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Schneider, F.

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Florian Schneider

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Delft University of Technology

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Spatial Activity-Travel Patterns of Cyclists

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by

Florian SCHNEIDER

Master of Science in Environmental Management and Science, Université Libre de Bruxelles, Belgium

born in Munich, Germany

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus	chairperson
Prof. dr. ir. S.P. Hoogendoorn	promotor
Dr. ir. W. Daamen	promotor

Independent members:

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Dedicated to all people riding headwind.

Preface

On July 16, 1969, at 13:32 UTC time, the maybe most remarkable journey in the history of transportation started. A Saturn V rocket was launched with Neil A. Armstrong and his crew on board. Four and a half days later, Armstrong climbed out of the Apollo lunar module to become the first human ever touching lunar surface. On July 4, 2016, approximately in the morning, a new adventure in transportation began. The nervous author of this book bravely entered the campus of Delft University of Technology with the noble intention to do a PhD on active mode travel behaviour. So, how did this journey go?

Admittedly, travel behaviour research is not rocket science. Yet, it is science, requiring some methodological and communication skills. While the adventurer was largely lacking these skills at the beginning, he was equipped with curiosity, naive enthusiasm for the active modes (or, more precisely, for cycling – sorry Winnie and Serge) and a portion of stubbornness. Considering the point of departure, a possible outcome of the mission could have been the Apollo 13 scenario.

Luckily, our brave adventurer was not alone on the mission. What Edwin E. Aldrin and Michael Collins were to Armstrong, Winnie and Serge were to him. Winnie helped the adventurer thanks to her reliable support to navigate through the difficult moments of his PhD and to land the spaceship on solid scientific grounds. Serge, the captain of the mothership, provided the supportive environment in which things were generally made possible. Speaking of the mothership: it was a lovely place in the lonely vastness of space. Instead of competition, there was mutual support between the astronauts - out of colleagues became friends (Alexandra, Alphonse, Danique, Giulia, Lara, Marieta, Martijn, Tim, Vincent and Yan).

Similarly to the atmosphere in the mothership, the spaceport was a fruitful workplace. Daily lunch gatherings and frequent coffee machine encounters were the moments for exchanging on scientific matters, for having political or philosophical discussions or for simply sharing jokes (Bahman, Bernat, Ding, Dorine, Flurin, Konstanze, Malvika, Maria, Nejc, Niharika, Paul, Victor, Yihong,…). And not to forget the tactical preparations of the upcoming match of the astronaut football team, which participated with increasing success in the ESA football league

(Ale, Nikola, Oguz, Pablo, Tin, Xavi and everybody else from DCF)! Furthermore, the frequent inspirational breaks with Bahman deserve a special mention ☺.

Thanks to the close ties to other space agencies, the adventurer could also rely on support from outside his institution (Sascha, Anders, Elias). An important element to overcome the initial deficiencies of the adventurer was the Space Research School. Within a wellness environment, its courses and meetings stimulated the exchange between the astronauts from different space agencies and helped them to comprehend the larger picture of their missions.

Very essential support came from outside the “space bubble”. Most importantly from Manon, the adventurer’s girlfriend. She backed him during difficult moments (in particular during the Corona crisis!) and strongly contributed to reaching at least an unstable equilibrium in his work-life balance (what is not a given in the space bubble). Other important stabilisers were climbing activities (Boudewijn, Ruben, Solène), game nights, dinners, pick nicks in the park or at the beach, bicycle tours, concerts, etc. And the good times and conversations with my old and reliable friends from Bavaria, Brussels and Freiburg (Alberto, Baptiste, Brenda, Cori, Dami, Fabi (2*), Jan, Jo, Julia, Magdalena, Marie, Maxi, Mäxx, Mélanie, Michi, Sanny, Simon, Svenja,..). And last but not least, there has always been unconditional support from my and Manon’s family!

The journey was largely broadening the horizons of the adventurer. He gradually developed some statistical skills, learnt to canalise his curiosity within a more systematic research approach and give the results a meaningful framing. The adventurer also realised that research does not have to land on the moon each time. But it should involve intensive intellectual friction (in particular with the inner laziness of thought) and be presented in an acknowledged format of scientific exchange.

So, how would Armstrong assess this mission? He would probably put it this way: “It was a giant leap for the author, but a small step for mankind.”

Florian Schneider, December 2020

Content

List of Figures

List of Tables

1. Introduction

Cities have a dilemma. In today's globalised world, cities compete among one another for jobs and investments. In this context, the quality of life is a key location factor, in particular for high value-added businesses (World Bank, 2015). Good quality of life implies that citizens do not only have access to activity locations that satisfy their basic needs but, in addition, all kinds of cultural events and other leisure activities (Morais, Miguéis, & Camanho, 2013). However, the necessary mobility of making destinations accessible is often associated with negative social and environmental impacts such as congestion or noise. These impacts contradict a high quality of life.

The economist Kate Raworth visualises in her inspiring book Doughnut Economics (2017) a similar problem in the form of a doughnut. The inner boundary of the doughnut stands for minimum human needs and the outer boundary for maximum available natural resources. To meet both conditions, the economic system should be (re-) designed and operated in such a way that it ensures collective human well-being while not using more resources than sustainably being at our disposal.

We argue that the same depiction can be used when we portray an urban land-use and transport system that is geared towards a good quality of life (see Figure 1.1). Such a system should on the inner side not fall short in providing enough mobility for activity participation. Mobility enables people to reach activity locations (e.g. supermarkets or workplaces) where they can satisfy their personal needs. On the outer side, mobility should not cause more negative impacts than what is collectively accepted. Using the image of the doughnut, we elaborate in the following on both system failures before indicating ways to design an urban land-use and transport system that meets the requirements of both edges of the doughnut.

Mobility-induced problems on both sides of the doughnut

We start with discussing mobility-induced problems that pose a risk for overshooting maximum acceptable impacts, the outer ring of the dougnut (see top part of Table 1.1). Air pollution and noise might be the most prominent issues that affect the quality of life in a city. Both problems have been associated with negative health effects. Less obvious are the effects of construction and maintenance costs of transportation infrastructure, which often represent heavy impacts on communal budgets. Public funds that are committed to these infrastructures cannot be spent for other ends enhancing the quality of life. The type of transport infrastructure also affects social cohesion (e.g. through the number of social interactions) and perceived safety in a neighbourhood. In this context, the attractiveness of public space strongly depends on speed and volume of motorised traffic and on the proportion of public space that is dedicated to other purposes than car transportation. Finally, traffic accidents do not only constitute a massive loss in economic terms but can also reach societally unacceptable numbers as the *Stop de kindermoord* movement in the Netherlands in the early 1970s showed (Reid, 2017).

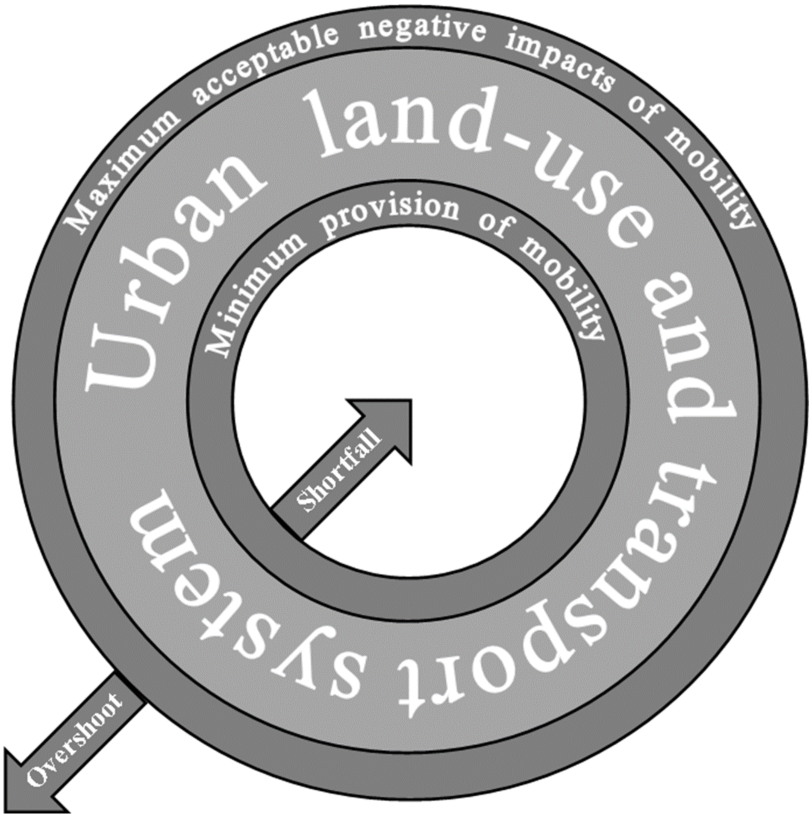

Figure 1.1 The "quality of life" urban land-use and transport system.

