car-sharing service and there can be a possibility to reduce car-ownership in the long run. To summarise, with properly designed car-sharing services, car-ownership levels could be reduced.

In contrast to car-sharing, bike-sharing has a negative relationship with the number of household private cars in Model *MS*, which is something expected as the comfort of a car is different from using bikes. Hence, the demand segment for bike-sharing is slightly different from that of car-sharing and this needs to be considered, when multimodal platforms, such as MaaS, are designed. Furthermore, household bicycle ownership is found to have a positive influence on the rare use of the small-scale car-sharing service in Regensburg, as can be observed in Model *MC1*. This is complemented by the positive influence observed for the frequency of bicycle use, strengthening the fact that the car-sharing service supports active mode users. PT use is also found to complement the car-sharing use. This can mean that the car-sharing service in Regensburg is used for trips for which PT is not suitable. Therefore, it can be stated that the car-sharing service supports both active mobility and PT users.

Special pricing packages for frequent bicycle and PT users can be explored, to check whether such schemes motivate the simultaneous use of all the three modes (i.e., car-sharing, PT and bicycle), leading to a possibility of a MaaS platform. In addition, the distribution of the trip departure and arrival times (presented in Section 3.1.2) show that the service is utilised during the usual peak hours, as well as beyond those hours. Especially, a significant use is observed during the night times. Thus, if the service is carefully expanded as an extension of PT, it can improve the overall accessibility of the PT system. Still, there will be a segment of population that uses PT whenever possible, and their private car when PT is not adequate, without using the car-sharing service. This is reflected by the negative coefficient for the variable 'isPTAndCarUser' (individual uses both PT and private for at least once a week) in Model *MC1*.

7.1.2.4 PT pass possession (MS, MC1)

Possession of a PT pass is found to positively influence the use of bike-sharing and car-sharing services, while a negative relationship is observed for ride-hailing. This can mean that car-sharing and bike-sharing services complement PT, while ride-hailing does not seem to. Therefore, car-sharing and bike-sharing services can be integrated well with PT. Within this regard, discount for PT pass holders or a multimodal app (i.e., a MaaS platform) combining PT and shared mobility services could be advantageous. Especially, targeting young PT pass holders may bring an attitudinal change at young age and stop them from getting attracted towards private cars at a later stage of life. On the other hand, since ride-hailing has a substitutional effect, it might be beneficial to introduce them in areas where PT is weak (i.e., to reinforce the PT system). PT authorities can form partnerships with ride-hailing service providers to offer customised services to passengers, especially for those with special needs. Such partnerships are already being envisioned by service providers, such as Lyft (Hamilton, 2017).

7.1.2.5 Employment (MC1)

Model *MC1* shows that students, fully employed persons ($\geq$ 35 hr/week) and individuals with half employment (between 18 to 34 hr/week) are more likely to use the small-scale car-sharing service in Regensburg. The higher use among students can be due to their tech-savviness and the higher willingness to share than own. For the individuals with at least half employment, their income and better educational background can be the motivation for using the service. Supporting this notion, the estimation results show that people with university degree are more probable to use the service.

Among the aforementioned three user groups, people with half employment have an higher affinity for the use category 'Occasional'. The reason could be that this group performs more ad hoc trips and the business model of the service (focusing on special trips) can be beneficial for them. However, students have a higher impetus to use the service rarely, probably to perform occasional weekend trips. Discounts for students and customised packages for individuals with half employment (to support their ad hoc trips) can be designed to support their use of the car-sharing service.

7.1.2.6 Household income (MB2, MC1)

When focusing on the mode choice between a bike-sharing system and a private car, as shown by Model *MB2*, individuals from households with monthly income below € 1200 are less probable to switch from using private car to a bike-sharing service. A financial motivation scheme can be designed to attract individuals from low income households. An example of such a scheme is to get paid for using a shared bike to commute to office. This scheme could be introduced by companies, and in fact, similar schemes (i.e., getting paid for cycling to companies) already exist (Hu, 2018). Nevertheless, awareness campaigns may have to be carried out to disseminate the benefits of cycling and attract more companies to initiate such schemes.

On a different note, as shown by Model *MC1*, low income households (who may not have the capacity to own a private car) may use a car-sharing service for rare trips, for which PT is not suitable (e.g., transporting goods from furniture stores). This can imply that the car-sharing service enhances transport equity. The car-sharing system in Regensburg (the data of which is used for the estimation of Model *MC1*) is currently operated at a small-scale and with expansion in future, I believe that this effect will gain further significance. Therefore, subsidies can be implemented for low income users to reinforce their use of the car-sharing service.

7.1.2.7 Perception of bike safety (MB2)

Perception of bike safety is an important factor for the mode choice between private car and bike-sharing service. Therefore, there is a need to establish a positive perception of bike safety among the citizens. Suggested measures include improvement of cycle infrastructure (e.g., implementation of dedicated cycle lanes) and creation of bike safety campaigns. Techniques from the field of growth hacking (Bohnsack & Liesner, 2019; Herttua et al., 2016) can be helpful.

7.1.2.8 Trip distance (MS)

Bike-sharing systems are expected to be used for a distance range of up to 5 km, with significantly higher probability for the range from 2 to 5 km. Distances beyond 5 km could be considered long for these services, which is observed in the estimation results. For distances less than 2 km, one can also walk, and therefore, a lower probability than the range 2 to 5 km. Compared to cycles, it is natural to expect a higher distance range for cars and the same is reflected in the estimates for car-sharing and ride-hailing services. Both services are expected to be used for a range 2 to 15 km, with a higher probability for the range 5 to 15 km. Interestingly, the odds for the distance range 2 to 5 km for car-sharing and the distance range 5 to 15 km for ride-hailing are same, which can be seen as a reflection of the effect of sharing a vehicle with a stranger (driver and other passengers). The above discussion shows that the bike-sharing system could be targeted majorly for trip distances 2 to 5 km, while distances between 5 to 15 km are better suited for car-sharing and ride-hailing. Within the distance range 5 to 15 km, ride-hailing could be implemented as a substitute to PT, in places where PT service is weak.

7.1.2.9 Travel time (MS, MB2)

Shared mobility services are expected to have a higher use for total travel times up to 30 minutes. Focusing specifically on the mode choice between private cars and bike-sharing services, Model *MB2* shows that the car users are highly sensitive (around 1.8 times higher) to the travel time associated with using a shared bike. To increase the competitiveness of bike-sharing services, shortcuts and dedicated cycle lanes with green wave can be implemented. The advantage of shortcuts for cycles is already shown in Gruber & Narayanan (2019). For ride-hailing systems, the finding of the time range of up to 30 minutes can be used as a basis for the operational design of the ride-sharing systems, i.e., to curtail the detours, which may result in longer travel times. Usually, for car-sharing systems, specific areas are designated for vehicle drop-off. The finding of higher probability of use for travel times up to 30 minutes has to be considered, when designating such areas. Dedicated parking facilities for shared cars could be introduced, while ensuring that the private cars have to travel substantially for finding parking spots. This can result in less total time for car-sharing systems, making them more competitive to the private cars.

7.1.2.10 Travel cost (MB2)

Between the use of shared bikes and private cars, individuals are more sensitive towards the cost of former than the cost of latter. This implies that, for a successful implementation of a bike-sharing system, the user cost should be kept low. A subsidisation scheme, similar to the ones implemented for PT in many cities around the world, would be beneficial. Especially, given that a bike-sharing system complements PT, as discussed in Section 7.1.2.3, the development of a subsidisation scheme for PT pass holders is suggested. Nevertheless, with a higher penetration, it might also be possible to lower the cost without subsidies in the future. On the other hand, the cost for car trips could be increased by the implementation of road pricing schemes.

7.1.2.11 Pricing strategy (MC2)

Focusing on the round-trip station-based car-sharing service, the estimation results of Model *MC2* show that there exists a fluctuation in the average daily demand, according to days of a week and the months of a year. This calls for price variations. Low prices can be introduced during days with low demand and off-seasons, to attract more customers. On the other hand, during days of high demand and popular months, with existence of inadequate supply, prices can be increased to close the gap between demand and supply. Such demand based price variations are not new, but have been utilised by taxi service providers, e.g., high rental prices in a location during tourist season or a major event. Pricing variation can also be based on supply, i.e., fleet availability (e.g., Giorgione et al., 2020).

With adequate growth of the car-sharing service, static pricing variations can be substituted with dynamic (i.e., real-time) pricing variations. A dynamic price based on various factors, including data-driven profiles (such as customers' socio-demographics and driving history), weather data, time of day and trip destination, can be beneficial (Valentin, 2019). A good driving profile maintained by customers can be converted to discounts or a lower price for future bookings. A mixture of multiple pricing strategies may also be useful (Hardt & Bogenberger, 2016). It is to be noted that such schemes have to be introduced only after a substantial demand base is reached, otherwise, there is a higher risk of system failure. Furthermore, to avoid development of aversion towards the service due to the dynamic pricing, price limits can be introduced and shared with the users, so that they can be more confident about the price capping.

7.1.2.12 Fleet system (MC3)

The change in demand share for individual stations according to the days of a week, as observed in Model (*MC3*), suggests for an implementation of a hybrid fleet system. Station-specific car-sharing vehicles (i.e., fixed fleet) and vehicles which can be relocated depending upon the predicted average daily demand for a station (i.e., variable fleet) can be introduced. For example, a higher number of vehicles for Stadtamhof is required on Fridays, while a lesser number is sufficient for Dachauplatz. Therefore, for Fridays, certain vehicles can be relocated from Dachauplatz to Stadtamhof.

7.1.3 Summary on policy and operational measures, and probable demand segments for the shared mobility services

The policy and operational related insights and suggestions discussed in Section 7.1.2 have been grouped and summarised in Table 7.1. The grouping has been performed based on the type of policy measure, namely (i) Finance, (ii) Infrastructure, (iii) Campaigns and nudges, and (iv) Service design. The finance related measures include subsidies and special rates for young age group and female travellers and free-ride promotions for older age group. Implementation of shortcuts, dedicated cycle lanes with green wave and introduction of dedicated parking facilities for shared cars fall under infrastructural aspects. With regards to campaigns, technology and social awareness campaigns for people with low education and educational campaigns to improve tech-savviness among older people are suggested. Nudging females to overcome the initial resistance towards innovative technology and personalised interventions that (digitally) nudge older people are also recommended. Finally, concerning service design, it is beneficial to design bike-sharing and car-sharing systems as a complementary service to PT, while ride-hailing as a substitution service in areas where PT is weak or absent. The need for the integration of shared mobility services, to avoid unwarranted modal shift patterns, is also reflected in the results of Regensburg case study (Section 6.3.3). Finally, gender differences must be considered in the operational design to remove gender inherent obstacles.

Table 7.1: Policy and operational measures based on the factors influencing the demand for shared mobility services

Policy measure	Relevant factors & models	Recommendations
Finance	Age_{20-44}(MS) Age(MC1) $\text{Employment}_{\text{Student}}$ (MC1)	Subsidies, discounts or special tickets to attract young age group (age<20) towards bike-sharing & ride-hailing, & bring an attitudinal change at young age & avoid getting attracted towards private cars. Similarly, such schemes could also be introduced for students, to draw them towards a car-sharing service with a business model focusing on serving special trips, such as the one in Regensburg. Free-ride promotions for older age group (age>44) to make them accustomed to the use of shared mobility services.
	isMale(MS) isMale(MB2)	Monetary incentives (e.g., special rates) for females-in-families or care givers around daycare centres, because of their long trip-chaining behaviour & necessity for interim parking.
	Cost:BS(MB2) Cost:Car(MB2) hasPTPass(MS)	Subsidisation packages for private car users to shift to bike-sharing, especially, for those who hold PT pass. Lowering of cost with a higher penetration in future, while removing the subsidies. Implementation of road pricing schemes to increase the cost for car trips.
	Household Income(MB2) Household Income(MC1)	Financial motivation scheme for lower income households, e..g, to get paid for using a shared bike to commute to office, which could be introduced in partnership with companies. Similarly, subsidies for such households to reinforce their use of shared cars for special trips (e.g., trips to furniture stores).
	$\text{Employment}_{\text{Half}}$(MC1) $\text{PTUse}_{\text{Often}}$(MC1) $\text{BicycleUse}_{\text{Often}}$(MC1)	Customised packages for individuals with half employment, to support their ad hoc trips using car-sharing service. Similarly, special pricing packages for frequent bicycle and PT users, to motivate the simultaneous use of the three modes.

Table 7.1: Policy and operational measures based on the factors influencing the demand for shared mobility services

Policy measure	Relevant factors & models	Recommendations
Infrastructure	TravelTime(MS) Time:BS(MB2) PerceptionOfBike-Safety(MB2)	Implementation of shortcuts & dedicated cycle lanes with green wave, to increase the competitiveness of bike-sharing services. Introduction of dedicated parking facilities for shared cars, while ensuring that the private cars have to detour substantially to find parking spots, thereby making car-sharing more competitive.
Campaigns & nudges	hasUniversityOr VocationalDegree(MS) hasUniversity Degree(MC1)	Technology & social awareness campaigns for people with low education.
	Age_{20-44}(MS) Age(MC1)	Educational campaigns to improve tech-savviness among older people (age>44). In addition, personalised interventions based on persuasive technologies that (digitally) nudge older people towards sustainable transportation habits. Nudging should be complemented with larger initiatives (e.g., vehicle access restrictions) or gamification strategies.
	isMale(MS) isMale(MB2)	Nudging for females to overcome the initial resistance towards innovative technology.
	PerceptionOfBike-Safety(MB2)	Bike safety campaigns to establish a positive perception among the citizens.
Service design	HHCarsNum(MS) hasPTPass(MS) $PTUse_{Often}$(MC1) Regensburg case study	Development of a MaaS package & integration of the shared mobility services with PT: Design of bike-sharing & car-sharing systems as a complementary service to PT, while ride-hailing as a substitution service in areas where PT is weak or absent. When formulating the complementary service, car-sharing should, especially, be targeting private car users, since it is easier to shift private car users to car-sharing, when compared to a shift towards bike-sharing.
	isMale(MS)	Consideration of gender differences in the design of shared mobility services to remove gender inherent obstacles.
	TravelTime(MS)	The finding of the time range up to 30 minutes could be used as a basis for the operational design of the ride-sharing services, i.e., to curtail the detours which may result in very longer times.
	Days of a week(MC2) Months of a year(MC2)	Static price variations during the initial stages & a dynamic pricing scheme or a mixture of multiple pricing strategies in the long run, with a price capping, which shall be informed to the users;
	Days of a week(MC3)	A fixed fleet per station & a variable fleet, which can be relocated to different stations based on the popularity of a station during the day of a week; for a round-trip station-based car-sharing service.

Note: The letters inside the bracket in the second column represents the models to which the factors belong.

Besides the aforementioned measures, Section 7.1.2 also throws light on other operational related aspects. The estimation results for Model *MS* and the insights derived in Section 7.1.2 show that there are some overlap on the user groups and use cases of the three shared mobility services (i.e., bike-sharing, car-sharing and ride-hailing), while some differences also exist. This supports the notion of having different shared systems co-existing in the city. Hence, it will be beneficial to optimally design the different shared mobility services to target different user groups and use cases, with a focus to integrate them for MaaS, along with PT. As a step towards this integration, the most probable demand segments for the different shared mobility services are summarised in Figure 7.2. As shown in the figure, when the trip distance is up to 2 km, bike-sharing is preferable. For distances between 2 and 5 km, car-sharing can be promoted for private car users with a PT pass (i.e., use PT for regular trips and car-sharing for special needs, during which private cars are generally used). If an individual has PT pass, but is not a private car user, then bike-sharing is recommended. On the other hand, if someone does not possess a PT pass, the individual can be attracted towards ride-hailing. For distances between 5 to 15 km, if a person has a license, car-sharing is proposed. Otherwise, ride-hailing is preferred.

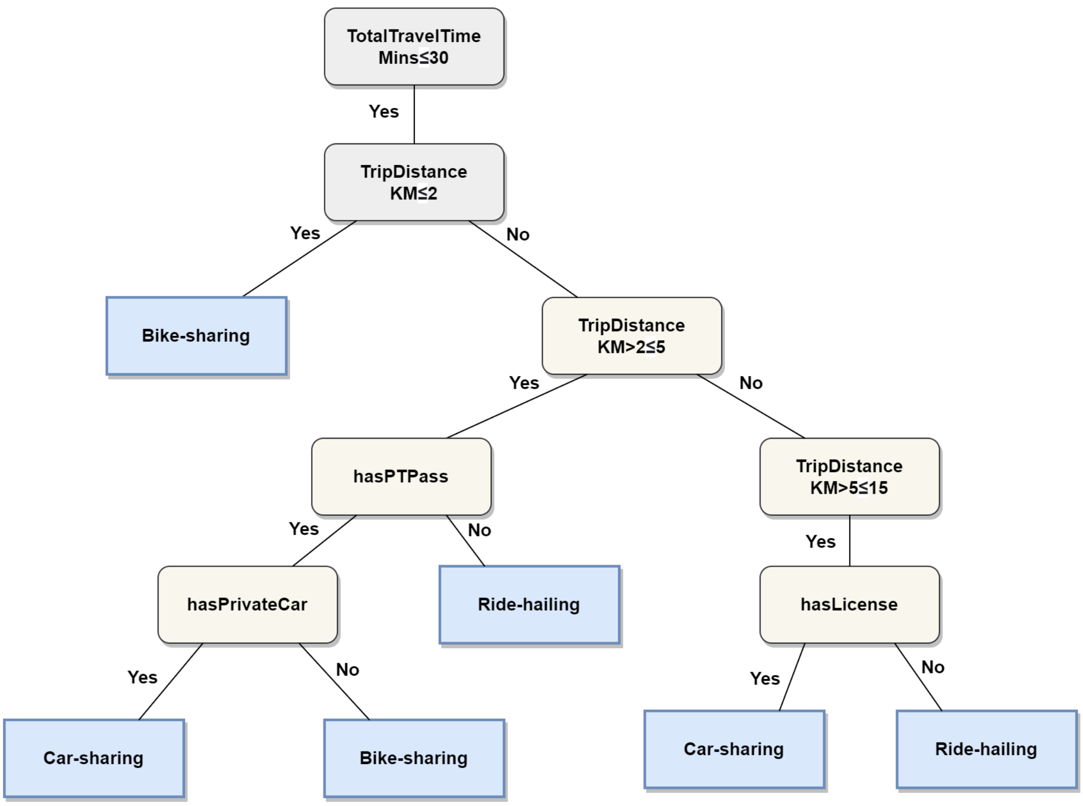


Figure 7.2: Most probable demand segments for different shared mobility services, based on the estimation results for Model MS

7.2 Household car-ownership

This section focuses on the insights obtained from the estimation results related to household car-ownership, presented in Section 5.4.

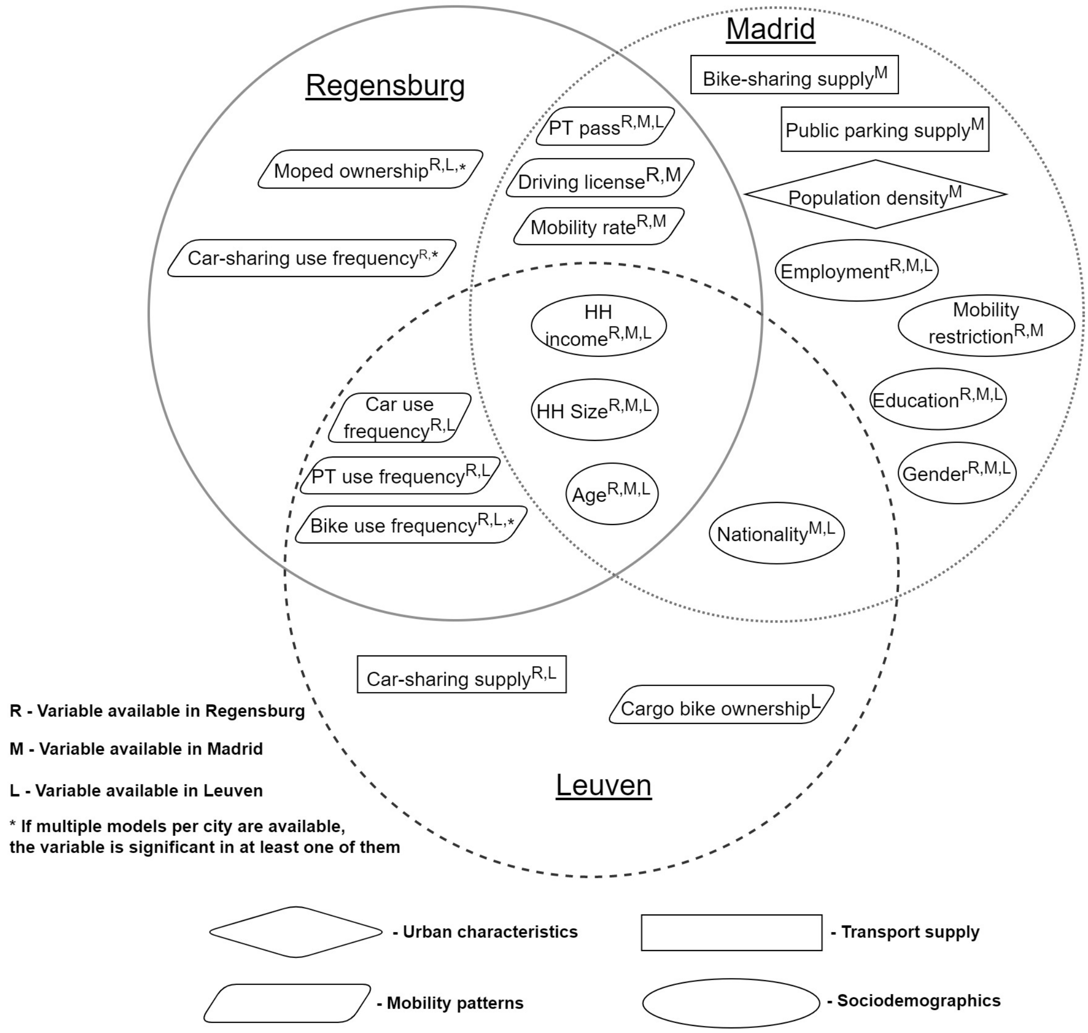
7.2.1 Commonality and disparity

A number of common patterns can be observed between the cities, while differences also exist. All these are summarised in Figure 7.3. As shown in the figure, the influence of household income, household size and age are common to three three cities. Furthermore, the significant influence of total number of trips (i.e., mobility rates), the possession of PT pass and driving license are observed for both Regensburg and Madrid. It is to be noted that the driving license information is not available for Leuven, and we believe that this variable would also have a significant impact on the household car-ownership in the city. Similarly, the data for the frequency of use of conventional transport modes (car, PT, and bike) is available only in Regensburg and Leuven, and the use frequency of these modes has a significant effect in both cities. Likewise, the data on nationality is available only in Madrid and Leuven, and it is a significant influencing variable in both the cities.

When it comes to the differences, although education, gender, and employment data are available in all the three cities, they are significant only in Madrid. The details on the possession of PT subscriptions is also available in the three cities, while its impact is only significant in Regensburg and Madrid. This shows the disparity in the behavioural traits in different cities. Moped-ownership and car-sharing supply data are available in Regensburg and Leuven. However, the moped-ownership variable is observed only in the Regensburg models and the car-sharing supply variable only in the Leuven model. In Regensburg, the car-sharing system is being operated at a very small scale ($<$ 10 vehicles) and the insignificance of the supply variable can be due to this reduced operation. The significance of the dummy variable for car-sharing use confirms that the service indeed impacts car-ownership. Therefore, with the expansion of the service in the future, the impact of the supply variable is foreseeable. Finally, mobility restriction is a significant factor in Madrid, while this is not the case in Regensburg. Probably, the mobility restriction pattern may differ between the cities, leading to this disparity. The unavailability of certain variables (e.g., cargo bike-ownership and bike-sharing supply) across all three cities restrains the possibility of exploring their common applicability.

7.2.2 Behavioural and policy insights

A look into the estimation results of the models of the three cities shows that the classical explanatory variables, such as household size, household income, and age, continue to influence household car-ownership. This section will describe the different behavioural findings obtained from the estimation results and the policy insights derived from these behavioural findings (which are also grouped and summarised in Figure 7.4).



Note: The commonality and disparity are reported based on the presence of a particular variable in the mode specification of the respective cities. The plausible difference in the direction of effect for some variables are not considered here and will be explored in Section 7.2.2

Figure 7.3: Significant variables in the car-ownership models of the three cities

7.2.2.1 Socio-demographic characteristics

The estimation results show that both household income and size have a positive logarithmic effect on car-ownership. The low-income group may not have the financial capacity to own and maintain a private car. As the income grows, the purchase capacity increases and intuitively, the likelihood for private car purchase increases too. A relevant finding is that the rate of this increase is not constant and it becomes smaller as income grows because of the logarithmic effect. This means that the difference in utility to own private cars may not be too high among high-income households. Thus, policy interventions, such as road pricing schemes, can be designed with a single price and may still be effective in curbing high-income private car owners with a range of salaries.

Regarding the household size, it is intuitive that mobility patterns differ with increasing household size, since there is a higher probability of chaining and combining trips of multiple household members. Hence, owning a car is a convenient option. Similarly, females also have different mobility patterns when compared to males (Narayanan & Antoniou, 2022c). Alternative mobility solutions should consider these aspects and their design should accommodate such heterogeneous needs. Especially, car-sharing services could be a feasible alternative. However, measures, such as providing child seats, ensuring planning reliability, and guaranteeing vehicle availability within shorter distances, are of higher importance. Financial incentives, such as special rates for families, could be explored.

Age has a piecewise effect, with no increase in utility beyond the retirement age. Today, young- and middle-aged individuals are becoming users of alternative mobility options, such as shared mobility services. The finding that there is no increase in utility to own a private car beyond the retirement age can mean that there is a possibility to alter the behaviour of older people. Personalized interventions based on persuasive technologies (Anagnostopoulou et al., 2020) that nudge individuals towards sustainable transportation habits can be formulated. It is to be remembered that nudging should be used as part of bigger initiatives (e.g., congestion charges, vehicle access restrictions, and parking bans), failing of which may not result in the achievement of intended result (Avineri, 2012; Kristal & Whillans, 2020). The combination of nudging with gamification strategies could also result in a positive impact. Besides the efforts to bring a behavioural change, proper access to alternative mobility options is of higher importance for older people.

Local citizenship has a significant influence on car-ownership, maybe due to the probable long-term plan to stay in the country or better settlement situation compared to non-citizens. On a different note, better education is associated with a higher likelihood of household car-ownership in Madrid, while this is not the case in Regensburg and Leuven. A better education can lead to an employment with higher income and social status, which can lead to interest in private car-ownership. It could be a case that, a higher awareness of the negative effects of private cars among the highly educated people in Leuven and Regensburg, has resulted in insignificance of the education variable in those cities. Thus, awareness campaigns in Madrid may help in reducing the interest towards private car-ownership.

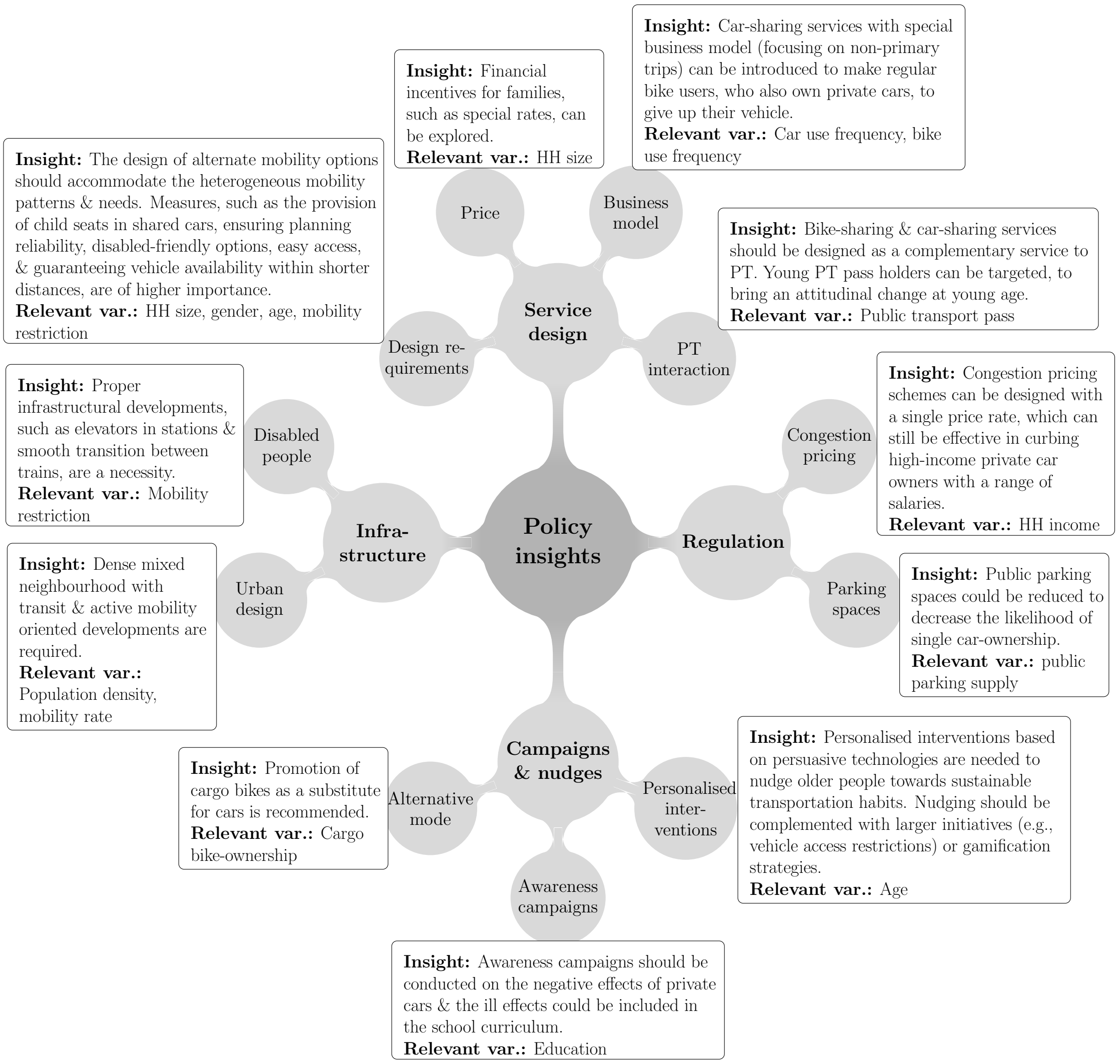
Employment leads to a higher probability of household car-ownership. This is reflected in both the Madrid and the generic models. However, the employment variables in Regensburg and Leuven models are insignificant, although they have a positive coefficient. Nevertheless, in a model specification with only employment as the independent variable, a significant estimate can be observed. Therefore, we believe that the explanatory power of employment in the Regensburg and Leuven models is reduced by the presence of other variables, With regards to individuals with mobility restrictions, to reduce their use of private cars, the accessibility for such individuals to using alternative mobility options has to be enhanced, as is the case for older people. Furthermore, proper infrastructural developments (e.g., elevators in stations and the possibility for smooth transition between trains) are necessary.

7.2.2.2 Urban characteristics and transport supply

The estimation results show that a higher population density results in a lower probability of household car-ownership, especially of multiple cars. This can be attributed to the possibility of shorter trips using active modes and also due to the better PT density. Therefore, denser areas with transit and active mobility oriented development can support the reduction of private car-ownership. With regards to parking spots, the availability of public parking spaces can increase the probability of owning a single car, while a significant influence is not found for owning multiple cars. This can mean that individuals think about public parking at their home zone, when they purchase their first car. For the subsequent cars, they may not care much about public parking, probably since they are more used to private cars or perhaps their situation compels them to. Finding an empty public parking space for a single vehicle is easier than finding multiple spaces. Naturally, multiple car owners prefer private parking spaces. Therefore, we believe that the reduction of private parking spaces will have a significant negative influence on multiple car-ownership, while the removal of public parking spaces may reduce the likelihood of single car-ownership. However, it is not possible to explore the impact of private parking spaces in this current study, since sufficient data is not available.