A shortfall of mobility is the other system failure of the doughnut model (see the bottom part of Table 1.1). Both travel costs and physical access to transport can be a constraint for sufficient mobility, leading to a lack of activity participation and, hence, social exclusion. Furthermore, congestion is an increasing issue in many cities. Longer travel times of people reduce the accessibility to activity locations and are equated with welfare losses for the society. A further, often overlooked problem is the barrier effect (often named community severance) that large transport infrastructures can have for the accessibility of separated areas to destinations.

Ways to establish an urban land-use and transport system that meets both doughnut requirements

A prerequisite for meeting both doughnut requirements is that activity participation is linked to less negative mobility impacts. In this way, the minimum mobility necessary for activity participation is more likely to not cause impacts beyond maximum acceptable levels. This goal can be achieved in two ways, which are intertwined.

First, the development of space-efficient land-use structures can attenuate the negative impacts related to mobility. The land-use system defines amongst other things the spatial distribution of where people live and where destinations can be found to which they need or want to have access (Geurs & van Wee, 2013). Many of the transport-induced problems such as air pollution or congestion are directly dependent on the amount of mobility (measured for example in vehicle-kilometres) which is required for activity participation. The amount of mobility in return depends on how close origins and destinations are placed to each other. Former research showed that particularly urban structures that are characterised by high urban densities and mixed land uses appear to significantly reduce travel distances (Leck, 2006). Consequently, a land-use system that incorporates both principles has the potential to reduce many of the negative impacts elaborated above. Having said this, high urban densities can also amplify some of the mentioned problems at the local level, such as noise or congestion. This is particularly true as long as mobility is car-dominated.

Table 1.1 Transport-induced problems in an urban environment.

Problem	**References**
Potential overshoot of maximum acceptable impacts	
Air pollution	Grahame & Schlesinger, 2010; Ketzel et al., 2007; Krzyzanowski, Kuna-Dibbert, & Schneider, 2005
Noise & vibrations	Kouroussis, Pauwels, Brux, Conti, & Verlinden, 2014; Passchier-vermeer, Passchier, & Passchier-vermeerl, 2000
Infrastructure costs	Schroten et al., 2019; Bushell, Poole, Zegeer, & Rodriguez, 2013
Social isolation	Sauter & Huettenmoser, 2008; van den Berg, Sharmeen, & Weijs-Perrée, 2017
Space consumption	McCahill & Garrick, 2012; Sauter & Huettenmoser, 2008
Accidents	Connelly & Supangan, 2006; European Road Safety Observatory, 2018; Schepers, Twisk, Fishman, Fyhri, & Jensen, 2017; Wegman, Zhang, & Dijkstra, 2012
Potential shortfall of mobility provision	
Travel costs	Hine, 2003; Karen, Mattioli, Verlinghieri, & Guzman, 2016; Boniface, Scantlebury, Watkins, & Mindell, 2015
Congestion	Annema, 2013; Bilbao-Ubillos, 2008
Spatial isolation (*community severance*)	Anciaes, Jones, & Mindell, 2016; Grisolía, López, & de Dios Ortúzar, 2015

Second, a considerable mode shift from car to active modes (i.e. walking and cycling) is an effective way to attenuate many of the problems presented in Table 1.1. Transport-related emissions and noise are mostly attributed to individual motorised traffic and, to a lower extent, to public transport. In this context, the effects of the active modes (i.e. walking and cycling) are noteworthy. While not causing health impacts for other people, they have additional positive health effects for the users themselves (Mueller et al., 2015). Compared to car and public transport, cycling and walking are in addition relatively cheap regarding travel and infrastructure costs. Research has also shown that active mode use increases the number of social interactions, enhancing social cohesion and integration. However, empirical research suggests that both modes are particularly exposed to accident risks. In addition, not everybody has the physical abilities to use a bicycle or walk long distances. While the reach of both modes depends besides the features of the network especially on personal fitness, the increasing spread of the e-bike can partially overcome this restriction and increase the distance range (and thereby the number of accessible destinations).

Considering the two presented approaches, an urban land-use and transport system that satisfies both conditions of the doughnut is probably active mode-oriented with the bicycle as its backbone. Such a system requires first and foremost a land-use structure that enables active mode activity-travelling (i.e. travel related to activity participation). In addition, safe, efficient and comfortable networks for both travel modes are necessary. Optimally, many recurring daily-life destinations such as supermarkets or day-care centres should be within a short distance. The rationale behind proximity is that it enables people to walk and ensures a certain freedom of (destination) choice within cycling distance. Other more specific destinations (e.g. workplaces or specialised health services) are difficult to plan within walking distance but mixed land-uses and high urban densities can increase the number of origin and destination pairs that can be travelled on foot or by bicycle. The advantage of proximity as a guiding principle of land-use planning is in addition that (necessary) car trips cause less negative impacts due to short travel distances. Moreover, such urban environments facilitate the provision of qualitative and efficient public transport services.

Lacking empirical underpinning of activity-travel behaviour for bicycle-oriented land-use planning

While cycling plays an important role in gearing our cities towards a good quality of life, surprisingly little is known about how the bicycle is used for activity-travelling. To date, dominating topics of bicycle travel behaviour research are mode choices (e.g. Heinen, van Wee, & Maat, 2010; Muñoz, Monzon, & Daziano, 2016; Pucher & Buehler, 2008), route choices (e.g Broach, Dill, & Gliebe, 2012; Sener, Eluru, & Bhat, 2009; Ton, Cats, Duives, & Hoogendoorn, 2017) and, since very recently, operational choices (e.g. Gavriilidou et al., 2019; Yuan et al., 2018). In these studies, the link to activities is at most of implicit (the use case is utilitarian travelling) or incomplete nature (not all trip purposes are considered). As a consequence, the available knowledge is not sufficient as input for designing urban environments that are optimised for activity-travelling by bicycle. To this end, dedicated empirical research on (spatial) activity-travel behaviour of cyclists is necessary that includes all activity-travelling.

The bicycle as a means of transport is characterised by some functional properties that are different from those of other travel modes, in particular, those of the car:

- Locomotion by bicycle is based on a physical effort, making cyclists more travel distance sensitive.
- The transport of people and goods is restricted for the bicycle. In addition, in-vehicle storage of purchases is not possible.
- Travelling together by bicycle requires more thorough planning than by car.
- Cycling is not only a means of transport but can be an activity (a purpose) in itself.
- Cyclists are more exposed to their environment such as weather. Moreover, they are more vulnerable due to missing crush-collapsible zones and airbags.

Related to these functional differences, one might expect some peculiarities of bicycle activity-travel behaviour, for instance, more frequent grocery shopping due to the limited capacity of transporting goods. The most important property, however, is distance sensitivity as it has implications for bicycle-friendly urban planning. This feature suggests both a limited reach and a propensity towards visiting more than one activity location in a home-based tour (due to the related potential to reduce total travel distances (Duncan, 2016)). For this reason, the topic of this thesis is the empirical analysis of spatial activity-travel behaviour of cyclists. More precisely, we study bicycle accessibility in a single destination travel pattern, but also the extent of multiple destinations patterns and their spatial features. By putting this focus, we provide much-needed insights into activity-travel behaviour by bicycle. Moreover, the results of this thesis can be used to assess and design bicycle-friendly urban land-use and transport systems. In this way, a contribution is made to develop urban environments that are in line with the principles of the doughnut.