The inverse relationship between the supply of emerging mobility solutions (such as bike-sharing and car-sharing) and the household car-ownership implies that, the proper design of these services and their introduction in appropriate places, has the potential to reduce household car-ownership levels. Especially, a higher influence is observed for the ownership of multiple cars. Non-primary vehicles are usually underused than the primary one in many households and the higher influence for multiple car-ownership may imply that alternative mobility options act as better substitutes to non-primary vehicles. Therefore, it easier to shift people from multiple car-ownership to single car-ownership through the introduction of shared mobility services. For individuals who have a subscription to a car-sharing service, the increase in supply of shared cars further reduces the probability of household car-ownership.

A comparison of the coefficient for the bike-sharing supply in the Madrid model and the car-sharing supply in the Leuven model shows that the latter is more influential in reducing the household car-ownership. This is also confirmed by the results of the scenario analysis performed as part of the case study on Regensburg. Although the difference in coefficients can also arise due to the (plausible) varying behaviour in cities, we believe that the conclusion (i.e., car-sharing has a higher impact on car-ownership reduction than bike-sharing) still holds. This is due to the fact that the comfort of and the activities that can be performed with a car are different from that of bikes. Hence, the demand segment for bike-sharing is different from that of car-sharing. This needs to be considered, when designing multimodal platforms, such as MaaS, aimed at reducing private car-ownership levels.



Note: HH - Household

Figure 7.4: Policy suggestions based on the behavioural insights related to household car-ownership

7.2.2.3 Mobility patterns

The possession of a PT pass is found to negatively influence household car-ownership. Given that shared mobility services can also reduce car-ownership, a well-integrated multimodal transport system based on MaaS platforms (combining PT and shared mobility services) could be advantageous. Especially, targeting young PT pass holders may bring an attitudinal change at a young age and stop them from getting attracted to private cars at a later stage of life. The piecewise effect for the share of household members with a driving license shows that, its increment does not linearly increase the utility for household car-ownership. This can mean that multiple household members may share a single vehicle, thus resulting in different household mobility patterns with an increase in the number of licenses in the household. On the one hand, this can be considered something positive, i.e., more people use a single vehicle. On the other hand, this results in difficulties to shift such households from private car use to alternative mobility options, as owning a car is a convenient option. This may also lead to the risk of producing captive drivers.

Considering the mobility rates of individuals (i.e., the number of daily trips per person), a decrease in the likelihood of owning a private car is observed in Regensburg, while an increase is observed in Madrid. Regensburg is a historical city and also a city of short distances (around 50% of the trips are conducted by walking or bicycling). As such, the negative coefficient for the mobility rates may indicate that people walk and bicycle to make more –but shorter– trips, whereas private car users make fewer –but probably longer– trips. However, people who make more trips in Madrid may try to use private cars, which indicates that the trips are either longer or unsuitable for using other modes. Thus, suitable urban design is necessary to enable enhanced mobility through active and sustainable modes. Concerning the influence of emerging alternative modes, the availability of a cargo bike in the household decreases the likelihood of household car-ownership (especially in the case of multiple cars). This could be due to the distinctive features of cargo bikes, which turn them into effective car-substitutes for certain activities, such as shopping and transport of mid-size/weight cargo. The suitability of cargo bikes to substitute cars is also confirmed by the analysis on the purchase of cargo cycles (Section 5.5.2). Therefore, cargo bikes can be promoted as a feasible alternative to private cars.

As expected, frequent car use (including non-private cars, e.g., business car) supports the ownership of cars. Nevertheless, the Leuven model shows that private car-ownership is influenced by the use of cars primarily for commuting, rather than for leisure trips. Moving on to bike use, based on the Regensburg models (Models $MR2$ and $MR3$), daily bike use reduces only the likelihood of owning multiple cars. This shows that people can use bikes daily and still own a single car. Probably, these people use the car for shopping trips (during which goods need to be carried) or non primary trips (e.g., leisure trips). The Leuven model shows that, if people always use bikes for leisure trips, then this impact is also applicable for single car-ownership. To sum up, although cars are predominantly purchased for primary trips, there are also households buying them for non-primary trips. To shift this group away from private cars, car-sharing services with special business model focusing on non-primary trips (e.g., trips to furniture stores or weekend trips to picnic spots) could be suitable. Based on the Regensburg models, daily PT use can also be concluded to decrease the probability of owning cars (both single and multiple). The Leuven model supports this effect, i.e., rare or non-users of PT for commuting and leisure trips are more likely to own cars. Interestingly, the rare or non-use of buses for leisure trips has the same impact on single and multiple car-ownership. However, the rare or non-use of trains for leisure trips leads to a higher probability of multiple car-ownership. This can be due to local PT network conditions.

7.2.3 Insights for modellers

The modelling insights obtained from the estimation results are summarised in Table 7.2, and discussed in the subsequent paragraphs. When comparing the models corresponding to different cities, commonality and disparity exist. On the one hand, the commonality can be utilised to develop generic models or transfer models from one city to another. On the other hand, the modellers shall be careful when hypothesising the influence of variables in one city based on the results from another city. The background and characteristics of the cities could be beneficial in this regard. For example, in Regensburg, as mentioned in the previous section, people walk and bicycle to make more –but shorter– trips, whereas private car users make fewer –but probably longer– trips. This is not the case in Madrid; thus, an increase in the probability of household car-ownership is observed for higher mobility rates.

Table 7.2: Summary of modelling insights based on the comparison of the household car-ownership models

Observation	Relevant model(s)	Remark(s)
Log and piecewise effects prevail for certain independent variables	All the models	Explore beyond the use of common linear expression
Same estimates occur for an independent variable for different levels of the dependent variable	All the models	Investigate the possibility of having a common estimate to build a more parsimonious model
There exists commonality across cities	*MR1*, *MM1*, *ML*	Utilise the common factors to develop generic models or transfer models from one city to another
There also exists disparity across cities	*MR1*, *MM1*, *ML*	Care should be taken when hypothesising the influence of variables in one city based on the results from another city
Based on the selection criteria for a household representative, different model specification is achieved	*MR1*, *MR2*, *MR3*	To explore the impact of certain variables, use an appropriate representative individual
Model with just the household level variables already has good summary statistics	*MR3*, *MM2*	Estimate such models when only household data is available and the required individual data is not available
Impact of the car-sharing service in Regensburg is shown only in the model with household level variables	*MR3*	During the early stages of the application of emerging mobility solutions or when a service is operated at a small-scale, models with aggregate variables may be beneficial to ascertain impacts of the mobility solutions

A comparison of the models from the three cities clearly shows the existence of a logarithmic effect for household size and income. Furthermore, a piecewise effect for age and share of license holders in the household is observed. This consistency across the three cities conveys that certain independent variables require exploration beyond the conventional use of linear expression and this is also applicable to different forms of the variable (e.g., the consideration of both the age of a representative individual and the average age of a household show a logarithmic effect). Furthermore, some variables can have identical estimates for the different levels of the dependent variable. Taking this into account will lead to a more parsimonious model. Besides, different selection criteria for a representative individual may result in different model specifications. For example, the oldest individual is not representative of the daily bicycle use, and hence, this variable is not seen as significant in Model *MR1*, while it is significant in Model *MR2*.

For Regensburg, although the model considering the individual with the highest car use has better summary statistics, the model based on the usual criteria for the representative individual (i.e., the oldest individual) still performs satisfactorily. Similarly, a model with just the household level variables performs good, and this kind of model can be beneficial in situations wherein it is possible to collect only household data and not individual data. Such a model can achieve good summary statistics with comparatively lower data requirements. The impact of emerging mobility solutions on car-ownership, at their early stages or when the system is operated at a small-scale, might be limited. In this case, it might be beneficial to use aggregated variables. For example, in Regensburg, when the share of household members using the car-sharing service is considered, a significant influence is observed. However, when the use by an representative individual is considered, the influence is not significant.

7.3 Purchase of cargo cycles

This section focuses on the insights obtained from the estimation results related to the purchase of cargo cycles, presented in Section 5.5.2.

7.3.1 Comparison between purchase intention and actual purchase decision

The descriptive statistics in Section 3.5.2 show that a higher share of intent is observed (48.5%), compared to the actual purchase (32.0%). Although only the final model is shown in Section 5.5.2, a model for actual purchase decision with intention as an explanatory variable was also tested. This model shows that the intention has a significant positive impact on the actual purchase decision. Nevertheless, as shown in Table 5.14, there are factors which are not common to both. Based on the sample descriptive statistics and the influencing factors, one can conclude that there is a need to convert intention to actual decision, when making conclusions based on intentions. This implies that the results from surveys, such as stated preference surveys, have to be carefully considered and corrections are needed to make right conclusions.

A comparison of the significant variables for the purchase intention and the actual purchase decision points out the differences in factors influencing them. The significance of F-OC for the purchase intention shows that the organisations have been thinking about the operational concerns associated with the cargo cycles, when they stated their purchase intention. However, despite the operational concerns, organisations tend to purchase cargo cycles (i.e., they do not care about potential concerns). This is shown by the insignificance of F-OC for the actual purchase decision. On the one hand, the participating organisations could have ascertained that the deteriorating conditions for the conventional vehicles might lead to a negative impact on their operations in future and on the other hand, they could have also thought about the cost benefits of cargo cycles. The significance of F-DC and F-CB for the actual purchase decision shows that organisations, which perceive the cost benefits of the cargo cycles and the negative impacts of the deteriorating conditions for the conventional vehicles, are more probable to purchase cargo cycles. To summarise, operational concerns take precedence for the purchase intention, while cost benefits and deterioration of conditions for conventional vehicles take precedence for the actual purchase decision.

Furthermore, decision-makers favouring technology and innovation seem to be enthusiastic when they state their intention to purchase cargo cycle (which is something expected). However, when they have to make the actual purchase decision, they could have perceived more disadvantages (e.g., larger catchment area of operations), reducing their interest to purchase cargo cycles. Hence, F-TI (i.e., interest towards technology and innovation) is significant for the purchase intention, while it is insignificant for the actual purchase.

7.3.2 Insights for policymakers and industry

7.3.2.1 Insights for policymakers

Commercial users perceive the political framework to be important for their business, indicating that policy measures majorly drive the design of their networks (Fraunhofer IML, 2010). The enforcement of regulations, which would affect the operations, influences the type of delivery model deployed by companies (Janjevic & Winkenbach, 2020). Supporting this view, the significance of F-DC shows that policies, which deteriorate the conditions for conventional vehicles, could be used as levers to reduce the usage of conventional vehicles and increase the cargo cycle penetration. Examples for such policies from the literature include infrastructural (road pricing, congestion zones, traffic calmed areas, low noise zones, zero emission zones, truck bans, parking reservation systems and increased parking fines), temporal (time access restrictions, daytime delivery restrictions and daytime delivery bans) and vehicular restrictions (loading-, size- and engine-related restrictions) (Yannis et al., 2006; Holguin-Veras et al., 2020). Organisations which utilise cargo cycles to substitute a higher number of car trips during the trial phase are more likely to purchase cargo cycles. This shows that organisations perceive cargo cycles to be more suitable to substitute car trips. Therefore, policies that deteriorate conditions for the conventional vehicles could be effective to shift current car users.

Concerning the benefits of cargo cycles, not only operational benefits but also soft benefits play a major role in the purchase decision. Interestingly, lower vehicle purchase cost alone is no significant driver for cargo cycle purchase, as shown by the insignificance of F-PC. However, a factor combining vehicle and maintenance cost (F-CB) has a significant effect. Hence, when vehicle design failures are present, purchase subsidies and lower vehicle cost may not be adequate and helpful. Therefore, robust and efficient cargo cycle designs are required to lower maintenance cost, along with provision of purchase subsidies. With regards to soft benefits, campaigns that aim at improving the perception of the soft benefits could be effective in increasing the cargo cycle penetration. Enforcement of strict corporate environment goals and certifying businesses with ecological fleets, such as cargo cycles, may also be beneficial. Concerning operational benefits, better cycling infrastructure, especially implementation of shortcuts and dedicated cycle lanes, can support cargo cycle penetration. Furthermore, for a safe operation, large cargo cycles require an appropriate cycling infrastructure (Taefi et al., 2016), including, but not limited to, larger lane widths and smooth turning angles.

The significance of the 'dailyMileage' variable shows that cargo cycle trials can help organisations to ascertain the suitability of cargo cycles for their use case. Such trials can increase the confidence of those organisations, which have reservations against cargo cycles, although cargo cycles are suitable for their use case. Every additional kilometre driven per day during the testing period increases the probability to purchase, on average, by 2.3%. Hence, trial schemes can be concluded as useful tools to increase cargo cycle penetration. Another supporting evidence to this statement is the significance of the dummy variable 'winterTesting': organisations which tested the cargo cycles during winter are more probable to purchase cargo cycles. The marginal effect show that the expected probability of purchase increases by 0.17, when the testing is done during winter season. This proves that trial schemes can reduce reservations against cargo cycles, i.e., the thought that cargo cycles cannot be effectively utilised in winter could be reduced.

Organisations covering a wider geographical area might still have negative reservations against the procurement of cargo cycles. Nevertheless, organisations that are able to restructure their catchment areas may find the cargo cycles suitable for purchase. Cargo cycles are competitive to motorised vehicles for smaller catchment areas and shorter delivery distances (Gruber & Narayanan, 2019), and hence, a feasible option is to introduce network configurations with intermediate shifting (i.e., parcels and packages are transferred to cargo cycles from other vehicles for last-mile delivery). Different types of intermediate shifting points are found in literature, which are Urban Consolidation Centre (UCC), Micro-hub/Micro Consolidation Centre (MCC) and Transit Point (TP). For more information on network configurations with intermediate shifting, the reader is referred to Narayanan & Antoniou (2022a).

As the negative intercept from the model points out, there exist multiple reservations towards cargo cycle purchase, which need to be taken care through policy instruments. To have a better view of the insights discussed in this section, which enable to reduce the reservations against cargo cycle purchase, the factors identified in Section 5.5.2 have been grouped and summarised according to policy measures in Table 7.3. The marginal effects of LVs show that the deterioration of conditions for conventional vehicles and soft benefits have a higher effect, than operational benefits and cost benefits. Therefore, among the policy instruments suggested based on LVs, regulations and campaigns on soft benefits will play a pivotal role in the penetration of cargo cycles.

Table 7.3: Policy measures suggested based on the factors influencing the actual purchase of cargo cycles

Policy measure	Relevant factors	Recommendation
Regulation	deteriorationOfConditions carSubstitution lightVehicleSubstitution	Regulative framework that discourage the use of conventional vehicles are encouraged to ameliorate the competitiveness of cargo cycles.
Infrastructure	operationalBenefits	Cycling infrastructure must be strengthened to improve operational benefits. Policies, such as implementation of dedicated cycles lanes (which ensures better travel time reliability), shortcuts and better cycle parking facilities, are recommended.
Finance	costBenefits	Purchase subsidies are suggested. However, given that subsidies alone would not be adequate, robust and efficient cargo cycle designs are required to lower maintenance cost. When vehicle design failures are present, purchase subsidies may not be adequate and helpful.
Campaigns	softBenefits	Campaigns can be conducted to improve the perception of the soft benefits. Techniques from the field of growth hacking and application of persuasive technology can be beneficial in projecting the soft benefits. Enforcement of strict corporate environment goals and certifying businesses with ecological fleets, such as cargo cycles, may also be beneficial.
Trial schemes	dailyMileage winterTesting catchmentArea	Trial schemes, especially during winter seasons, have to be implemented to enable commercial users to ascertain the suitability of cargo cycles for their use case, thereby reducing negative reservations.

7.3.2.2 Insights for cargo cycle manufacturers

While the availability of cargo cycle construction types 2 (Long John bikes) and 4 (front-load trikes) are high, types 3 (longtail bike) and 5 (heavy-load trike) are less common. However, estimation results show that the organisations, which utilised types 3 and 5 to substitute commercial light vehicles, are more probable to purchase cargo cycles. This could be seen as a market opportunity for manufacturers. Hence, cargo cycle manufacturers should concentrate on improving and optimising these two models with the view to substitute commercial light vehicles.

Given the significance of soft benefits, cargo cycle manufacturers should also work on promoting the soft benefits of cargo cycles. In this regard, advertising campaigns through different types of media might be helpful, especially when car users are targeted, since the estimation results show that the cargo cycles have higher potential to substitute car trips. A collaboration between policymakers and cargo cycle manufacturers for conducting campaigns, to promote the soft benefits of cargo cycles (e.g., better company image, higher enjoyment, improved employees' health and the possibility to achieve corporate environment goals), is a viable option to increase cargo cycle penetration, especially when combined with purchase incentives. Techniques from the field of growth hacking and application of persuasive technology can be beneficial in projecting the soft benefits.

The significance of cost benefits, which includes maintenance costs, points out the need for robust and efficient cargo cycle designs. As stated in Heinrich et al. (2016), technical deficits have a decisive impact on the penetration of cargo cycles. Hence, cargo cycle manufacturers are required to ensure proper design of cargo cycles to lower the technology failure likelihood, thereby lowering the maintenance costs.

7.3.2.3 Insights for organisations looking out for alternatives to conventional vehicles

For organisations which face higher deteriorating conditions for their operations using conventional vehicles, especially cars, it is a good time to shift to cargo cycles. Organisations with negative reservations regarding the effectiveness of cargo cycles during winter can be more confident. For organisations looking out for an alternative to commercial light vehicles (e.g., van), longtail bikes and heavy load trikes are suggested. Organisations belonging to the business sectors D, E, G, H, I, J, K, L, R and S (see Section 3.5.2.1 for the business sector names) are found to have higher probability of purchasing cargo cycles. The marginal effect shows that the probability to purchase is around 18% higher for organisations belonging to these business sectors.

The reason for the higher probability could be better suitability of cargo cycles for operations in those sectors. Hence, organisations that have no cargo cycle testing experience but belong to these sectors can be more confident about the suitability of cargo cycles for their operations. Concerning the business sectors with lower probability, involvement of heavy and large materials could be a reason for the lesser likelihood to purchase cargo cycles in the following business sectors: 1) Agriculture, forestry and fishing (A); 2) Manufacturing (C); 3) Construction (F). With regards to the business sectors 1) Professional, scientific and technical activities (M); 2) Administrative and support service activities (N); 3) Public administration and defence (O); 4) Education P); 5) Human health and social work activities (Q), the reason for lower probability is still not clear, and hence, we cannot provide a consistent explanation at this point. Although a probable reason could be that individuals from these sectors may expect a better comfort level for travel (i.e., they prefer cars to cargo cycles), the effect could also be due to the existence of heterogeneity within each of the sectors. Therefore, this needs to be explored in future research works.

8 Directions for future research

Contents

Naturally, this dissertation can lead to several future works, under each of the explored topics. This chapter lists ideas for further research and at the same time, highlights some of those which have already been initiated.

8.1 Intermediate modelling approach

- The framework has not yet been packed as a single tool. We envision that this dissertation will act as a fundamental work, which will lead to the development of a standalone tool in future for easy uptake by cities, much similar to how earlier papers on agent-based approaches have lead to stand-alone tools today.
- In this dissertation, the approach has been applied for a case study on Regensburg. Future studies could focus on its exploitation and use for other cities. This process is underway: the approach has already been adapted and used for case studies on Madrid (Martín et al., 2023), Thessaloniki (Salanova et al., 2022) and Leuven (Vanherck et al., 2022). Specifically, Vanherck et al. (2022) conclude that this framework is less intensive on the computational side (when compared to agent-based approaches) and provides adequate quantitative results on the impacts of a growing shared mobility ecosystem, especially for small- and medium-sized cities like Leuven, notwithstanding only having a limited amount of additional data on shared mobility services.
- The intermediate modelling approach has been designed to accommodate a model for induced demand. The second future work can involve the development of a framework for quantifying induced demand. This work has also been initiated in the form of a master thesis (Kalliga, 2021), which has to be extended further.
- The third future work can consist of extending the approach for multimodal trips. Within this regard, a disaggregate multimodal mode choice model can be developed. My research stay at the Technical University of Denmark involved the development of such a model, which is still an ongoing task.
- A completely data-driven machine learning based surrogate can be developed as an alternative to the intermediate modelling framework. As a first step towards this direction, such a surrogate needs to be tested for the traditional four-step approach, to ascertain its feasibility. Towards this direction, a master thesis has already been accomplished (Makarov, 2021) and the idea requires further exploration.

8.2 Demand for shared mobility services

- The disaggregate mode choice model, which focuses on the choice between conventional modes-as-a-whole and three different shared mobility services, is based on a household survey data, wherein only details about the trips taken by the respondents are available. Therefore, a generalised multinomial logit model (personal-level model) is developed, instead of the classical multinomial logit model (wherein mode specific parameters are included). This may lead to a (minor) bias in the results during the model application in later studies. The extent of this bias needs to be assessed in future, through the application of this model for case studies on other cities.

- It is not possible to differentiate between exclusive and shared rides for ride-hailing services and the (plausible) distinction between these two services has to be investigated in future. Similarly, the distinction between free-floating and station-based services has to be examined.

- Subsequent studies can focus on the inclusion of other shared mobility services (e.g., scooter-sharing).

- The framework presented for the most probable demand segments for the three shared mobility services (i.e., bike-sharing, car-sharing and ride-hailing) is not comprehensive and can be extended based on other variables.

- With regards to the demand model for the small-scale car-sharing service, the impact of travel distance and time on the service use frequency is not assessed, as it is not possible to fuse the household survey and operator datasets. Therefore, future studies can focus on these aspects.

- I acknowledge the importance of the influence of travel cost on the demand for the service. Unfortunately, the investigation of the effect of cost is not possible with the type of data available and is a future research.

- Optimal strategies for the design of a hybrid fleet system (i.e., fixed and variable fleet) and price variations can be analysed.

- The small-scale car-sharing system investigated in this dissertation is a round-trip station-based system. For one-way station-based systems, the dependent variables in the dirichlet model can be the combinations of stations. Alternatively, separate dirichlet models can be predicted for each station with dependent variables as destinations. For free floating systems, manual zones can be created and the share for these zones can be the dependent variable. Within the zone, random or some systematic sampling can be implemented to distribute the demand.

- None of the demand related models include the effect of external factors (e.g., built environment). Analysing this is a topic for upcoming studies.

- Future research can also inspect the effect of implementing a MaaS platform and the impacts of the suggested policy and operational measures.

8.3 Household car-ownership

- Subsequent studies can focus on including the effect of additional alternative modes (e.g., e-bikes) and mobility solutions (e.g., ride-hailing and scooter-sharing) in the utility specification.

- There is a growing emphasis on multimodal trips and future research could also explore the impact of multimodal trip behaviour.

- The impact of emerging policy measures, such as vehicle access restrictions and congestion pricing, has to be added to the model specification.

- The influence of curbing private parking areas on household car-ownership, especially in new residential development areas, is not investigated in this dissertation and is a topic for upcoming studies.

- The household car-ownership models estimated in this dissertation can be further improved by including relevant LVs (e.g., environmental concern). Such variables can be developed based on EFA of relevant questions with Likert scale answers.

- The inclusion of variables, such as accessibility, PT density, and quality of biking infrastructure, has to be analysed.

- The generic model need to be expanded with additional variables, particularly, those that are relevant to emerging mobility options and policies.

- The application and the validation of the generic model in additional cities need to be performed and the model can be made more robust with data from other cities.

8.4 Purchase of cargo cycles

- The literature on cargo cycles is growing. Therefore, a comprehensive review to derive existing knowledge base can be beneficial to the academic group, as well as for industries and policymakers. This has already been performed as a complimenting task to this dissertation (Narayanan & Antoniou, 2022a).

- The estimation results for the actual purchase decision shows that the probability to purchase reduces with higher catchment area of the commercial trips. An appropriate threshold, till which cargo cycles are suitable, has to be identified.

- The estimation results show that a group of business sectors is associated with a higher probability for the cargo cycle purchase. However, this group involves a variety of subgroups. Future studies can explore the suitability of different cargo cycle models for each of these subgroups.

- The impact of network topology parameters (e.g., road elevation) on cargo cycle purchase can be studied in future.

- The results from this dissertation shows that cargo cycles are appropriate to substitute cars and commercial light vehicles (e.g., van). A simulation study to evaluate the impacts of such substitution will be interesting and support in determining the actual potential of cargo cycles.

8.5 Regensburg case study

- Only the pilot implementation of an autonomous shuttle service is evaluated in this dissertation. Future studies can focus on its impacts for a large-scale application, especially characterising its demand side.

- The current car-sharing service is Regensburg is operated at a small-scale. The evaluation results are positive and, therefore, the service can be expanded. The analysis of impacts of such an expansion also calls for a future study.

- With regards to the bike-sharing service, their integration with PT has to be studied, to prevent unwarranted mode shift and enhance their potential to reduce car-ownership. Moreover, the fleet deployment has to be optimised to reduce the percentage of idle vehicles.

- An equilibrium mechanism between (i) car-ownership model and (ii) trip generation, distribution and mode choice steps are not implemented in this dissertation. Exploration of such a mechanism is a topic for upcoming studies.

- Modelling of (probable) induced demand due to the availability of shared mobility services is also a future work.

9 Conclusions

Shared mobility systems are slowly entering cities around the world. However, the traditional strategic transport models of the cities do not have the capability to evaluate such systems. Furthermore, the existing approaches for evaluating such systems are based on agent-based approaches. Te Brommelstroet (2010) conclude that the model developers should not only focus on scientific rigour, detail, and comprehensiveness, but also should try to achieve a balance between rigour and relevance, in order to increase the implementation success of advanced models. Considering the aforementioned facts, this research presents a methodology, which extends the traditional four-step approach, by integrating the principles from agent-based approaches, along with other necessary additions. In particular, the extension focuses on the inclusion of individual modules for synthetic population generation and fleet management. Pertaining to the increasing interest of the cities towards emissions, car-ownership and induced demand, separate modules are also added for them in the framework. However, they are applied as post processing steps, in order to reduce model complexity and avoid convergence issues.

The aforementioned additions provide an opportunity to cities, especially, small- and medium-sized ones, to evaluate and integrate shared mobility systems, and form long term planning strategies. Furthermore, this intermediate modelling approach fills the gap between traditional strategic models and agent-based models, acting as a bridge between the worlds of simple and complex modelling approaches and pave the way for reducing the reservations of the cities towards complex approaches and prepare them for a smoother transition in future. Besides, Te Brommelstroet (2010) suggest that there is a need to have a shift in the approach from "developing for" to "developing with", when designing modelling frameworks. Following this principle, the intermediate modelling framework has been developed with the involvement of four cities, which are Madrid, Leuven, Regensburg and Thessaloniki. It is to be noted that the intermediate modelling framework per se is software agnostic, and allows the use of equivalent models as alternatives to the extension models suggested in this dissertation, provided the inputs and outputs are consistent.

Given that the characteristics of shared mobility system users and the use patterns are mostly similar across different cities, a bilevel procedure for modal share calculation is suggested. The split between conventional modes-as-a-whole and the different shared services are estimated at the upper level using a multinomial logit model, which could be utilised by numerous cities. For the conventional modes, which differs from city to city and hence the characteristics, cities can continue using their existing mode choice models. Such a separation of mode choices is not unrealistic, as the shared mobility services can be safely assumed to not have a nesting effect with the conventional modes (Li & Kamargianni, 2020). The estimation results for the multinomial logit model show that a number of common factors exist, which influence the three shared mobility services, showing that the services have several overlapping user and use characteristics. These common factors include age group, education, possession of PT pass, trip distance and travel time. Besides these factors, gender and household car-ownership influence both bike-sharing and car-sharing. With regards to the users, young people belonging to the age group 20 to 44 and individuals with vocational or university degree are more probable to use all the three types of shared mobility services.

While males have a higher likelihood to use bike-sharing and car-sharing, a significant difference between males and females is not observed for ride-hailing. The possession of (any) license and owning a PT pass have a negative influence on the use of ride-hailing service, although the latter improves the odds of using bike-sharing and services car-sharing services. However, households with higher number of cars are less probable to use bike-sharing, while a positive impact is seen for car-sharing. Therefore, bike-sharing and car-sharing services can be designed as complementary services to PT, while ride-hailing can be implemented as a substitution service in areas where PT is weak. Concerning trip characteristics, bike-sharing systems are more likely to be used for trips with distances up to 5 km, with significantly higher probability for the range 2 to 5 km. However, car-sharing and ride-hailing systems are expected to be used for a longer distance range of 2 to 15 km, with a higher probability for the range 5 to 15 km. For all the three services, there is a lower probability to use them for travel times beyond 30 minutes. Overall, different demand segments have to be targeted for the three shared mobility services for efficient operations and a framework of the most probable demand segments has been presented in this dissertation.

Even though a reduction in car ownership is found to be an impact of bike-sharing systems in literature, there are also studies, which hypothesise that the shift towards bike-sharing is mainly from sustainable modes of transport, rather than from private car. Aligning with this, as mentioned in the previous paragraph, households with higher number of cars are found to be less probable to use bike-sharing. This finding led to the development of a mode choice model, focusing specifically on the mode shift of private car users towards a bike-sharing service, to study their perceptions and their attitudes. The estimation results show that the cost of using a shared bike plays a major role in the (reluctance to) shift from private cars and the private car users do not think much about the cost of using a private car. In addition to the cost, the travel time also plays a major role, with the travel time associated with a shared bike valued 1.8 times higher than the one associated with private car use. Apart from the cost and travel time factors, the shift of car users towards bike-sharing also depends on the perception of bike safety.

On a different note, mode choice models can be utilised when the modal split for a service is substantial. However, an alternative framework is required, when a service is operated at a small-scale (especially at earlier stages), during which the modal split will be very low (e.g. $\leq$50 trips per day for the entire system). As a consequence, this dissertation addresses the methodological challenge of modelling such a car-sharing service by developing a data-driven multi-method demand estimation framework, to be integrated with the intermediate modelling approach. The multi-method framework consists of a multinomial logit model (to characterise the users), a linear regression model (to estimate the average daily demand for the whole system) and a dirichlet regression model (to distribute the system level daily demand to individual stations). The formulated methodology can be adapted and used by many cities, who struggle with several questions and are caught up in a dilemma regarding the expansion of a service. The results from the multinomial logit model suggest that students, individuals with half employment, low income population segment, and bicycle and PT users are prone to use the small-scale car-sharing service. With regards to other socio-demographic characteristics, as the age increases, there is a decrease in the probability to use the service. Both the multinomial logit and the linear regression models support the need for expansion of the service (i.e., increasing the service supply). The linear regression model indicates a fluctuation in the average daily demand, according to the days of a week and months (i.e., seasonal variation). The dirichlet regression model indicates that the demand share for the stations differ according to the days of a week.

The aforementioned three analysis share a common aspect, i.e., they all focus on the calculation of demand for different shared mobility services. Based on their combined results, numerous policy and operational measures are derived under the following categories (i) Finance, (ii) Infrastructure, (iii) Campaigns and nudges, and (iv) service design. Some of the policy suggestion made include: (i) the introduction of a MaaS package and customised pricing packages for students, females, low-income households, older people, and bicycle and PT users; (ii) the improvisation of the bicycle infrastructure, by establishing shortcuts and dedicated cycles lanes with green wave; (iii) the implementation of technology, education and social awareness campaigns; (iv) the consideration of gender differences in the operational design of shared mobility services to remove gender inherent obstacle; (v) the initiation of hybrid fleet system.

Given the interests of cities towards private car-ownership reduction, the intermediate modelling approach has been formulated to accommodate a disaggregate household car-ownership model. Hence, a comprehensive analysis of household car-ownership is conducted, based on the data from the cities of Regensburg, Madrid and Leuven. The novelty of this analysis lies in the methodological framework combining multiple data sources from multiple cities. The estimation results show that the traditional explanatory variables, such as household size and age, continue to influence private car-ownership. However, with changes happening today, there are additional pertinent variables. For example, emerging mobility solutions (car-sharing and bike-sharing) and alternative modes (cargo bikes) have an inverse relationship with private car-ownership, i.e., they reduce the car-ownership levels. Between car-sharing and bike-sharing, the former has a greater influence. Furthermore, the reduction of public parking spaces (a policy measure being envisioned by policymakers worldwide to reduce car-ownership) indeed has the potential to reduce private car-ownership.