The rest of the thesis introduction is structured as follows. First, we develop a conceptualisation of spatial activity-travel behaviour in section 1.1. Next, we formulate the research objective and address five related research questions in section 1.2. Subsequently, we explain the research approach in section 1.3. In section 1.4, we discuss the contributions of this research for both science and practice. Finally, we shortly describe the outline of the thesis in section 1.5.

1.1 Relevant concepts, theories and definitions for understanding spatial activity-travel behaviour

Activity-travel behaviour takes place in the interplay between the demand for activities and the supply of corresponding activity locations by urban land-use and transport systems (see Figure 1.2). The purpose of activity-travel is to connect the demand for activity participation with a spatially separated supply of destinations. In the following, we shortly describe the demand for activity participation and the supply of destinations. Furthermore, we briefly present a few key concepts and theories that provide relevant explanatory approaches for understanding spatial activity-travel behaviour and resulting activity-travel patterns. More specifically, we outline how *utility theory* can be applied to activity-travel behaviour, indicate decision space for activity-travelling based on *time geography* and explain the activity scheduling process departing from the *activity-peg theory*. Finally, we describe the patterns that result from spatial activity-travel behaviour.

Demand for activity participation

The demand side of Figure 1.2 is driven by activities. An activity can be defined as an operation that serves to fulfil a certain need (Mcnally & Rindt, 2007). According to the same authors, the activities stem from an individual activity programme, which reflects both individual and household needs. Often, these activities are attributed to the function they have in daily life, such as work, education, shopping or leisure. Depending on the location, activities can be classified as home-based or (travel inducing) out-of-home activities. Only the latter requires travelling and will be examined in this thesis.

Supply of destinations

The supply-side of Figure 1.2 depends on how urban land-use and transport systems provide access to activity locations. Accessibility can be defined as “the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)” (Geurs & van Wee, 2013, p. 208). While the land-use system determines the locations where people live and where activities can be found, the transport system generates the disutility of overcoming the distance between an origin and a destination (in terms of time, costs and any kind of physical or psychological effort) for a particular travel mode (Geurs & van Wee, 2013).

Activity-travelling and utility

From an economic perspective, the spatial activity-travel behaviour linking the demand and supply sides of Figure 1.2 can be described using *utility theory*. This concept relies on the notion that people are fully informed about the choice set and make rational decisions which maximise their utility (Fishburn, 1968). Following this line of reasoning, observed behaviour reveals the choice that maximised the utility for the considered person. In the context of activity-travel behaviour, activity participation is assumed to provide utility, while travelling (in the transport system) is associated with disutility (Annema, 2013). As a consequence, travellers are expected to minimise travel and mostly pick the nearest (in terms of travel distance or travel time) suitable destination that provides utility. More distant destinations would only be chosen if a related utility surplus outweighs the additional disutility.

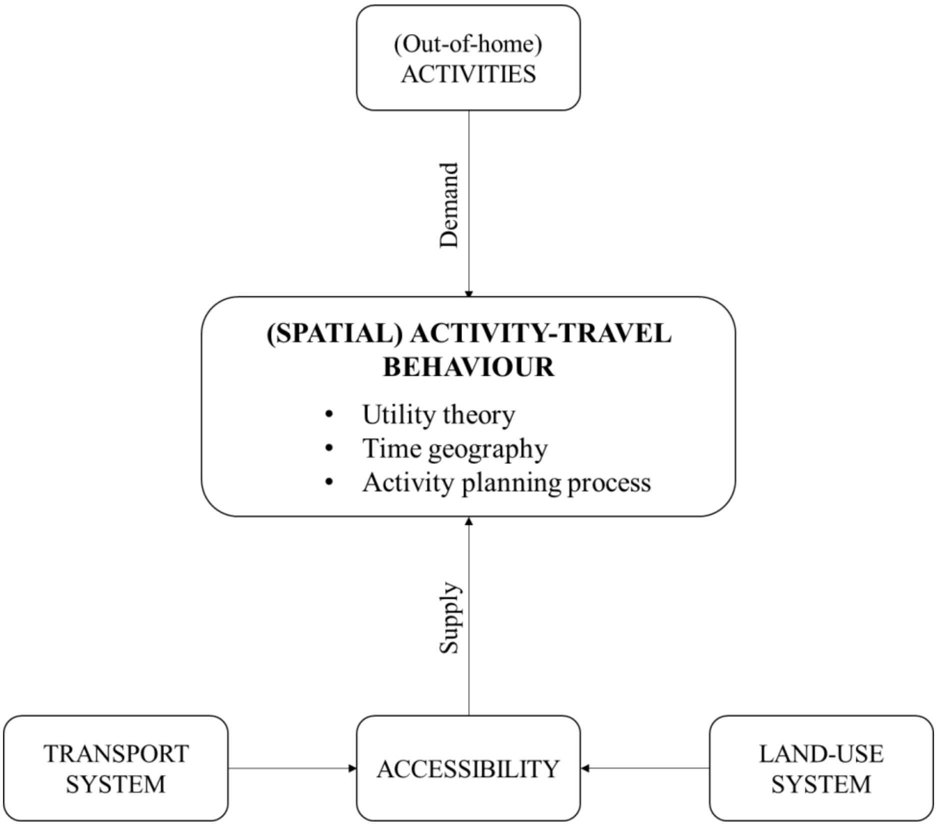

Figure 1.2 Spatial activity-travel behaviour.

Activity-travelling and time geography

Another fundamental theoretical contribution that helps to comprehend the spatial bounds in which activity-travel behaviour can take place is the so-called *time geography* of Hägerstrand (1970). The concept splits up the available time for out-of-home activity participation of a person into activity time and travel time. By doing so, the relationship between time and space becomes evident. The more a person spends time on travelling, the larger is the spatial reach (given a particular transport system) from which activity locations can be picked, but the shorter remains the time for performing activities and vice versa. In addition to the interdependency of time and space, Hägerstrand introduced three categories of constraints that affect the decision space for activity-travelling, namely i) constraints related to the capability of the traveller (e.g. the personal fitness state), ii) time and space constraints induced by travelling or performing activities jointly, iii) constraints arising from rules and regulations (e.g. opening hours of a supermarket).

Activity scheduling process

The planning process that underlies activity-travelling is commonly called activity scheduling, activity planning or, considering only out-of-home activities, trip chaining, trip chain formation or tour formation (Lee & McNally, 2006). Cullen and Godson (1975) proposed the so-called *activity peg theory* to explain this process. The theory assumes that activity planning is an ongoing process that is structured around a skeleton of important activities. These important activities are often routine activities and have been planned far ahead (Auld, Mohammadian, & Nelson, 2011; Doherty, 2005). The study of Auld et al (2011) further suggests that not all attributes of activities such as location, timing or related travel mode are planned at the same time. Since location and mode choice together affect travel times (and hence the necessary window of free time in a schedule), it would principally make sense if both choices would be made simultaneously. However, a clear decision order cannot be derived from the scarce empirical evidence on activity planning horizons and modelling approaches using different hierarchical structures (Auld et al., 2011; Newman & Bernardin, 2010).

Spatial activity-travel patterns

Depending on supply and demand and various constraints, different spatial activity-travel patterns evolve. The spatial dimension of a pattern can be described by the number of kilometres travelled. Furthermore, a pattern is characterised by the used travel mode(s). A useful observation unit is a pattern that represents a spatial loop, starting and ending at the home location. Such a pattern is usually named a home-based trip chain or tour (Primerano, Taylor, Pitaksringkarn, & Tisato, 2008). Depending on the number of activity locations visited, these patterns have different so-called complexities (Currie & Delbosc, 2011). Simple trip chains or tours include only one out-of-home activity while complex ones at least two. Since not all recurring activities are visited on a daily basis (and within one trip chain), a single home-based pattern is often not enough to get a footprint of a person's typical activity-travel behaviour. For this reason, longer time horizons (e.g. a week) are used (Lee & McNally, 2003). Longer time horizons have, amongst other things, the advantage to exhaustively represent how an activity programme is related to travel. In contrast, shorter periods enable to link more consistently activity-travel behaviour to a single travel mode.