The explanatory variables in the car-ownership models corresponding to Regensburg, Madrid, and Leuven show several common factors with similar effects, while disparity is also observed due to inter-cultural behavioural patterns. Based on the common factors, a generic model has also been developed, to support transport modellers and policymakers who do not have adequate data to estimate a model of their own. Examples of the behavioural insights obtained from the car-ownership models are the following: (i) the logarithmic effect for household size and income, and the piecewise effect for the share of driving licenses among the household members and the age variable (with no increase in utility beyond the retirement age); (ii) the contrasting influence of mobility rates in Regensburg and Madrid; and (iii) the insignificant impact of public parking space on ownership of multiple cars, but a pertinent effect on single car-ownership. Similarly, some of the modelling insights from this analysis include: (i) the possibility of having common estimates to build more parsimonious models; (ii) the effect of intercultural differences between the cities; (iii) the requirement of different representative variables to determine the influence of certain independent variables; and (iv) the suitability of aggregate household variables to analyse the impact of shared mobility services during their early stages or small-scale of operation. Several policy insights are also derived from this analysis, including but not limited to, (i) the possibility to influence high-income private car owners (having a range of salaries) with a single rate for congestion pricing; (ii) the importance of having proper access to alternative mobility options; (iii) the prominence of denser areas with transit and active mobility oriented developments.

One of the estimated car-ownership models shows that the probability of owning private cars reduces with the ownership of a cargo bike. This finding lead to the exploration of the car substitution potential of cargo cycles, based on the estimation of models for actual purchase decision and the intention to purchase cargo cycles. To the best of my knowledge, there is no suitable dataset in the field of passenger transport and hence, as an alternative, appropriate datasets from the field of commercial transport is identified and utilised. Looking into the factors affecting the actual purchase, cargo cycles have the potential to substitute car trips, supporting cities to achieve air quality and carbon emission reduction goals. Hence, there is a need to support their penetration. Cities are suggested to implement (i) push measures, such as the regulative frameworks deteriorating the conditions for conventional vehicles, and (ii) pull measures, such as the improvement of operational benefits and the perception of soft benefits, and implementation of trial schemes, along with ensuring (iii) robust and efficient cargo cycle designs. Vehicle manufacturers and policymakers are advised to target the development of longtail bikes and heavy load trikes, as substitutes to commercial light vehicles. Finally, although trial schemes may not ensure the purchase of cargo cycles by every participating organisation, they are effective tools in reducing the negative reservations.

Several researchers, both in passenger and commercial transport research, base their conclusions on intentions (e.g., based on stated preference surveys). However, the research performed on cargo cycles show that a high share of intent is observed, while the share of actual purchase is less. Although intention is found to be a significant factor for the actual purchase decision, there are factors which are not common to both. A comparison of these factors shows that the actual purchase decision is influenced by the deterioration of conditions for the conventional vehicles (e.g., vehicle access restriction, higher fuel prices and higher parking cost), while the purchase intention is influenced by the operational concerns towards cargo cycles. Furthermore, the purchase intention of technology and innovation enthusiasts is naturally more inclined towards cargo cycle purchase. However, when it comes to the actual purchase decision, the scenario is different, i.e., interest towards technology and innovation is not a significant contributing factor. All these clearly show the difference in thought process when stating the purchase intention and when planning for the actual purchase. Hence, there is a need to convert intention to actual decision, when making conclusions based on intentions.

The final focus of this dissertation is a case study on the historical city of Regensburg (Germany). The case study focuses on the evaluation of the introduction of (i) dedicated bus lanes, (ii) an autonomous shuttle service for first- and last-mile of PT trips and (iii) shared mobility services. The former two are evaluated through an adaptation of a four-step transport model existing in the city. The shared mobility services are modelled by adapting the intermediate modelling approach. The results from the case study show that dedicated bus lanes lead to a modal shift of around 1.6% from car modes to PT and an emission reduction of 3.25% to 6.65%. The shuttle service is found to complement the PT system. Finally, the shared mobility services show the potential to reduce car-ownership. However, looking at the mode shift pattern, about 41% of the bike-sharing trips are those shifted from PT, while only 15% are from car mode, which is not a positive sign. Therefore, proper integration of PT system with the bike-sharing service is essential, to enable complementary effects, rather than a substitution pattern. Moreover, the shared bike utilisation rate shows that there is a need to optimise the service to reduce the percentage of idle vehicles (around 16%). The results of the scenario analysis on bike-sharing and car-sharing fleet size show that the bike-sharing and the car-sharing services have to be designed with a focus to serve different demand segments, supporting the notion of combining these services in the form of a MaaS platform, in order to cater to a wider set of individuals.

To conclude, the methodological concepts from this dissertation, the estimation results and the insights obtained (behavioural, policy, operational and modelling) can help cities to (i) evaluate shared mobility services, (ii) design MaaS platforms, (iii) devise policies to shape their mobility plans and finally, (iv) promote sustainable urban mobility. Furthermore, the intermediate modelling approach can be adapted and used for studying many other emerging mobility solutions, as it combines the powerful capabilities of the agent-based approach with the simplicity and user-friendliness of the classical four-step approach. Specifically, the intermediate modelling approach acts as a bridge between the worlds of simple and complex modelling approaches and pave the way for reducing the reservations of the cities towards complex approaches and prepare them for a smoother transition in future. Besides the Regensburg case study included in this dissertation, the intermediate modelling approach has already been utilised and validated in Vanherck et al. (2022), Salanova et al. (2022), and Martín et al. (2023). Specifically, Vanherck et al. (2022) conclude that this framework is less intensive on the computational side and provides adequate quantitative results on the impacts of a growing shared mobility ecosystem, especially for small- and medium-sized cities like Leuven, notwithstanding only having a limited amount of additional data on shared mobility services.

Bibliography

Abdelghany, K. F., Mahmassani, H. S., & Abdelghany, A. F. (2007). A modeling framework for bus rapid transit operations evaluation and service planning. *Transportation Planning and Technology*, *30*, 571–591. doi:10.1080/03081060701698219.

Acheampong, R. A., Siiba, A., Okyere, D. K., & Tuffour, J. P. (2020). Mobility-on-demand: An empirical study of internet-based ride-hailing adoption factors, travel characteristics and mode substitution effects. *Transportation Research Part C: Emerging Technologies*, *115*, 102638. doi:10.1016/j.trc.2020.102638.

Aimsun (2021). Aimsun Next 20 user's manual, Aimsun Next version 20.0.3, Barcelona, Spain. URL: qthelp://aimsun.com.aimsun.20.0/doc/UsersManual/Intro.html.

Aitchison, J. (1982). The statistical analysis of compositional data. *Journal of the Royal Statistical Society: Series B (Methodological)*, *44*, 139–160. doi:10.1111/j.2517-6161.1982.tb01195.x.

Alam, A., Diab, E., El-Geneidy, A. M., & Hatzopoulou, M. (2014). A simulation of transit bus emissions along an urban corridor: Evaluating changes under various service improvement strategies. *Transportation Research Part D: Transport and Environment*, *31*, 189–198. doi:10.1016/j.trd.2014.06.010.

Alemi, F., Circella, G., Mokhtarian, P., & Handy, S. (2019). What drives the use of ridehailing in California? Ordered probit models of the usage frequency of Uber and Lyft. *Transportation Research Part C: Emerging Technologies*, *102*, 233–248. doi:10.1016/j.trc.2018.12.016.

Alonso-González, M. J., Cats, O., van Oort, N., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2020). What are the determinants of the willingness to share rides in pooled on-demand services? *Transportation*, . doi:10.1007/s11116-020-10110-2.

Amin-Naseri, M. R., & Baradaran, V. (2015). Accurate estimation of average waiting time in public transportation systems. *Transportation Science*, *49*, 213–222. doi:10.1287/trsc.2013.0514.

Anagnostopoulou, E., Urbančič, J., Bothos, E., Magoutas, B., Bradesko, L., Schrammel, J., & Mentzas, G. (2020). From mobility patterns to behavioural change: Leveraging travel behaviour and personality profiles to nudge for sustainable transportation. *Journal of Intelligent Information Systems*, *54*, 157–178. doi:10.1007/s10844-018-0528-1.

Anderson, M. S., & Simkins, J. M. (2012). Development of long distance multimodal passenger travel modal choice model. URL: https://www.fhwa.dot.gov/policy/modalchoice/modalchoice.pdf.

Anowar, S., Eluru, N., & Miranda-Moreno, L. F. (2014). Alternative Modeling Approaches Used for Examining Automobile Ownership: A Comprehensive Review. *Transport Reviews*, *34*, 441–473. URL: http://www.tandfonline.com/doi/abs/10.1080/01441647.2014.915440. doi:10.1080/01441647.2014.915440.

Arasan, V. T., & Vedagiri, P. (2010). Microsimulation study of the effect of exclusive bus lanes on heterogeneous traffic flow. *Journal of Urban Planning and Development*, *136*, 50–58. doi:10.1061/(ASCE)0733-9488(2010)136:1(50).

Avineri, E. (2012). On the use and potential of behavioural economics from the perspective of transport and climate change. *Journal of Transport Geography*, *24*, 512–521. doi:10.1016/j.jtrangeo.2012.03.003.

Bakogiannis, E., Siti, M., Tsigdinos, S., Vassi, A., & Nikitas, A. (2019). Monitoring the first dockless bike sharing system in Greece: Understanding user perceptions, usage patterns and adoption barriers. *Research in Transportation Business & Management*, *33*, 100432. doi:10.1016/j.rtbm.2020.100432.

Bayrak, M., & Guler, S. I. (2021). Optimization of dedicated bus lane location on a transportation network while accounting for traffic dynamics. *Public Transport*, *13*, 325–347. doi:10.1007/s12469-021-00269-x.

Beauchamp, É., Saunier, N., & Cloutier, M.-S. (2022). Study of automated shuttle interactions in city traffic using surrogate measures of safety. *Transportation Research Part C: Emerging Technologies*, *135*, 103465. doi:10.1016/j.trc.2021.103465.

Becker, H., Balac, M., Ciari, F., & Axhausen, K. W. (2020). Assessing the welfare impacts of shared mobility and Mobility as a Service (MaaS). *Transportation Research Part A: Policy and Practice*, *131*, 228–243. doi:10.1016/j.tra.2019.09.027.

Becker, H., Ciari, F., & Axhausen, K. W. (2017). Comparing car-sharing schemes in Switzerland: User groups and usage patterns. *Transportation Research Part A: Policy and Practice*, *97*, 17–29. doi:10.1016/j.tra.2017.01.004.

Ben-Dor, G., Ben-Elia, E., & Benenson, I. (2018). Assessing the impacts of dedicated bus lanes on urban traffic congestion and modal split with an agent-based model. *Procedia Computer Science*, *130*, 824–829. doi:10.1016/j.procs.2018.04.071.

Bertsimas, D. J., & Tsitsiklis, J. N. (1997). *Introduction to linear optimization* volume 6 of *Athena scientific series in optimization and neural computation*. Belmont, Mass.: Athena Scientific.

Bhat, C. R., & Pulugurta, V. (1998). A comparison of two alternative behavioral choice mechanisms for household auto ownership decisions. *Transportation Research Part B: Methodological*, *32*, 61–75. URL: https://linkinghub.elsevier.com/retrieve/pii/S0191261597000143. doi:10.1016/S0191-2615(97)00014-3.

Böcker, L., Anderson, E., Uteng, T. P., & Throndsen, T. (2020). Bike sharing use in conjunction to public transport: Exploring spatiotemporal, age and gender dimensions in Oslo, Norway. *Transportation Research Part A: Policy and Practice*, *138*, 389–401. URL: https://doi.org/10.1016/j.tra.2020.06.009. doi:10.1016/j.tra.2020.06.009.

Boesch, P. M., & Ciari, F. (2015). Agent-based simulation of autonomous cars. In *2015 American Control Conference (ACC)* (pp. 2588–2592). IEEE. doi:10.1109/ACC.2015.7171123.

Bohnsack, R., & Liesner, M. M. (2019). What the hack? a growth hacking taxonomy and practical applications for firms. *Business Horizons*, *62*, 799–818. doi:10.1016/j.bushor.2019.09.001.

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Methodology in the social sciences (2nd ed.). New York and London: The Guilford Press.

Campbell, A. A., Cherry, C. R., Ryerson, M. S., & Yang, X. (2016). Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. *Transportation Research Part C: Emerging Technologies*, *67*, 399–414. doi:10.1016/j.trc.2016.03.004.

Campbell, G., & Mosimann, J. E. (1987). Multivariate methods for proportional shape. In *ASA Proceedings of the Section on Statistical Graphics* (pp. 10–17).

Cartenì, A., Cascetta, E., & de Luca, S. (2016). A random utility model for park & carsharing services and the pure preference for electric vehicles. *Transport Policy*, *48*, 49–59. doi:10.1016/j.tranpol.2016.02.012.

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). Smote: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, *16*, 321–357. doi:10.1613/jair.953.

Chee, P. N. E., Susilo, Y. O., & Wong, Y. D. (2020). Determinants of intention-to-use first-/last-mile automated bus service. *Transportation Research Part A: Policy and Practice*, *139*, 350–375. doi:10.1016/j.tra.2020.06.001.

Cheng, L., Chen, X., Wei, M., Wu, J., & Hou, X. (2014). Modeling mode choice behavior incorporating household and individual sociodemographics and travel attributes based on rough sets theory. *Computational intelligence and neuroscience*, . doi:10.1155/2014/560919.

Choubassi, C., Seedah, D. P. K., Jiang, N., & Walton, C. M. (2016). Economic analysis of cargo cycles for urban mail delivery. *Transportation Research Record: Journal of the Transportation Research Board*, *2547*, 102–110. doi:10.3141/2547-14.

Ciari, F., Balac, M., & Axhausen, K. W. (2016). Modeling carsharing with the agent-based simulation MATSim: State of the art, applications, and future developments. *Transportation Research Record: Journal of the Transportation Research Board*, *2564*, 14–20. doi:10.3141/2564-02.

Cirillo, C., & Liu, Y. (2013). Vehicle Ownership Modeling Framework for the State of Maryland: Analysis and Trends from 2001 and 2009 NHTS Data. *Journal of Urban Planning and Development*, *139*, 1–11. URL: http://ascelibrary.org/doi/10.1061/%28ASCE%29UP.1943-5444.0000128. doi:10.1061/(ASCE)UP.1943-5444.0000128.

Clark, S. D. (2009a). Characterising and predicting car ownership using rough sets. *Transportation Research Part C: Emerging Technologies*, *17*, 381–393. URL: https://linkinghub.elsevier.com/retrieve/pii/S0968090X09000114. doi:10.1016/j.trc.2009.01.006.

Clark, S. D. (2009b). The determinants of car ownership in England and Wales from anonymous 2001 census data. *Transportation Research Part C: Emerging Technologies*, *17*, 526–540. URL: https://linkinghub.elsevier.com/retrieve/pii/S0968090X09000308. doi:10.1016/j.trc.2009.04.004.

Clewlow, R. R. (2016). Carsharing and sustainable travel behavior: Results from the san francisco bay area. *Transport Policy*, *51*, 158–164. doi:10.1016/j.tranpol.2016.01.013.

Costain, C., Ardron, C., & Habib, K. N. (2012). Synopsis of users' behaviour of a carsharing program: A case study in Toronto. *Transportation Research Part A: Policy and Practice*, *46*, 421–434. doi:10.1016/j.tra.2011.11.005.

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation*, *10*, 1–9. doi:10.1063/1.5092073.

Croissant, Y. (2020). Estimation of random utility models in R: The mlogit package. *Journal of Statistical Software*, *95*. doi:10.18637/jss.v095.i11.

Currie, G., & Delbosc, A. (2011). Understanding bus rapid transit route ridership drivers: An empirical study of Australian BRT systems. *Transport Policy*, *18*, 755–764. doi:10.1016/j.tranpol.2011.03.003.