1.2 Research objective and related research questions

In this thesis, we aim to achieve the following research objective:

To gain empirical insights into spatial activity-travel behaviour of cyclists and to empirically underpin factors that affect their spatial activity-travel patterns

To achieve this research objective, we study activity-travel behaviour from different angles (see Figure 1.3). We set the scene by looking at activity-travel behaviour from the broad perspective of a cyclist. This traveller-based focus on activity-travelling shows, which travel mode combinations are used by cyclists to implement daily life activity programmes. After considering this holistic view, we analyse how bicycle-related activity participation is typically organised in terms of trip chain complexity compared to other modes. Before studying the spatial dimension of activity-travel behaviour for simple and complex trip chains, we derive a hierarchy scheme of activity types. This scheme is necessary knowledge to interpret detours related to the inclusion of a secondary activity to a bicycle or car tour and the effects of associated influence factors. For simple bicycle trip chains, we study travel distances of outbound trips to destinations and related determinants. In the following, we explain these different elements in more detail and formulate related research questions.

1. A cyclist is a person that uses the bicycle for activity-travelling. However, this does not mean that he or she exclusively travels by bicycle to reach activity locations. On the contrary, the functional properties of the bicycle (such as a limited transport capacity and range) rather suggest that cyclists implement their (out-of-home) activity programmes using a combination of travel modes. To gain a better understanding of these combinations and, thereby, of the role of the bicycle for activity-travelling of cyclists, we formulate the first research question as follows: *To what extent are cyclists multi-modal travellers in daily-life activity-travelling?*

2. An essential element of activity-travel behaviour is trip chaining. Visiting more than one activity location within a home-based tour can be an efficient way of implementing an activity programme. While some functional features of the bicycle (distance-sensitivity, parking flexibility) suggest that home-based bicycle tours are often complex, that is including more than one activity, other characteristics (limited number of activity locations in reach) might impede complex trip chaining. For this reason, we pose the following research question: *To what extent does activity-travelling by bicycle involve complex trip chains compared to other travel modes?*

3. In the activity scheduling literature, the hierarchy of activities in the planning process is debated and a tangible classification is missing. Since such information is necessary to understand which activity purposed the travel (primary activity) and which activity has been added later (secondary activity), we propose a new method to identify prevailing hierarchies based on spatial travel patterns. This methodological contribution is linked to the subsequent research question: *Which hierarchies between activity types in tours can be derived based on spatial travel patterns?*

4. The daily commute is a good use case to study the spatial arrangements of activity locations that facilitate trip chaining. As ‘work’ can be expected to be the primary activity (Schneider, Daamen, Hoogendoorn-Lanser, & Hoogendoorn, n.d.), trip chaining depends on the spatial proximity of another activity from the activity programme to the home-work route. This accessibility can be expressed by the additional travel distance that is necessary to include the activity in the tour. Since the car is still the dominant travel mode in many cities (and as a private means of transport the main competitor of the bicycle), we do not only study bicycle but also car trip chaining behaviour as a benchmark. In this context, we ask the following question: *What are the factors that explain commute tour distance extensions by bicycle to accommodate a secondary activity compared to those of the car?*

5. Bicycle accessibility of activities is a key requirement for activity-travelling by bicycle. By implication, areas with high levels of utilitarian cycling have many destinations accessible by bicycle. The accessibility depends on both the distances between origins and destinations and the features of the bicycle network connecting them. Since it is hard to disentangle these different components, travel distance is a useful measuring unit of accessibility. Therefore, we look at revealed travel distances in best-practice environments by asking the following question: *How far do people cycle from home to typical daily-life destinations in best-practice environments and which factors explain related travel distances?*

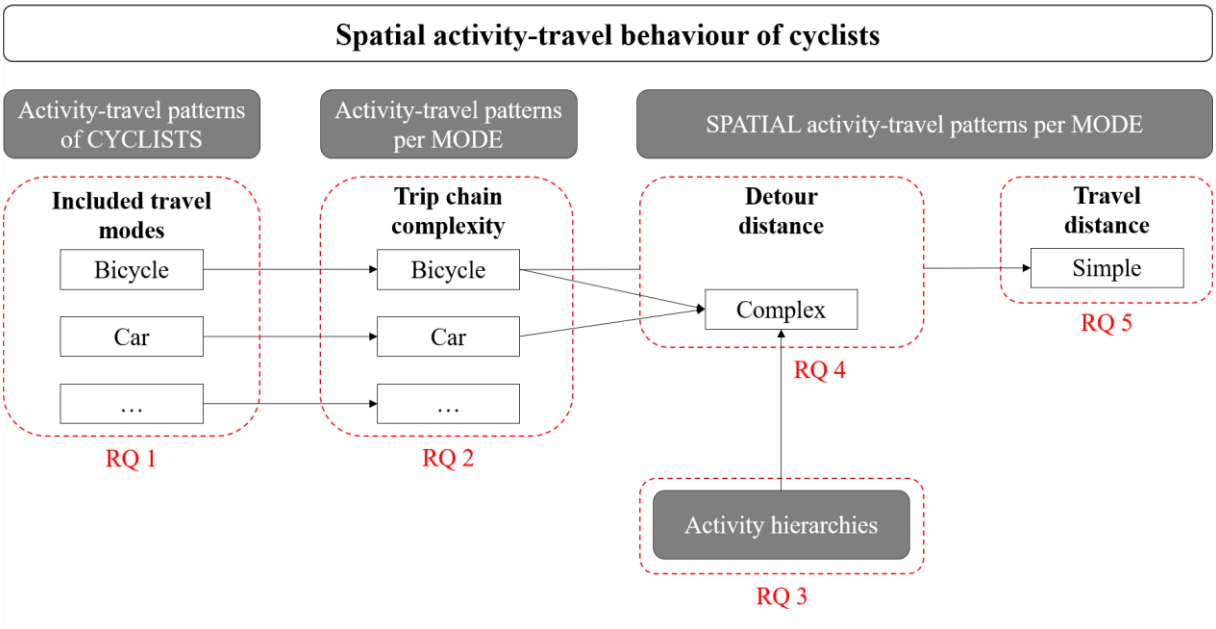

Figure 1.3 Links between research questions (RQs).

Note: The red frames highlight the respective focus of each question.

1.3 Research approach

This section outlines how we intend to explore spatial activity-travel behaviour of cyclists using data analyses. Since the research objective is gaining empirical insights into spatial activity-behaviour, quantitative data is necessary. Moreover, the descriptive nature of the research objective calls for the use of revealed travel behaviour data, representing actual and not hypothetical activity-travel behaviour. In a nutshell, the research approach of this thesis is analysing data on revealed activity-travel behaviour by means of a set of different analysis techniques to answer the research questions put forward in section 1.2. A visualisation of this approach is provided in Figure 1.4, specifying per research question the respective research focus, employed data, conducted data processing and applied analysis techniques. In the following, we shortly describe these elements.

Research focus

The research focus is adapted to the respective research question, starting from a broad perspective that is increasingly narrowed down. This zooming in refers to two elements, the activity-travel pattern and the number of travel modes. Regarding the activity-travel pattern, we depart from a daily travel pattern. Next, we focus on complex home-based trip chains, which are a common set-up since personal means of transport can easily be returned to the point of departure (usually the home location). For the last research question, we only look at outbound trips to a single destination.

Concerning the considered travel modes, we first include all relevant means of transport to capture the complete activity-travel behaviour. In a second step, we compare car and bicycle travel. The contrast between these two modes is expected to reveal behavioural peculiarities of bicycle travel due to functional differences. Thirdly, we put the focus on the bicycle to disclose typical travel distances to destinations.