Diab, E. I., & El-Geneidy, A. M. (2012). Understanding the impacts of a combination of service improvement strategies on bus running time and passenger's perception. *Transportation Research Part A: Policy and Practice*, *46*, 614–625. doi:10.1016/j.tra.2011.11.013.

Dong, Y., Wang, S., Li, L., & Zhang, Z. (2018). An empirical study on travel patterns of internet based ride-sharing. *Transportation Research Part C: Emerging Technologies*, *86*, 1–22. URL: https://www.sciencedirect.com/science/article/pii/S0968090X17302954. doi:10.1016/j.trc.2017.10.022.

D'Orazio, M. (2019). Statistical learning in official statistics: The case of statistical matching. *Statistical Journal of the IAOS*, *35*, 435–441. doi:10.3233/SJI-190518.

D'Orazio, M., Di Zio, M., & Scanu, M. (2006). *Statistical matching: Theory and practice*. Wiley series in survey methodology. Chichester: John Wiley. URL: http://www.loc.gov/catdir/enhancements/fy0658/2006040184-d.html.

Douma, J. C., & Weedon, J. T. (2019). Analysing continuous proportions in ecology and evolution: A practical introduction to beta and dirichlet regression. *Methods in Ecology and Evolution*, *10*, 1412–1430. doi:10.1111/2041-210X.13234.

Faxér, A. Y., Olausson, E., Olsson, L., Smith, G., & Pettersson, S. (2018). Electric cargo bike with a twist - A field test of two innovative bicycle concepts. In *31st International Electric Vehicle Symposium and Exhibition, EVS 2018 and International Electric Vehicle Technology Conference 2018, EVTeC 2018*. Kobe. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85073121242&partnerID=40&md5=a9fa0d89fe8375361c83adc458d81f6c.

Ferrari, S., & Cribari-Neto, F. (2004). Beta regression for modelling rates and proportions. *Journal of Applied Statistics*, *31*, 799–815. doi:10.1080/0266476042000214501.

Fishman, E. (2016). Bikeshare: A review of recent literature. *Transport Reviews*, *36*, 92–113. doi:10.1080/01441647.2015.1033036.

Fishman, E., Washington, S., & Haworth, N. (2013). Bike share: A synthesis of the literature. *Transport Reviews*, *33*, 148–165. doi:10.1080/01441647.2013.775612.

Franssens, S., Botchway, E., de Swart, W., & Dewitte, S. (2021). Nudging commuters to increase public transport use: A field experiment in Rotterdam. *Frontiers in psychology*, *12*, 633865. doi:10.3389/fpsyg.2021.633865.

Fraunhofer IML (2010). *Trends in der Handelslogistik: Ergebnisse einer Online-Befragung führender Handelsunternehmen in Deutschland, Österreich und der Schweiz*. Köln: EHI Retail Institute.

Frei, C., Hyland, M., & Mahmassani, H. S. (2017). Flexing service schedules: Assessing the potential for demand-adaptive hybrid transit via a stated preference approach. *Transportation Research Part C: Emerging Technologies*, *76*, 71–89. URL: https://www.sciencedirect.com/science/article/pii/S0968090X1630273X. doi:10.1016/j.trc.2016.12.017.

Friedrich, M., Hartl, M., & Magg, C. (2018). A modeling approach for matching ridesharing trips within macroscopic travel demand models. *Transportation*, *45*, 1639–1653. doi:10.1007/s11116-018-9957-5.

Friedrich, M., & Noekel, K. (2017). Modeling intermodal networks with public transport and vehicle sharing systems. *Euro Journal on Transportation and Logistics*, *6*, 271–288. doi:10.1007/s13676-015-0091-7.

Gardner, B. (2019). Nudging for sustainable mobility. URL: https://datasmart.ash.harvard.edu/news/article/nudging-sustainable-mobility.

Gasper, R., Beutelschieß, S., Krumnow, M., Simon, L., Baksa, Z., & Schwarzer, J. (2018). Simulation of autonomous roboshuttles in shared space. In *SUMO 2018 - Simulating Autonomous and Intermodal Transport Systems* EPiC Series in Engineering (pp. 183–171). EasyChair. doi:10.29007/h58z.

Giesel, F., & Nobis, C. (2016). The impact of carsharing on car ownership in German cities. *Transportation Research Procedia*, *19*, 215–224. URL: https://linkinghub.elsevier.com/retrieve/pii/S2352146516308687. doi:10.1016/j.trpro.2016.12.082.

Gilibert, M., Ribas, I., Maslekar, N., Rosen, C., & Siebeneich, A. (2019). Mapping of service deployment use cases and user requirements for an on-demand shared ride-hailing service: MOIA test service case study. *Case Studies on Transport Policy*, *7*, 598–606. URL: https://www.sciencedirect.com/science/article/pii/S2213624X18304036. doi:10.1016/j.cstp.2019.07.004.

Giorgione, G., Ciari, F., & Viti, F. (2020). Dynamic pricing on round-trip carsharing services: Travel behavior and equity impact analysis through an agent-based simulation. *Sustainability*, *12*, 6727. doi:10.3390/su12176727.

Givoni, M., Beyazit, E., & Shiftan, Y. (2016). The use of state-of-the-art transport models by policymakers – Beauty in simplicity? *Planning Theory & Practice*, *17*, 385–404. doi:10.1080/14649357.2016.1188975.

Gruber, J., Ehrler, V., & Lenz, B. (2013). Technical potential and user requirements for the implementation of electric cargo bikes in courier logistics services. In *13th World Conference on Transport Research*. Rio de Janeiro.

Gruber, J., Kihm, A., & Lenz, B. (2014). A new vehicle for urban freight? an ex-ante evaluation of electric cargo bikes in courier services. *Research in Transportation Business & Management*, *11*, 53–62. doi:10.1016/j.rtbm.2014.03.004.

Gruber, J., & Narayanan, S. (2019). Travel time differences between cargo cycles and cars in commercial transport operations. *Transportation Research Record: Journal of the Transportation Research Board*, *2673*, 623–637. doi:10.1177/0361198119843088.

Gurumurthy, K. M., de Souza, F., Enam, A., & Auld, J. (2020). Integrating supply and demand perspectives for a large-scale simulation of shared autonomous vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, *2674*, 181–192. doi:10.1177/0361198120921157.

H2020 MOMENTUM consortium (2020). Deliverable 2.2: Specification of the MOMENTUM test cases. URL: https://h2020-momentum.eu/wp-content/uploads/2020/03/MOMENTUM_D2.2-Specification_Test_Cases.pdf.

H2020 MOMENTUM consortium (2021a). Deliverable 4.1: Transport modelling approaches for emerging mobility solutions: Supply and demand models. URL: https://h2020-momentum.eu/wp-content/uploads/2021/06/MOMENTUM-D4.1-New-Transport-Modelling-Approaches-Issue-1-Draft-2.pdf.

H2020 MOMENTUM consortium (2021b). Deliverable 5.1: Enhancement of transport simulation frameworks with models of emerging mobility solutions. URL: https://h2020-momentum.eu/wp-content/uploads/2021/07/MOMENTUM_D5.1_Enhancement_of_Transport_Simulation_Frameworks__final-1.pdf.

Habib, K. N. (2019). Mode choice modelling for hailable rides: An investigation of the competition of uber with other modes by using an integrated non-compensatory choice model with probabilistic choice set formation. *Transportation Research Part A: Policy and Practice*, *129*, 205–216. doi:10.1016/j.tra.2019.08.014.

Hahn, R., Ostertag, F., Lehr, A., Büttgen, M., & Benoit, S. (2020). "i like it, but i don't use it": Impact of carsharing business models on usage intentions in the sharing economy. *Business Strategy and the Environment*, *29*, 1404–1418. doi:10.1002/bse.2441.

Hamann, T. K., Güldenberg, S., & Renzl, B. (2019). Overshare and collapse: How sustainable are profit-oriented company-to-peer bike-sharing systems? *Die Unternehmung*, *73*, 345–373. doi:10.5771/0042-059X-2019-4-345.

Hamilton, A. B. (2017). Mobility on demand: Operational concept report. URL: https://rosap.ntl.bts.gov/view/dot/34258.

Hardt, C., & Bogenberger, K. (2016). The price of shared vehicles - On current and future pricing strategies in mobility sharing systems. In *95th Annual Meeting of the Transport Research Board*.

Heilig, M., Hilgert, T., Mallig, N., Kagerbauer, M., & Vortisch, P. (2017). Potentials of autonomous vehicles in a changing private transportation system: A case study in the Stuttgart region. *Transportation Research Procedia*, *26*, 13–21. doi:10.1016/j.trpro.2017.07.004.

Heilig, M., Mallig, N., Schröder, O., Kagerbauer, M., & Vortisch, P. (2015). Multiple-day agent-based modeling approach of station-based and free-floating carsharing. In *94th Annual Meeting of the Transport Research Board*.

Heinrich, L., Schulz, W. H., & Geis, I. (2016). The impact of product failure on innovation diffusion: The example of the cargo bike as alternative vehicle for urban transport. *Transportation Research Procedia*, *19*, 269–271. doi:10.1016/j.trpro.2016.12.086.

Heinze, G., & Schemper, M. (2002). A solution to the problem of separation in logistic regression. *Statistics in Medicine*, *21*, 2409–2419. doi:10.1002/sim.1047.

Herttua, T., Jakob, E., Nave, S., Gupta, R., & Zylka, M. P. (2016). Growth hacking: Exploring the meaning of an internet-born digital marketing buzzword. In M. P. Zylka (Ed.), *Designing Networks for Innovation and Improvisation* Springer Proceedings in Complexity (pp. 151–161). Place of publication not identified: Springer International Publishing. doi:10.1007/978-3-319-42697-6{_}15.

Highway Agency (1996). Traffic appraisal in urban areas. In *Design Manual for Roads and Bridges*. volume 12. URL: https://assets.highwaysengland.co.uk/roads/road-projects/a2-bean-ebbsfleet-junction-improvements/Orders/I.8+DMRB+Part+1+Traffic+Appraisal.pdf.

Hijazi, R. (2003). *Analysis of Compositional data using Dirichlet Covari-ate Models*. Phd dissertation Washington D.C. URL: https://auislandora.wrlc.org/islandora/object/thesesdissertations%3A3045.

Hijazi, R. H. (2006). Residuals and diagnostics in dirichlet regression. In *ASA Proceedings of the General Methodology Section* (pp. 1190–1196). URL: https://www.aau.ac.ae/uploads/2018/12/201812051216332.pdf.

Hijazi, R. H., & Jernigan, R. W. (2009). Modelling compositional data using dirichlet regression models. *Journal of Applied Probability & Statistics*, *4*, 77–91. URL: https://business.aau.ac.ae/uploads/2018/12/201812051153252.pdf.

Holguin-Veras, J., Amaya Leal, J., Sánchez-Diaz, I., Browne, M., & Wojtowicz, J. (2020). State of the art and practice of urban freight management. *Transportation Research Part A: Policy and Practice*, *137*, 360–382. doi:10.1016/j.tra.2018.10.037.

Hörl, S., & Balac, M. (2021). Synthetic population and travel demand for paris and île-de-france based on open and publicly available data. *Transportation Research Part C: Emerging Technologies*, *130*, 103291. doi:10.1016/j.trc.2021.103291.

Hu, E. (2018). By paying staff to cycle to work, companies benefit from more savings, less sick leave and improved satisfaction. *Business Insider*, . URL: https://www.businessinsider.com/heres-how-companies-paying-staff-to-cycle-to-work-end-up-saving-money-2018-7?r=DE&IR=T.

Huang, Y., Kockelman, K. M., Garikapati, V., Zhu, L., & Young, S. (2021). Use of shared automated vehicles for first-mile last-mile service: Micro-simulation of rail-transit connections in Austin, Texas. *Transportation Research Record: Journal of the Transportation Research Board*, *2675*, 135–149. doi:10.1177/0361198120962491.

Huber, D., Viere, T., Horschutz Nemoto, E., Jaroudi, I., Korbee, D., & Fournier, G. (2022). Climate and environmental impacts of automated minibuses in future public transportation. *Transportation Research Part D: Transport and Environment*, *102*, 103160. doi:10.1016/j.trd.2021.103160.

Ich entlaste Städte (2020). Der Fuhrpark. URL: https://www.lastenradtest.de/testraeder/.

International Association of Public Transport (2017). Autonomous vehicles: A potential game changer for urban mobility. URL: https://www.uitp.org/sites/default/files/cck-focus-papers-files/PolicyBrief_Autonomous_Vehicles_LQ_20160116.pdf.

Jager, B., Agua, F. M. M., & Lienkamp, M. (2017). Agent-based simulation of a shared, autonomous and electric on-demand mobility solution. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 250–255). IEEE. doi:10.1109/ITSC.2017.8317947.

Janjevic, M., & Winkenbach, M. (2020). Characterizing urban last-mile distribution strategies in mature and emerging e-commerce markets. *Transportation Research Part A: Policy and Practice*, *133*, 164–196. doi:10.1016/j.tra.2020.01.003.

Jochem, P., Frankenhauser, D., Ewald, L., Ensslen, A., & Fromm, H. (2020). Does free-floating carsharing reduce private vehicle ownership? The case of SHARE NOW in European cities. *Transportation Research Part A: Policy and Practice*, *141*, 373–395. URL: https://linkinghub.elsevier.com/retrieve/pii/S0965856420307291. doi:10.1016/j.tra.2020.09.016.

Jong, G. D., Fox, J., Daly, A., Pieters, M., & Smit, R. (2004). Comparison of car ownership models. *Transport Reviews*, *24*, 379–408. URL: http://www.tandfonline.com/doi/abs/10.1080/0144164032000138733. doi:10.1080/0144164032000138733.

Kalliga, V. (2021). *Who Does New Trips and Why*. Master's thesis Technical University of Munich. URL: https://mediatum.ub.tum.de/doc/1618550/br71wbwu53arbhw9de27ijswu.Master_Thesis_Kalliga.pdf.

Kassens-Noor, E., Kotval-Karamchandani, Z., & Cai, M. (2020). Willingness to ride and perceptions of autonomous public transit. *Transportation Research Part A: Policy and Practice*, *138*, 92–104. doi:10.1016/j.tra.2020.05.010.

Kawgan-Kagan, I. (2020). Are women greener than men? A preference analysis of women and men from major German cities over sustainable urban mobility. *Transportation Research Interdisciplinary Perspectives*, *8*, 100236. doi:10.1016/j.trip.2020.100236.

Kim, D., Park, Y., & Ko, J. (2019). Factors underlying vehicle ownership reduction among carsharing users: A repeated cross-sectional analysis. *Transportation Research Part D: Transport and Environment*, *76*, 123–137. URL: https:

//linkinghub.elsevier.com/retrieve/pii/S1361920919309678. doi:10.1016/j.trd.2019.09.018.

King, G., & Zeng, L. (2001). Logistic regression in rare events data. *Political Analysis*, *9*, 137–163.

Kosmidis, I., & Firth, D. (2021). Jeffreys-prior penalty, finiteness and shrinkage in binomial-response generalized linear models. *Biometrika*, *108*, 71–82. doi:10.1093/biomet/asaa052.

Kristal, A. S., & Whillans, A. V. (2020). What we can learn from five naturalistic field experiments that failed to shift commuter behaviour. *Nature human behaviour*, *4*, 169–176. doi:10.1038/s41562-019-0795-z.

Kucharski, R., & Cats, O. (2022). Simulating two-sided mobility platforms with maassim. *PloS one*, *17*, e0269682. doi:10.1371/journal.pone.0269682.

Lau, S. T., & Susilawati, S. (2021). Shared autonomous vehicles implementation for the first and last-mile services. *Transportation Research Interdisciplinary Perspectives*, *11*, 100440. doi:10.1016/j.trip.2021.100440.

Lavieri, P. S., & Bhat, C. R. (2019). Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. *Transportation Research Part C: Emerging Technologies*, *105*, 100–125. doi:10.1016/j.trc.2019.05.037.

Le Vine, S., Lee-Gosselin, M., Sivakumar, A., & Polak, J. (2014). A new approach to predict the market and impacts of round-trip and point-to-point carsharing systems: Case study of London. *Transportation Research Part D: Transport and Environment*, *32*, 218–229. doi:10.1016/j.trd.2014.07.005.

Le Vine, S., & Polak, J. (2019). The impact of free-floating carsharing on car ownership: Early-stage findings from London. *Transport Policy*, *75*, 119–127. URL: https://linkinghub.elsevier.com/retrieve/pii/S0967070X16305984. doi:10.1016/j.tranpol.2017.02.004.

Lee, S., Smart, M. J., & Golub, A. (2021). Difference in travel behavior between immigrants in the US and US born residents: The immigrant effect for car-sharing, ride-sharing, and bike-sharing services. *Transportation Research Interdisciplinary Perspectives*, *9*, 100296. doi:10.1016/j.trip.2020.100296.

Lesaffre, E., & Albert, A. (1989). Partial separation in logistic discrimination. *Journal of the Royal Statistical Society. Series B (Methodological)*, *51*, 109–116. URL: http://www.jstor.org/stable/2345845.

Leulescu, A., & Agafitei, M. (2013). Statistical matching: A model based approach for data integration. URL: https://ec.europa.eu/eurostat/documents/3888793/5855821/KS-RA-13-020-EN.PDF.

Li, W., & Kamargianni, M. (2019). An integrated choice and latent variable model to explore the influence of attitudinal and perceptual factors on shared mobility choices and their value of time estimation. *Transportation Science*, . doi:10.1287/trsc.2019.0933.

Li, W., & Kamargianni, M. (2020). Steering short-term demand for car-sharing: A mode choice and policy impact analysis by trip distance. *Transportation*, *47*, 2233–2265. doi:10.1007/s11116-019-10010-0.

Liang, L., Xu, M., Grant-Muller, S., & Mussone, L. (2020). Household travel mode choice estimation with large-scale data—an empirical analysis based on mobility data in Milan. *International Journal of Sustainable Transportation*, *15*, 70–85. doi:10.1080/15568318.2019.1686782.

Liu, Y., & Cirillo, C. (2016). Small area estimation of vehicle ownership and use. *Transportation Research Part D: Transport and Environment*, *47*, 136–148. URL: https://linkinghub.elsevier.com/retrieve/pii/S1361920916302498. doi:10.1016/j.trd.2016.05.002.

Liu, Y., Tremblay, J.-M., & Cirillo, C. (2014). An integrated model for discrete and continuous decisions with application to vehicle ownership, type and usage choices. *Transportation Research Part A: Policy and Practice*, *69*, 315–328. URL: https://linkinghub.elsevier.com/retrieve/pii/S0965856414002122. doi:10.1016/j.tra.2014.09.001.

Lloyd, S. (1982). Least squares quantization in pcm. *IEEE Transactions on Information Theory*, *28*, 129–137. doi:10.1109/TIT.1982.1056489.

Loa, P., & Habib, K. N. (2021). Examining the influence of attitudinal factors on the use of ride-hailing services in Toronto. *Transportation Research Part A: Policy and Practice*, *146*, 13–28. doi:10.1016/j.tra.2021.02.002.

Lokhandwala, M., & Cai, H. (2018). Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC. *Transportation Research Part C: Emerging Technologies*, *97*, 45–60. doi:10.1016/j.trc.2018.10.007.

de Luca, S., & Di Pace, R. (2015). Modelling users' behaviour in inter-urban carsharing program: A stated preference approach. *Transportation Research Part A: Policy and Practice*, *71*, 59–76. URL: https://www.sciencedirect.com/science/article/pii/S0965856414002675. doi:10.1016/j.tra.2014.11.001.

Ma, J., Ye, X., & Shi, C. (2018). Development of multivariate ordered probit model to understand household vehicle ownership behavior in Xiaoshan district of Hangzhou, China. *Sustainability*, *10*, 3660. URL: http://www.mdpi.com/2071-1050/10/10/3660. doi:10.3390/su10103660.

Ma, X., Yuan, Y., van Oort, N., & Hoogendoorn, S. (2020). Bike-sharing systems' impact on modal shift: A case study in Delft, the Netherlands. *Journal of Cleaner Production*, *259*, 120846. URL: https://www.sciencedirect.com/science/article/pii/S0959652620308933. doi:10.1016/j.jclepro.2020.120846.

Magee, L. (1990). r^2 measures based on wald and likelihood ratio joint significance tests. *The American Statistician*, *44*, 250–253. doi:10.1080/00031305.1990.10475731.

Maier, M. J. (2014). Dirichletreg: Dirichlet regression for compositional data in R. URL: https://epub.wu.ac.at/4077/1/Report125.pdf.

Makarov, N. (2021). *Development of a Deep Learning Surrogate for the Four-Step Transportation Model*. Master's thesis Technical University of Munich. URL: https://mediatum.ub.tum.de/doc/1638691/dwz10x0l0w38xdklv9zkrprqs.pdf.

Maltha, Y., Kroesen, M., Van Wee, B., & van Daalen, E. (2017). Changing influence of factors explaining household car ownership levels in the Netherlands. *Transportation Research Record: Journal of the Transportation Research Board*, *2666*, 103–111. URL: http://journals.sagepub.com/doi/10.3141/2666-12. doi:10.3141/2666-12.

MARG (2016). Popgen: Synthetic population generator. URL: http://www.mobilityanalytics.org/popgen.html.

Martín, I., Tympakanaki, A., Cantú-Ros, O. G., Burrieza-Galán, J., Casas, J., Narayanan, S., Ayfantopoulou, G., Antoniou, C., & Maleas, Z. (2023). Data-driven modelling and simulation evaluation of shared mobility services: A case study for bike-sharing in Madrid. In *102nd Annual Meeting of the Transport Research Board*. Washington D.C.

Martínez, L. M., Correia, G. H. A., Moura, F., & Mendes Lopes, M. (2017). Insights into carsharing demand dynamics: Outputs of an agent-based model application to Lisbon, Portugal. *International Journal of Sustainable Transportation*, *11*, 148–159. doi:10.1080/15568318.2016.1226997.

Matas, A., & Raymond, J.-L. (2008). Changes in the structure of car ownership in Spain. *Transportation Research Part A: Policy and Practice*, *42*, 187–202. URL: https://linkinghub.elsevier.com/retrieve/pii/S0965856407000705. doi:10.1016/j.tra.2007.08.005.

Matas, A., Raymond, J.-L., & Roig, J.-L. (2009). Car ownership and access to jobs in Spain. *Transportation Research Part A: Policy and Practice*, *43*, 607–617. URL: https://linkinghub.elsevier.com/retrieve/pii/S0965856409000421. doi:10.1016/j.tra.2009.04.003.

Moorthy, A., de Kleine, R., Keoleian, G., Good, J., & Lewis, G. (2017). Shared autonomous vehicles as a sustainable solution to the last mile problem: A case study of Ann Arbor-Detroit area. *SAE International Journal of Passenger Cars - Electronic and Electrical Systems*, *10*. doi:10.4271/2017-01-1276.

Morais, J., Thomas-Agnan, C., & Simioni, M. (2018). Using compositional and dirichlet models for market share regression. *Journal of Applied Statistics*, *45*, 1670–1689. doi:10.1080/02664763.2017.1389864.

Morrison, D. G. (1979). Purchase intentions and purchase behavior. *Journal of Marketing*, *43*, 65. doi:10.2307/1250742.

Morwitz, V. (2012). Consumers' purchase intentions and their behavior. *Foundations and Trends in Marketing*, *7*, 181–230. doi:10.1561/1700000036.

Namazu, M., MacKenzie, D., Zerriffi, H., & Dowlatabadi, H. (2018a). Is carsharing for everyone? Understanding the diffusion of carsharing services. *Transport Policy*, *63*, 189–199. doi:10.1016/j.tranpol.2017.12.012.

Namazu, M., Zhao, J., & Dowlatabadi, H. (2018b). Nudging for responsible carsharing: using behavioral economics to change transportation behavior. *Transportation*, *45*, 105–119. doi:10.1007/s11116-016-9727-1.

Namias, J. (1959). Intentions to purchase compared with actual purchases of household durables. *Journal of Marketing*, *24*, 26–30. doi:10.2307/1249361.

Narayanan, S., & Antoniou, C. (2022a). Electric cargo cycles - A comprehensive review. *Transport Policy*, *116*, 278–303. doi:10.1016/j.tranpol.2021.12.011.

Narayanan, S., & Antoniou, C. (2022b). Expansion of a small-scale car-sharing service: A multi-method framework for demand characterisation and derivation of policy insights. *Journal of Transport Geography*, *104*. doi:10.1016/j.jtrangeo.2022.103438.

Narayanan, S., & Antoniou, C. (2022c). Shared mobility services towards Mobility as a Service (MaaS): What, who and when? *Under review*, . URL: https://papers.ssrn.com/abstract=4175398.

Narayanan, S., Arango, J. P. R., Frederix, R., Tympakianaki, A., & Antoniou, C. (2022a). Can emerging mobility solutions complement public transport and lead to a sustainable future? *Under review*, . URL: https://papers.ssrn.com/abstract=4219590.

Narayanan, S., Chaniotakis, E., & Antoniou, C. (2020a). Factors affecting traffic flow efficiency implications of connected and autonomous vehicles: A review and policy recommendations. In D. Milakis, N. Thomopoulos, & B. van Wee (Eds.), *Advances in Transport Policy and Planning : Policy Implications of Autonomous Vehicles* (pp. 1–50). Academic Press volume 5. URL: https://www.sciencedirect.com/science/article/pii/S254300092030007X. doi:10.1016/bs.atpp.2020.02.004.

Narayanan, S., Chaniotakis, E., & Antoniou, C. (2020b). Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C: Emerging Technologies*, *111*, 255–293. URL: https://www.sciencedirect.com/science/article/pii/S0968090X19303493. doi:10.1016/j.trc.2019.12.008.

Narayanan, S., Gruber, J., Liedtke, G., & Antoniou, C. (2022b). Purchase intention and actual purchase of cargo cycles: Influencing factors and policy insights. *Transportation Research Part A: Policy and Practice*, *155*, 31–45. doi:10.1016/j.tra.2021.10.007.

Narayanan, S., Makarov, N. M., Magkos, E., Salanova Grau, J. M., Aifadopoulou, G., & Antoniou, C. (2022c). Can bike-sharing systems reduce private car use? - An exploration through the comparison of discrete choice and machine learning models. *Under review*, . URL: https://papers.ssrn.com/abstract=4176171.

Narayanan, S., Álvarez Ossorio Martinez, S., & Antoniou, C. (2022d). A multilevel analysis on what is common (and not) across the cities when it comes to private car-ownership: Behavioural, policy and modelling insights. *Under review*, . URL: https://papers.ssrn.com/abstract=4147622.

Narayanan, S., Salanova Grau, J. M., Frederix, R., Tympakianaki, A., Masegosa, A. D., & Antoniou, C. (2022e). Modelling of shared mobility services - An approach in between traditional strategic models and agent-based models. *Journal of Intelligent Transportation Systems*, *Under revision*.

Navya (2022). Regulations are constantly changing to keep pace with the deployment of autonomous vehicles. URL: https://navya.tech/en/regulations-are-constantly-changing-to-keep-pace-with-the-deployment-of-autonomous-vehicles/.

Nemhauser, G. L., & Wolsey, L. A. (1999). *Integer and combinatorial optimization*. New York and Chichester: Wiley.

Nesbitt, K., & Sperling, D. (2001). Fleet purchase behavior: Decision processes and implications for new vehicle technologies and fuels. *Transportation Research Part C: Emerging Technologies*, *9*, 297–318. doi:10.1016/S0968-090X(00)00035-8.

Nicholas, M., & Bernard, M. R. (2021). Success factors for electric carsharing. URL: https://theicct.org/publication/success-factors-for-electric-carsharing/.

Nobis, C., & Kuhnimhof, T. (2018). Mobilitaet in Deutschland (MiD): Ergebnisbericht. URL: http://www.mobilitaet-in-deutschland.de/pdf/MiD2017_Ergebnisbericht.pdf.

Nourinejad, M., & Roorda, M. J. (2016). Agent based model for dynamic ridesharing. *Transportation Research Part C: Emerging Technologies*, *64*, 117–132. doi:10.1016/j.trc.2015.07.016.

Ntziachristos, L., Samaras, Z., Kouridis, C., Hassel, D., McCrae, I., Hickman, J., Zierock, K.-H., Keller, M., Andre, M., Gorissen, N., Boulter, P., Joumard, R., Rijkeboer, R., Geivanidis, S., & Hausberger, S. (2020). Methodology for the calculation of exhaust emissions. URL: https://www.emisia.com/utilities/copert/documentation/.

Nürnberg, M. (2019). Analysis of using cargo bikes in urban logistics on the example of Stargard. *Transportation Research Procedia*, *39*, 360–369. doi:10.1016/j.trpro.2019.06.038.

Nygaard, M. F., & Tørset, T. (2016). Waiting time strategy for public transport passengers. *Selected Proceedings from the Annual Transport Conference at Aalborg University*, *11*. doi:10.5278/UTD.V11I1.3840.

O'Flaherty, C. A., & Mancan, D. O. (1970). Bus passenger waiting times in central areas. *Traffic Engineering & Control*, .

Pajecki, R., Ahmed, F., Qu, X., Zheng, X., Yang, Y., & Easa, S. (2019). Estimating passenger car equivalent of heavy vehicles at roundabout entry using micro-traffic simulation. *Frontiers in Built Environment*, *5*. doi:10.3389/fbuil.2019.00077.

Paredes, M., Hemberg, E., O'Reilly, U.-M., & Zegras, C. (2017). Machine learning or discrete choice models for car ownership demand estimation and prediction? In *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)* (pp. 780–785). Naples, Italy: IEEE. URL: http://ieeexplore.ieee.org/document/8005618/. doi:10.1109/MTITS.2017.8005618.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Peter, J. P., & Olson, J. C. (2010). *Consumer behavior & marketing strategy*. (9th ed.). Boston: McGraw-Hill.

Picasso, E., Postorino, M. N., Bonoli-Escobar, M., & Stewart-Harris, M. (2020). Car-sharing vs bike-sharing: A choice experiment to understand young people behaviour. *Transport Policy*, *97*, 121–128. doi:10.1016/j.tranpol.2020.06.011.

Pinto, H. K., Hyland, M. F., Mahmassani, H. S., & Verbas, I. Ö. (2019). Joint design of multimodal transit networks and shared autonomous mobility fleets. *Transportation Research Part C: Emerging Technologies*, . URL: http://www.sciencedirect.com/science/article/pii/S0968090X18317728. doi:10.1016/j.trc.2019.06.010.

Potoglou, D., & Kanaroglou, P. S. (2008a). Disaggregate Demand Analyses for Conventional and Alternative Fueled Automobiles: A Review. *International Journal of Sustainable Transportation*, *2*, 234–259. URL: http://www.tandfonline.com/doi/abs/10.1080/15568310701230398. doi:10.1080/15568310701230398.

Potoglou, D., & Kanaroglou, P. S. (2008b). Modelling car ownership in urban areas: A case study of Hamilton, Canada. *Journal of Transport Geography*, *16*, 42–54. URL: https://linkinghub.elsevier.com/retrieve/pii/S0966692307000099. doi:10.1016/j.jtrangeo.2007.01.006.

Potoglou, D., & Susilo, Y. O. (2008). Comparison of vehicle-ownership models. *Transportation Research Record: Journal of the Transportation Research Board*, *2076*, 97–105. URL: http://journals.sagepub.com/doi/10.3141/2076-11. doi:10.3141/2076-11.

Poudel, K. P., & Temesgen, H. (2016). Methods for estimating aboveground biomass and its components for douglas-fir and lodgepole pine trees. *Canadian Journal of Forest Research*, *46*, 77–87. doi:10.1139/cjfr-2015-0256.

PTV Group (2021). PTV Visum 2021 manual.

R Core Team (2022). R: A language and environment for statistical computing. URL: https://www.R-project.org/.

Raux, C., Zoubir, A., & Geyik, M. (2017). Who are bike sharing schemes members and do they travel differently? the case of Lyon's velo'v scheme. *Transportation Research Part A: Policy and Practice*, *106*, 350–363. doi:10.1016/j.tra.2017.10.010.