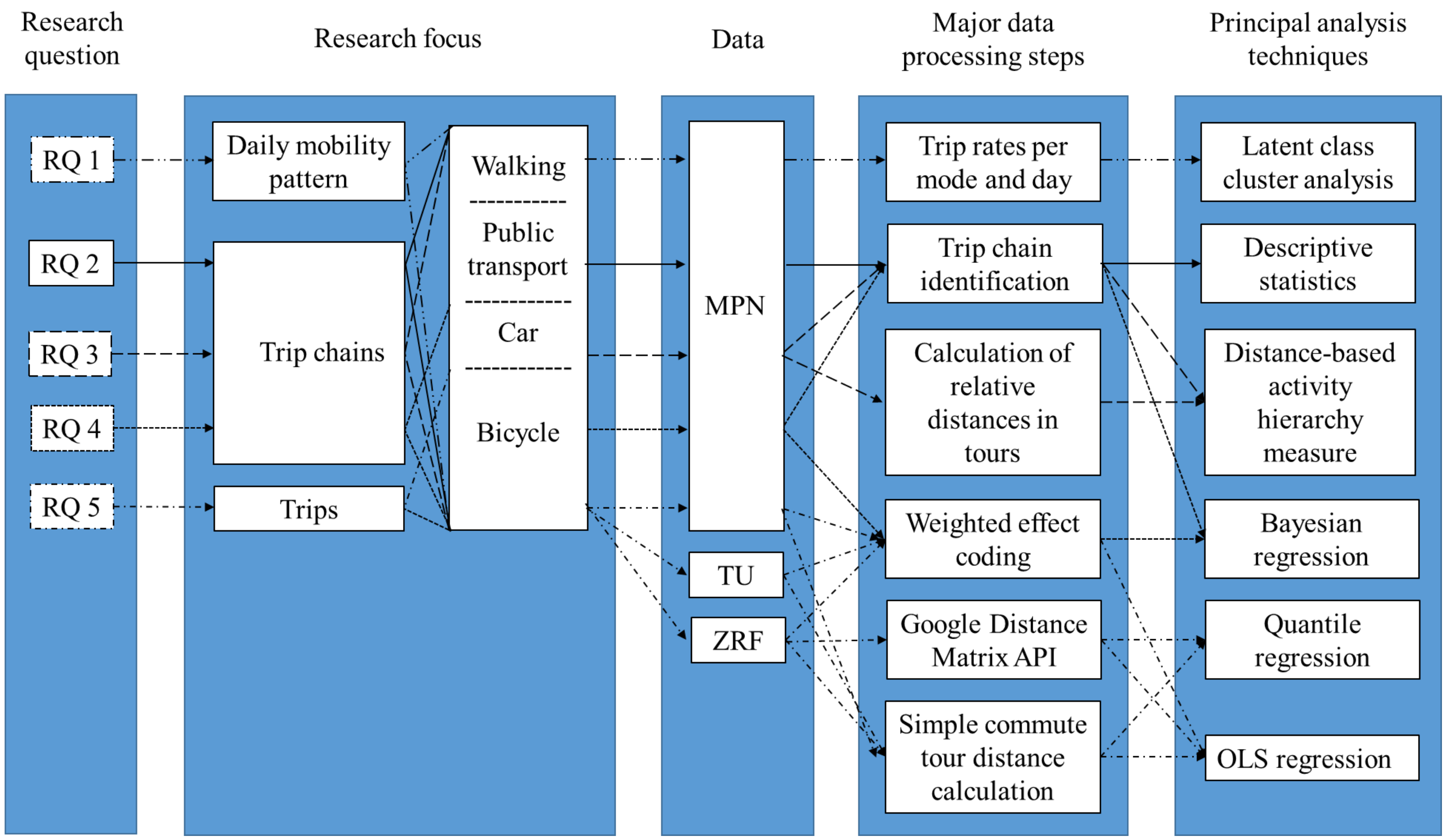

Figure 1.4 Research approach.

Note: RQ = Research Question, MPN = Netherlands Mobility Panel, TU = Danish National Travel Survey, ZRF = Freiburg Region Travel Survey, API = Application Programming Interface, OLS = Ordinary Least Square.

Data

To answer the formulated research questions, quantitative data are necessary that capture both activity participation and related spatial travel behaviour. Since the main focus of the thesis is activity-travelling of cyclists, the data should include a large proportion of observations related to the bicycle. Moreover, data are desirable that fully represent the cycling population (and not only a particular subgroup of it such as students or bicycle activists). In addition, research question one requires data of more than one day per person to derive typical daily travel patterns. Finally, research questions three to five impose that these observations are widely spread across activity types.

The travel diary data of the Netherlands mobility panel (MPN) meet these requirements (Hoogendoorn-Lanser, Schaap, & Oldekalter, 2015). Since 2013, around 4,000 participants from all over the Netherlands are urged each year to report their daily trips and related activities over a 3-day period in time and space. The Netherlands are the international frontrunner of bicycle transportation, accounting for a mode share of 27% of all trips in the country in 2016 (Harms & Kansen, 2018). Or as Fishman puts it, “there is a lot the world can learn from the Dutch experience” (Fishman, 2016, p.1). For these reasons, this thesis mostly used Dutch data from the MPN. In addition to the MPN, data from two other pioneering bicycle regions, the Copenhagen Metropolitan Area in Denmark (TU, Christiansen & Skougaard, 2015) and the Freiburg Region in Southwest Germany (ZRF) were employed in this thesis (Buehler & Pucher, 2011; Pucher & Buehler, 2008). Since both regions have developed separate characteristic bicycle cultures, they provide insights into how the specific environment affects observed activity-travel behaviour by bicycle.

Data pre-processing

The use of travel diary data to study activity-travel behaviour requires recurring data processing. Travel diary data mostly contain a trip-based representation of a person’s travel behaviour during the period of observation. The data usually include the travel mode(s) of the trip, spatial information (starting and ending locations, derived or reported travel distance), trip timing (starting and ending time, derived or reported travel time), the trip purpose and personal characteristics of the traveller. A consequence of the trip-based data format is that activity features have to be (partly) derived. When the activity location equals the ending location of the trip and the activity type corresponds to the trip purpose, the activity duration is the time span between ending time of a trip and starting time of the subsequent trip. Moreover, trip chains have to be derived by merging all trips and activities of home-based cycles. Further data processing steps are described in the respective chapters of the thesis.

Self-reported travel diary data is known to be imprecise. While travel mode (and probably trip purpose) information is relatively reliable, travel times, travel distances and travel frequency have been proven to be error-prone (Berger & Platzer, 2015; Kelly et al., 2014; Witlox, 2007). In this context, in particular short (active mode) trips appear to be often subject to inaccuracy (Witlox, 2007). Since travel distance is the most important measurement unit in this thesis, we compared reported bicycle trip distances to bicycle distances between reported origin and destination, which we calculated using the Google Distance Matrix API. Figure 1.5 presents a percentage histogram of deviations for an exemplary sample of bicycle trips of the MPN travel survey 2016. On average, reported distances were 211 metres longer than the suggested routes from

Google. This systematic deviation is not necessarily linked to over-reporting but can also be caused by route preferences that deviate from the Google routing algorithm. Apart from this small systematic positive difference, most reported distances were very close to the Google distances and positive and negative deviations were quite equally distributed. This symmetry entails that errors (mostly) cancel out at the sample level. The validity of travel diary data at the group level has also been noted in former research (Kelly et al., 2014).

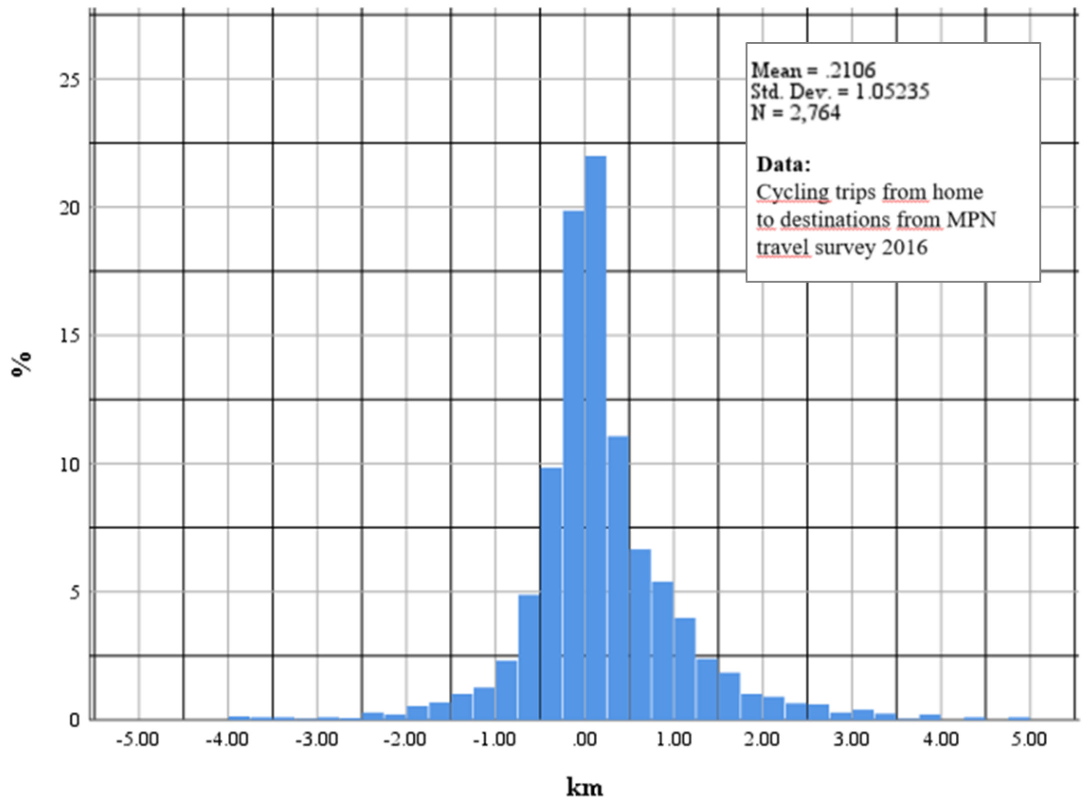

Figure 1.5 Deviations between reported and calculated cycling trip distances.
Google Distance Matrix API was used to calculate cycling distances between origin and destination pairs for which travel distances were reported in the MPN 2016 travel diary.

Analysis techniques

Different types of statistical models are employed, revealing quantitative relationships in the data concerning one of the postulated research questions. The applied methods mostly rely on widely used statistical tools, such as different regression techniques or latent class cluster analysis (LCCA). In addition, we develop a new analysis technique (distance-based activity hierarchy measure) related to research question 3. The LCCA is used to answer research question 1, identifying prevailing mobility patterns in Dutch society. Research question 2 involves descriptive statistics to show typical trip chain patterns for all relevant travel modes. With regard to the regression techniques, we employ Bayesian inference for answering research question 4 due to its advantages when faced with small sample sizes (which resulted from the comparison of car and bicycle trip chaining). Related to research question 5, we use two different regression techniques, namely Ordinary Least Square regression (OLS) and Quantile regression. The former investigates the effects of influence factors on mean travel distances while the latter also reveals the effects of these factors on a part of the distribution that is of particular interest, for instance, the 25 per cent longest trips.

Considering that the formulated research questions are more of explanatory than of predictive nature, the comprehensibility of results is more important than their transferability to other samples. For this reason, we employed weighted effect coding, a coding technique that is particularly useful when investigating differences between groupings such as car and bicycle or the considered study areas. This coding technique can only be used with generalised linear models (such as OLS regression or Bayesian linear regression), which are built on assumptions, such as homogeneity of variance and normally distributed residuals. Since our data did not meet these assumptions, many findings of this thesis pertain to the used samples and cannot be generalised for the underlying population.

1.4 Contributions

This thesis provides several original contributions for both the scientific community and practitioners, which are presented in the subsections 1.4.1 and 1.4.2 respectively.

1.4.1 Scientific contributions

In this subsection, we outline the most relevant scientific contributions of the thesis, extending the understanding of activity-travel behaviour in general and of activity-travelling by bicycle in particular.

Identifying multimodality in daily-life travelling and its implications for activity-travel behaviour by bicycle

In this thesis, we identify typical mobility patterns to indicate the extent to which travellers use more than one travel mode in daily life. These mobility pattern classes extend our understanding of the role of the bicycle for activity-travelling in the Netherlands. Moreover, we extend the literature by providing insights into activity-travel interactions between travel modes of multimodal cyclists. By comparing trip chain complexity distributions of the bicycle between differently composed mobility pattern classes, we reveal bicycle-specific strategies of activity participation.

Analysing the relationship between mode choice and trip chain complexity for all relevant travel modes

We review and extend the relationship between trip chain complexity and mode choice, considering all relevant means of transport. Former research suggests that the complexity of a trip chain affects the related mode choice. It has been hypothesized that the higher temporal and spatial flexibility of the car compared to public transport explains why complex trip chains are rather travelled by car. While the relationship is mostly studied for car and public transport trip chains, we extend the literature by the separate consideration of walking and cycling trip chains. As both modes are characterised by a similar temporal and spatial flexibility than the car, differences in trip chain complexity point to further mode-specific properties affecting trip chaining behaviour. In addition, this study adds to current knowledge by considering multimodal trip chains in an independent travel mode category. This way, the relationship between mode choice and trip chain complexity is fully disentangled.

Developping a method to determine and assess hierarchies of activities in tours based on travel diary data

We propose a data-driven method to derive and assess hierarchies between activities using travel diary data. Knowledge on activity hierarchies is important to understand, for example, how activity-travel patterns are formed. In this context, our method allows for a differentiated and context-specific activity hierarchy analysis. More specifically, it enables researchers to determine prevailing hierarchy schemes for a sample or situation of interest. Moreover, this method also provides a measure of hierarchy strength, which indicates the consistency of a hierarchy across observations. These properties are an improvement over fixed hierarchy schemes between activity types, which assume a stable hierarchy gradient between mandatory and discretionary activities.

Quantifying detours of bicycle and car commuters to include a second activity in home-based tours

We quantify detours within home-based commute tours by bicycle and car in terms of additional travel distance, which are related to the visit of a secondary activity. Furthermore, these detours are explained by a set of factors, such as the type of the secondary activity and characteristics of the traveller. The quantification of detours and the identification of related determinants add to our understanding of spatial trip chaining behaviour and extend the current trip chaining literature. A further contribution pertains to the comparison between bicycle and car trip chaining behaviour. By estimating a comparative model, which disentangles all effects for bicycle and car travel, behavioural similarities and differences are unveiled, indicating bicycle-specific features of travel behaviour in general and trip chaining behaviour in particular.

Identifying determinants of observed cycling distances within an accessibility framework

In this thesis, we identify determinants of revealed cycling distances from three different bicycle-friendly regions within an accessibility framework. Using only outbound trips in simple tours, we show how far people cycle to different types of destinations and how these distances vary depending on a set of contextual factors. This empirical analysis of cycling distances adds to our understanding of the spatial dimension of activity-travelling by bicycle. Notable contributions thereby arise from the way how we analyse the effects of destination type and contextual factors. The model design disaggregates these effects for the three considered regions, shedding light on local peculiarities of bicycle activity-travel behaviour. In addition, we do not only model the effects on mean-distances but also on different quantiles of the cycling distance distribution (in particular quantiles of the highly informative right tail). By doing so, meaningful insights are gained about the context in which longer cycling distances can be expected. Thanks to the study design, the findings of this analysis especially contribute to the increasing literature on bicycle accessibility. Since travel distance is a common measure of accessibility, the analysis provides much needed empirical underpinning of what is accessible by bicycle.

1.4.2 Practical implications

As set out in the introduction, a mode shift from car to bicycle is a way for cities to solve many transport-related issues. The findings of this thesis contribute to the knowledge that is necessary to create seductive urban environments for bicycle activity-travelling. More specifically, insights gained in this thesis are expected to support both policy-makers and urban planners.

First, this thesis provides valuable insights for policy-makers. The disclosure of the current cycling population and the trip purposes to which they prevailingly travel by bicycle is valuable knowledge to elaborate dedicated policy measures to increase the bicycle mode share. These measures could be dedicated to tempting the non-cycling population to use the bicycle from time to time or to make underrepresented activity types more attractive for those that cycle already. In addition, the international comparison between the Netherlands, the Copenhagen Metropolitan Area and the Freiburg Region (Germany) provides some signals about how political and regulatory conditions might be linked to local peculiarities of cycling behaviour. These conditions can include for example road traffic regulations, financial conditions for (e-)bicycle or car use and prevailing bicycle infrastructure and network design principles.

Second, the findings of this thesis can be used by urban planners. In the past, several theoretical concepts such as the compact city have been developed to make urban land-use structures more attractive for bicycles. However, while the related principles such as urban density and land-use mix can guide the urban planning process, the elaboration of concrete plans requires reference values of bicycle accessibility. For instance, to assess the catchment area of a supermarket for cyclists, an understanding of how far people travel by bicycle for grocery shopping is necessary. Similarly, other frequently visited activity locations such as schools or day-care centres can be planned according to the bicycle reach of the respective user groups. This thesis aims to provide first insights into typical travel distances by analysing revealed bicycle-activity travel behaviour in best-practice environments.