Ritter, N., & Vance, C. (2013). Do fewer people mean fewer cars? Population decline and car ownership in Germany. *Transportation Research Part A: Policy and Practice*, *50*, 74–85. URL: https://linkinghub.elsevier.com/retrieve/pii/S0965856413000426. doi:10.1016/j.tra.2013.01.035.

Rodrigues, V., Lopes, M., Rafael, S., Coelho, S., de Oliveira, K., Vanherle, K., Papics, P., Himpe, W., Diafas, I., Angreine Kewo, Trozzi, C., Piscitello, E., & Soares, J. (2020). D5.7 city impact analysis report. doi:10.5281/ZENODO.3972940.

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, *20*, 53–65. doi:10.1016/0377-0427(87)90125-7.

Russo, A., Adler, M. W., & van Ommeren, J. N. (2022). Dedicated bus lanes, bus speed and traffic congestion in Rome. *Transportation Research Part A: Policy and Practice*, *160*, 298–310. doi:10.1016/j.tra.2022.04.001.

Salanova, J. M., Ayfantopoulou, G., Magkos, E., Mallidis, I., Maleas, Z., Narayanan, S., Antoniou, C., Tympakianaki, A., Martin, I., & Fajardo-Calderin, J. (2022). Developing a multilevel decision support tool for urban mobility. *Sustainability*, *14*, 7764. doi:10.3390/su14137764.

Salazar, M., Rossi, F., Schiffer, M., Onder, C. H., & Pavone, M. (2018). On the interaction between autonomous mobility-on-demand and public transportation systems. In *2018 International Conference on Intelligent Transportation Systems (ITSC)* (pp. 2262–2269). doi:10.1109/ITSC.2018.8569381.

Sanko, N., Maesoba, H., Dissanayake, D., Yamamoto, T., Kurauchi, S., & Morikawa, T. (2009). Inter-temporal analysis of household car ad motorcycle ownership behaviors: The case in the Nagoya metropolitan area of japan, 1981–2001. *IATSS*

Research, *33*, 39–53. URL: https://linkinghub.elsevier.com/retrieve/pii/S0386111214602430. doi:10.1016/S0386-1112(14)60243-0.

Scheltes, A., & de Almeida Correia, G. H. (2017). Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to Delft, Netherlands. *International Journal of Transportation Science and Technology*, *6*, 28–41. doi:10.1016/j.ijtst.2017.05.004.

Schmöller, S., Weikl, S., Müller, J., & Bogenberger, K. (2015). Empirical analysis of free-floating carsharing usage: The Munich and Berlin case. *Transportation Research Part C: Emerging Technologies*, *56*, 34–51. doi:10.1016/j.trc.2015.03.008.

Schonlau, M., & Zou, R. Y. (2020). The random forest algorithm for statistical learning. *The Stata Journal: Promoting communications on statistics and Stata*, *20*, 3–29. doi:10.1177/1536867X20909688.

Shao, Q., Zhang, W., Cao, X. J., & Yang, J. (2022). Nonlinear and interaction effects of land use and motorcycles/E-bikes on car ownership. *Transportation Research Part D: Transport and Environment*, *102*, 103115. URL: https://linkinghub.elsevier.com/retrieve/pii/S1361920921004107. doi:10.1016/j.trd.2021.103115.

Shen, Y., Zhang, H., & Zhao, J. (2018a). Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. *Transportation Research Part A: Policy and Practice*, *113*, 125–136. doi:10.1016/j.tra.2018.04.004.

Shen, Y., Zhang, X., & Zhao, J. (2018b). Understanding the usage of dockless bike sharing in Singapore. *International Journal of Sustainable Transportation*, *12*, 686–700. doi:10.1080/15568318.2018.1429696.

Simão, H. P., Day, J., George, A. P., Gifford, T., Nienow, J., & Powell, W. B. (2009). An approximate dynamic programming algorithm for large-scale fleet management: A case application. *Transportation Science*, *43*, 178–197. doi:10.1287/trsc.1080.0238.

Soltani, A. (2017). Social and urban form determinants of vehicle ownership; evidence from a developing country. *Transportation Research Part A: Policy and Practice*, *96*, 90–100. URL: https://linkinghub.elsevier.com/retrieve/pii/S0965856416309351. doi:10.1016/j.tra.2016.12.010.

Statistisches Bundesamt (2008). Classification of economic activities (WZ 2008). URL: https://www.klassifikationsserver.de/klassService/jsp/common/url.jsf?variant=wz2008&lang=EN.

Surprenant-Legault, J., & El-Geneidy, A. M. (2011). Introduction of reserved bus lane. *Transportation Research Record: Journal of the Transportation Research Board*, *2218*, 10–18. doi:10.3141/2218-02.

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. Adaptive computation and machine learning (second edition ed.). Cambridge, Massachusetts: The MIT Press.

Sweet, M. N., & Scott, D. M. (2021). Shared mobility adoption from 2016 to 2018 in the Greater Toronto and Hamilton Area: Demographic or geographic diffusion? *Journal of Transport Geography*, *96*, 103197. doi:10.1016/j.jtrangeo.2021.103197.

Taefi, T. T., Kreutzfeldt, J., Held, T., & Fink, A. (2016). Supporting the adoption of electric vehicles in urban road freight transport – a multi-criteria analysis of policy measures in germany. *Transportation Research Part A: Policy and Practice*, *91*, 61–79. doi:10.1016/j.tra.2016.06.003.

Te Brommelstroet, M. (2010). Equip the warrior instead of manning the equipment: Land use and transport planning support in the Netherlands. *Journal of Transport and Land Use*, *3*. doi:10.5198/jtlu.v3i1.99.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions about health, wealth, and happiness / Richard H. Thaler, Cass R. Sunstein*. London: Yale University Press. URL: https://yalebooks.yale.edu/book/9780300122237/nudge.

Thoma, L., & Gruber, J. (2020). Drivers and barriers for the adoption of cargo cycles: An exploratory factor analysis. *Transportation Research Procedia*, *46*, 197–203. doi:10.1016/j.trpro.2020.03.181.

Thorhauge, M., Fjendbo Jensen, A., & Rich, J. (2022). Effects of autonomous first- and last mile transport in the transport chain. *Transportation Research Interdisciplinary Perspectives*, *15*, 100623. doi:10.1016/j.trip.2022.100623.

Toth, P., & Vigo, D. (2014). *Vehicle routing: Problems, methods, and applications*. MOS-SIAM series on optimization (second edition ed.). Philadelphia: Society for Industrial and Applied Mathematics : Mathematical Optimization Society. URL: http://www.loc.gov/catdir/enhancements/fy1503/2014029491-d.html.

Tran, T. D., Ovtracht, N., & d'Arcier, B. F. (2015). Modeling bike sharing system using built environment factors. *Procedia CIRP*, *30*, 293–298. URL: https://doi.org/10.1016/j.procir.2015.02.156. doi:10.1016/j.procir.2015.02.156.

Truong, L. T., Sarvi, M., & Currie, G. (2015). Exploring multiplier effects generated by bus lane combinations. *Transportation Research Record: Journal of the Transportation Research Board*, *2533*, 68–77. doi:10.3141/2533-08.

Tsitsokas, D., Kouvelas, A., & Geroliminis, N. (2021). Modeling and optimization of dedicated bus lanes space allocation in large networks with dynamic congestion. *Transportation Research Part C: Emerging Technologies*, *127*, 103082. doi:10.1016/j.trc.2021.103082.

Tzouras, P. G., Mitropoulos, L., Stavropoulou, E., Antoniou, E., Koliou, K., Karolemeas, C., Karaloulis, A., Mitropoulos, K., Tarousi, M., Vlahogianni, E. I., & Kepaptsoglou, K. (2022). Agent-based models for simulating e-scooter sharing services: A review and a qualitative assessment. *International Journal of Transportation Science and Technology*, . doi:10.1016/j.ijtst.2022.02.001.

Valentin, P. (2019). The automotive industry's road to dynamic pricing. URL: https://www.simon-kucher.com/en/blog/automotive-industrys-road-dynamic-pricing.

Vanherck, J., Narayanan, S., Frederix, R., Tympakianaki, A., Torrent, F., Antoniou, C., & Ayfantopoulou, G. (2022). Can carsharing reduce car ownership and emissions? an analysis based on an intermediate modelling approach. In C. Antoniou, F. Busch, A. Rau, & M. Hariharan (Eds.), *Proceedings of the 12th International Scientific Conference on Mobility and Transport: Mobility Innovations for Growing Megacities* A Springer book series Lecture Notes in Mobility.

Wang, C., Bi, J., Sai, Q., & Yuan, Z. (2021). Analysis and prediction of carsharing demand based on data mining methods. *Algorithms*, *14*, 179. doi:10.3390/a14060179.

Wang, K., Akar, G., & Chen, Y.-J. (2018). Bike sharing differences among millennials, gen xers, and baby boomers: Lessons learnt from New York City's bike share. *Transportation Research Part A: Policy and Practice*, *116*, 1–14. URL: https://doi.org/10.1016/j.tra.2018.06.001. doi:10.1016/j.tra.2018.06.001.

Wielinski, G., Trépanier, M., & Morency, C. (2017). Carsharing versus bikesharing. *Transportation Research Record: Journal of the Transportation Research Board*, *2650*, 112–122. doi:10.3141/2650-13.

Wilkes, G., Briem, L., Heilig, M., Hilgert, T., Kagerbauer, M., & Vortisch, P. (2021). Determining service provider and transport system related effects of ridesourcing services by simulation within the travel demand model mobitopp. *European Transport Research Review*, *13*. doi:10.1186/s12544-021-00493-3.

Wong, K. I. (2013). An analysis of car and motorcycle ownership in Macao. *International Journal of Sustainable Transportation*, *7*, 204–225. URL: http://www.tandfonline.com/doi/abs/10.1080/15568318.2013.710057. doi:10.1080/15568318.2013.710057.

Yamamoto, T. (2009). Comparative analysis of household car, motorcycle and bicycle ownership between Osaka metropolitan area, Japan and Kuala Lumpur, Malaysia. *Transportation*, *36*, 351–366. URL: http://link.springer.com/10.1007/s11116-009-9196-x. doi:10.1007/s11116-009-9196-x.

Yannis, G., Golias, J., & Antoniou, C. (2006). Effects of urban delivery restrictions on traffic movements. *Transportation Planning and Technology*, *29*, 295–311.

Yap, M. D., Correia, G., & van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A: Policy and Practice*, *94*, 1–16. doi:10.1016/j.tra.2016.09.003.

Yoon, T., Cherry, C. R., & Jones, L. R. (2017). One-way and round-trip carsharing: A stated preference experiment in Beijing. *Transportation Research Part D: Transport and Environment*, *53*, 102–114. URL: https://www.sciencedirect.com/science/article/pii/S1361920917303139. doi:10.1016/j.trd.2017.04.009.

Young, M., & Farber, S. (2019). The who, why, and when of uber and other ride-hailing trips: An examination of a large sample household travel survey. *Transportation Research Part A: Policy and Practice*, *119*, 383–392. doi:10.1016/j.tra.2018.11.018.

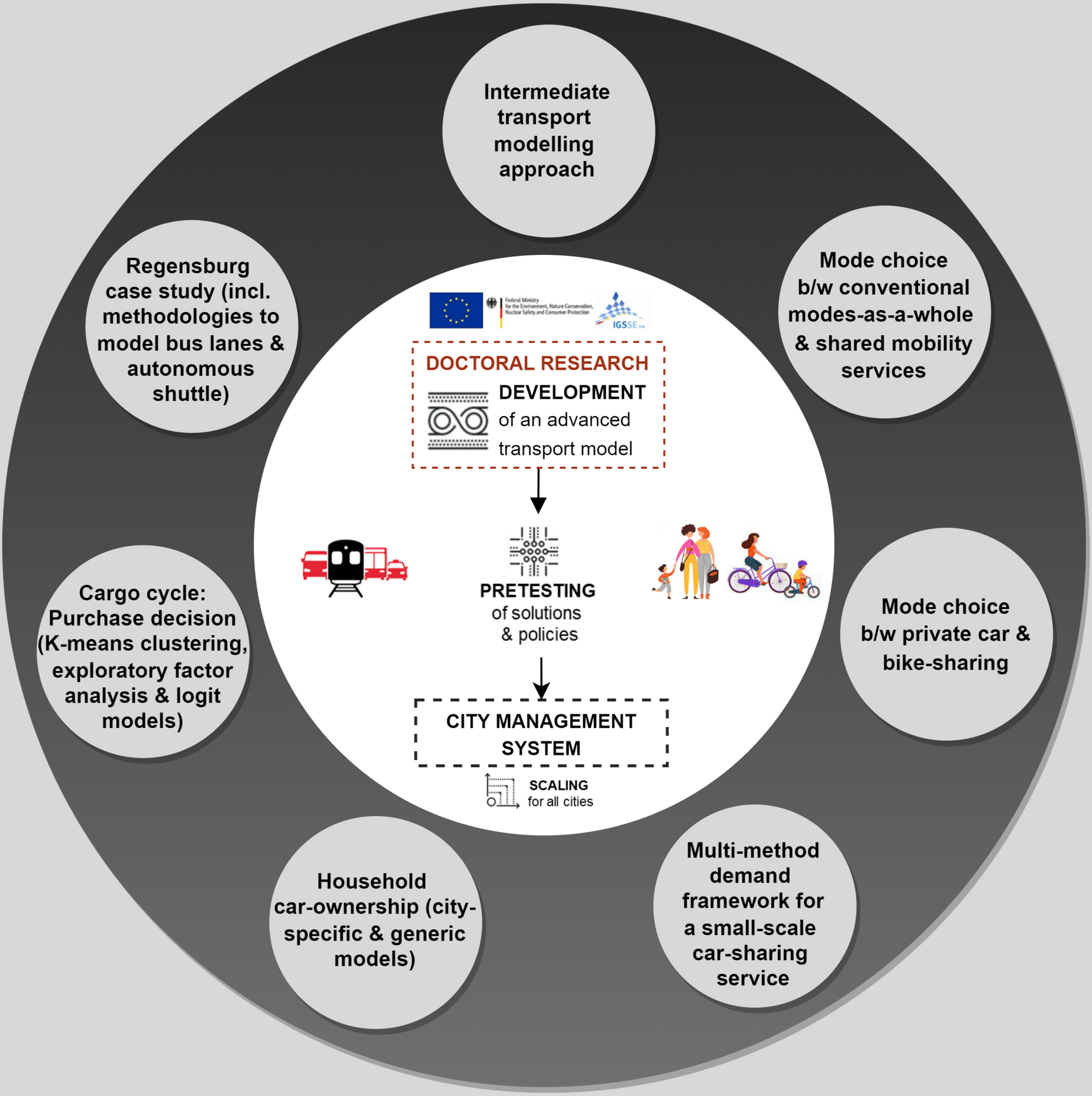
Zhao, Y., & Kockelman, K. M. (2018). Anticipating the regional impacts of connected and automated vehicle travel in austin, texas. *Journal of Urban Planning and Development*, *144*. doi:10.1061/(ASCE)UP.1943-5444.0000463.

Zhou, F., Zheng, Z., Whitehead, J., Perrons, R. K., Washington, S., & Page, L. (2020a). Examining the impact of car-sharing on private vehicle ownership. *Transportation Research Part A: Policy and Practice*, *138*, 322–341. URL: https://linkinghub.elsevier.com/retrieve/pii/S0965856420306121. doi:10.1016/j.tra.2020.06.003.

Zhou, F., Zheng, Z., Whitehead, J., Washington, S., Perrons, R. K., & Page, L. (2020b). Preference heterogeneity in mode choice for car-sharing and shared automated vehicles. *Transportation Research Part A: Policy and Practice*, *132*, 633–650. doi:10.1016/j.tra.2019.12.004.

Zwick, F., Kuehnel, N., Moeckel, R., & Axhausen, K. W. (2021). Agent-based simulation of city-wide autonomous ride-pooling and the impact on traffic noise. *Transportation Research Part D: Transport and Environment*, *90*, 102673. doi:10.1016/j.trd.2020.102673.

Aggregate four-step & Disaggregate agent-based modelling approaches, but what is in between?: Development of an intermediate Modelling approach



Santhanakrishnan Narayanan
(santhanakrishnan.narayanan@tum.de)