1.5 Outline of the thesis

The outline of this thesis is illustrated in Figure 1.6. It presents the sequence of the five chapters and the research questions to which they refer (in red).

Chapter 2 provides context on the activity-travel behaviour of cyclists. A latent class cluster analysis on mobility patterns shows with which other travel modes the bicycle is often combined in daily life travelling. In addition, typical trip chaining behaviour was studied for all mobility pattern classes and all separate travel modes. Moreover, an analysis of trip chain patterns was performed looking into interdependencies between the travel modes of a mobility pattern.

To interpret spatial patterns of complex trip chains, a method for activity hierarchy analysis has been developed in Chapter 3. A hierarchy scheme is established based on relative distances in home-based tours. These hierarchies between activity types are compared to hierarchies derived from activity durations (since duration was found to be a good proxy for the importance of an activity in the activity planning process (Doherty & Mohammadian, 2011)). As a use case, the method is applied to investigate both the effect of bicycle compared to car travel and the effect of urban density on activity hierarchies.

Since work appeared to be the most consistent primary activity in the activity hierarchy analysis, Chapter 4 investigates spatial trip chaining behaviour for commute tours. The chapter studies the determinants of distance extensions related to adding a secondary activity to a commute tour. In the analysis, trip chaining behaviour of cyclists and car users are contrasted.

Chapter 5 provides benchmarking data on bicycle accessibility from the Netherlands, the Copenhagen Metropolitan Area and the Freiburg Region in Germany. Embedded in a description of the respective cycling environments, the analysis identifies typical travel distances from home to destinations and reveals underlying determinants. Both observed travel distances and the effects of explanatory variables are compared between the three considered regions.

In Chapter 6, conclusions are drawn based on the main findings. Furthermore, results are discussed in light of the used data source. Finally, the implications of this thesis for practice are outlined before indicating directions for future research.

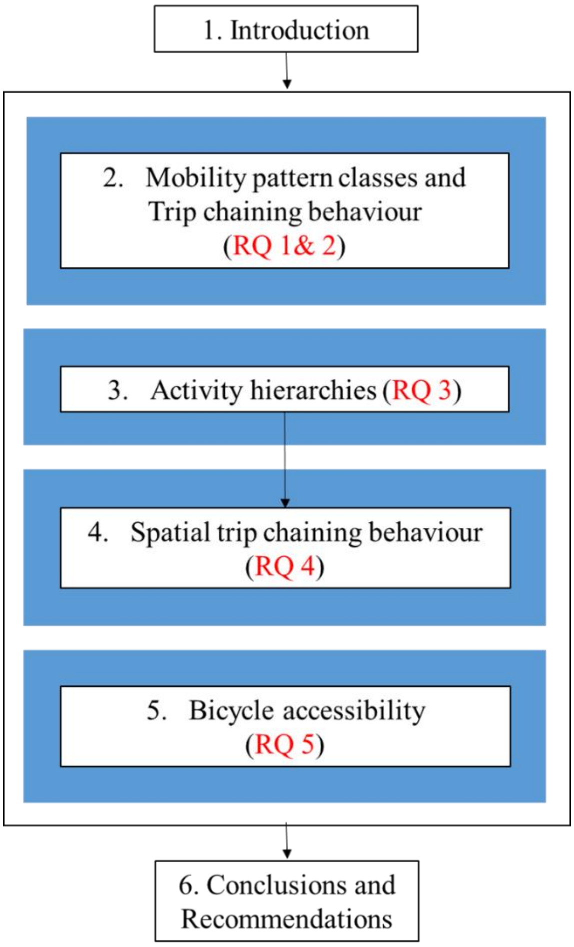

Figure 1.6 Outline of the thesis.

2. Mobility Pattern Classes and Trip chaining behaviour

First, this second chapter sets the scene for the analysis of activity-travel behaviour of cyclists by examining daily travel mode combinations that are used to implement an activity programme. In the context of this thesis, a cyclist is a person who uses the bicycle to reach locations where he or she is performing activities from his or her personal activity agenda. This definition includes people who do all their activity-travelling by bicycle, but also people who use the bicycle occasionally. Depending on the travel mode mix, the bicycle can have different roles in implementing a daily activity programme. By deriving daily mobility patterns, we indicate typical travel mode combinations that are used for activity-travelling as well as the respective contribution of the bicycle to each of them. This way, the extent to which cyclists are multimodal activity-travellers will be revealed, answering research question 1. With respect to the research objective of the thesis, this first part of Chapter 2 sheds light on the notion of what is a cyclist in the context of activity-travelling. Moreover, it puts activity-travel behaviour by bicycle into perspective concerning its role for implementing the activity programme of a cyclist.

And second, Chapter 2 analyses travel mode-related activity-travel patterns. This represents a change of perspective in comparison to the first part of Chapter 2. The former looks at typical travel mode combinations that people use to implement an activity agenda, whereas the latter investigates mode-specific features of activity-travelling with a focus on the bicycle. More specifically, this second part analyses the so-called trip chain complexity, that is the number of activities included in a trip chain. While little is known about the complexity of bicycle trip chains, trip chaining behaviour is an important aspect of understanding activity-travel behaviour. Complex (i.e. multiple destinations) trip chaining has the potential to allow activity participation with less travel (Duncan, 2016). Differences in complexity degrees between travel modes point to mode-specific features, which are relevant for understanding activity-travel behaviour. By investigating typical trip chain complexity patterns of all relevant travel modes, we reveal the extent of complex trip chaining by bicycle and, thereby, respond to research question 2.

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2.1 Introduction

Mode choices can realistically be studied within the scope of trip chains. A trip chain or tour describes a sequence of trips that starts and ends at the home location (Primerano et al., 2008). Since the decision of the first travel mode often determines the available travel modes at subsequent stages of a journey, mode choice decisions are likely to consider more than only the next trip. Most studies on travel behaviour indicate that trip chaining precedes mode choice (Krygsman et al., 2007; Li et al., 2013; Yang et al, 2016; Ye et al., 2007). This means that people first arrange their out-of-home activities in trip chains and then select one or more available travel modes that are convenient for the planned trip chain. The number of included activity locations, generally referred to as trip chain complexity (e.g., Currie & Delbosc, 2011), seems to influence mode choice. Most studies suggest that the more trip chains are getting complex, the more the traveller is inclined to use the car and the less likely he or she is to choose public transport (Hensher & Reyes, 2000; Krygsman et al., 2007; Primerano et al., 2008). While these findings revealed a mode choice propensity for independent trip chains, the implications for a person's day-to-day mode choice behaviour remain unclear. However, it is precisely these implications that are of great interest when performing any kind of scenario analysis that affects trip chain complexities (e.g., changing levels of time scarcity). For this reason, we study the relationship between trip chain complexity and mode choice behaviour using the full activity-travel pattern of a person as a starting point.

The planning process that underlies activity-travel patterns is named trip chain or tour formation (Lee & McNally, 2006). In this process, a person schedules his or her out-of-home activities and, thereby, determines the proportion of simple compared to more complex trips chains in the activity-travel pattern. Former research identified features of the traveller such as age, gender or working hours which affect associated trip chain complexities (Chen & Akar, 2017; Currie & Delbosc, 2011; Frank et al., 2008; Frignani et al., 2011; Hensher & Reyes, 2000; Islam & Habib, 2012; Primerano et al., 2008; Ye et al., 2007). This means that all trip chains of this person have a similar complexity tendency and are therefore not independent. Besides these factors describing the traveller and his or her environment, dependencies between trip chains also arise from the person's activity programme. As the activity programme (i.e., a list of recurring out-of-home activities that have to be performed) is input for the trip chain formation, the complexities of trip chains are often interdependent. For instance, people might not go to the gym every day, entailing that trip chain complexity potentially boosts on one day but not on another.

Based on the literature that we have seen above, the dependencies between trip chains within an activity-travel pattern can have two different implications for a person's day-to-day mode choice behaviour. First, the literature suggests that people with considerably different characteristics regarding trip chain complexity factors are supposed to have clearly distinguishable trip chain complexity profiles (i.e., the composition of simple chains compared to complex trip chains), which in return result in specific mode choice patterns. Assuming this causal relationship, one would expect to find people who mostly use the car to have a more complex trip chain complexity profile than people who regularly use public transport. Second, the dependencies induced by a person's activity programme might entail interactions between trip chains, which again affect mode choices. For instance, one might observe regular public transport users that outsource a part of the necessary trip chain complexity to implement their activity programmes to moments in which a car is available. However, it would also not be surprising if people simply travel with their routine travel mode, regardless of the complexity of their trip chains.

In order to reveal the interactions between trip chain complexity and mode choice within the activity-travel pattern of a person, all travel modes have to be considered. To date, however, research on trip chain complexity has mainly focused on the comparison between car and public transport (e.g. Hensher & Reyes, 2000; Yang et al., 2016) or, similarly, non-car trip chains (Ye et al., 2007). Only within a full activity-travel pattern, we can understand how an activity programme is implemented with regard to complexity across trip chains and how these complexities affect a person's day-to-day mode choice behaviour. The given examples illustrate that current knowledge is not sufficient to understand this relationship. Therefore, one key question needs to be answered. That is, whether a person's aggregated mode choices are reflected by the complexities of his or her trip chains. Or, differently formulated, if trip chain complexities vary between people that have distinct mode choice behaviour.

This paper extends the literature by investigating exactly this latter question. We meet this research objective by first identifying classes of people with homogeneous mode choice behaviour (in the following referred to as mobility pattern classes) using a latent class cluster analysis on data from the Netherlands Mobility Panel. Subsequently, we derived individual trip chains from the same data set and assigned each trip chain to a travel mode and the mobility pattern class of the traveller. Trip chain complexity was then analysed and compared between travel modes and mobility pattern classes.

This paper has two major contributions. The first contribution is the consideration of all relevant travel modes. The explicit inclusion of the active modes and the independent travel mode category "multimodal trip chains" extends current knowledge and gives more differentiated insights into the relationship between trip chain complexity and mode choice. The second contribution is the change of scope from independent trip chains to dependent trip chains within a person's activity-travel pattern. This approach provides valuable information on how trip chain complexity relates to average mode choice behaviour rather than to detached components of it.

In the remainder of this paper, we describe the data sample in section 2.2. In section 2.3, we outline the research methodology, including performed mobility pattern derivation, trip chain identification and trip chain complexity analyses. Subsequently, the results of all analysis steps are presented and discussed in section 2.4. Finally, we provide concluding comments and recommendations for future research in section 2.5.

2.2 Data: the Netherlands Mobility Panel

The latent class cluster analysis and the trip chain identification imply specific requirements on the data (see also sections 2.3.1 and 2.3.2). Enriched travel diary data are needed that represent typical activity-travel behaviour. This entails that for every trip complete information on the origin and destination, its travel mode and the related trip purpose is necessary. Moreover, further characteristics related to the traveller and the traveller's environment are needed to comprehend the composition of the sample and the different mobility pattern classes regarding important trip chain factors. In addition, the data should provide trip observations of more than one day to better represent a person's average travel behaviour and trip chain complexity profile. Finally, enough people should be included in the sample to identify prevailing mobility patterns.

We based our research on data of the Netherlands Mobility Panel (MPN) of 2016. The Netherlands Mobility Panel includes a series of different surveys conducted repeatedly with the same participants. It has been described in more detail in Hoogendoorn-Lanser et al., 2015. The current analysis used data from a fusion of a 3-day travel diary, a linked personal and household survey and a dedicated survey on perceptions, attitudes and wayfinding strategies. While the fusion between travel diary data and related personal and household attributes was required for the present study, the inclusion of the survey on perceptions, attitudes and wayfinding strategies was conducted in view of follow-up analyses.

The data processing embraced the following steps:

- Only participants were selected who completed all surveys.
- Weekend trips were eliminated. As weekday and weekend travel behaviour is quite different (e.g. Ho & Mulley, 2013b; Liu, 2009; Yang et al., 2016), we focussed on weekday travel behaviour which is assumed to be more routine-driven (hence, fewer observations are necessary to derive the average mode choice behaviour of a person).
- Only utilitarian trip purposes were considered that lead towards an activity location in order to correspond to the concept of activity-travelling (e.g. no strolling, touring or professional driving).
- Suspicious trip data (i.e. trips that have unlikely reported properties), as well as trips with an origin or destination outside of the Netherlands, were grouped in the category “Other trips”. This approach allows displaying the complete activity-related travel behaviour of a person (and e.g. recognizes that a person travelled on a day) while taking into account the potential misrepresentation of data.
- Trips were assigned to one of the travel mode categories car, public transport, bicycle, walking and ‘others’. The category car includes both trips as a driver and trips as a car passenger (including taxi). Public transport covers heavy rail and all means of urban mass transit. Rather uncommon travel modes such as inline skates or boats are assigned to the category ’Other trips’.

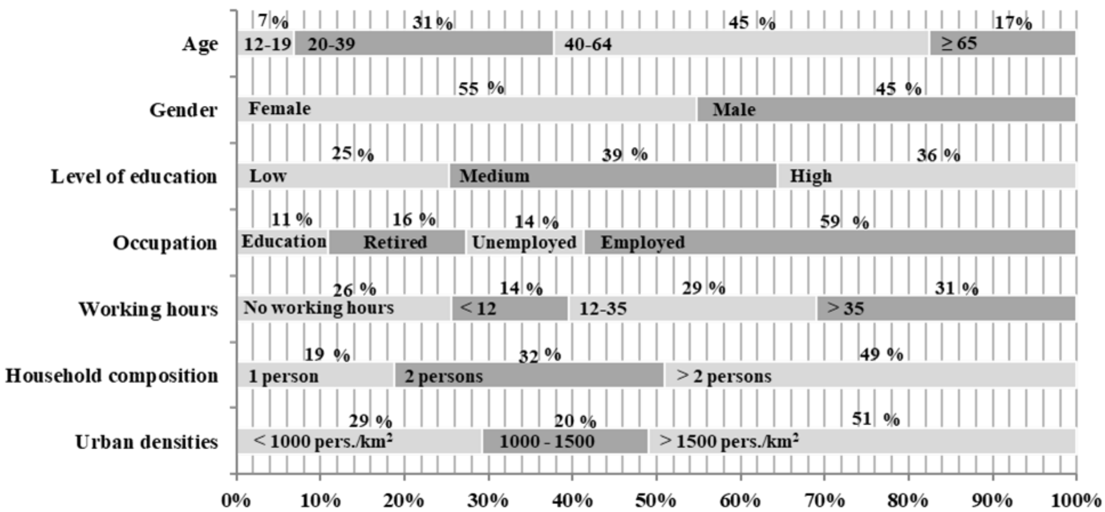


Figure 2.1 Socio-demographic characteristics of the sample.

Altogether, the data contains 17,189 trips stemming from 2,425 persons. Figure 2.1 gives an overview of the socio-demographic characteristics of the participants. The sample is characterized by a high share of females, a predominant proportion of people in working age and a substantial part of respondents that work part-time. Furthermore, people live prevailingly in multi-person households and in urban environments.

Table 2.1 presents mobility rates per travel mode, the extent of non-travel behaviour and the average number of reported travel days of the sample. The indicated mobility rates represent the means of the sample that were calculated based on average mobility rates of each participant over the reported days (excluding weekend). The percentage of non-travel behaviour gives the mean value of the proportion between indicated days without any travel activity and the reported days of each participant. A comparison with data from Statistics Netherlands (Centraal Bureau voor de Statistiek, 2016) shows that mobility rates of the sample are essentially in line with Dutch mobility behaviour.

Table 2.1 Mobility indicators of the sample.

	Car trips/day	PT trips/day	Bicycle trips/day	Walking trips/day	Other trips/day	Non-travel ratio [%]	Reported days
MPN	1.4	0.2	0.9	0.4	0.4	12.8	2.1
CBS[1]	1.2	0.2	0.8	0.5	0.1[2]	-	1

[1] Average mobility rates per travel mode are shown for trips made on Wednesdays in 2016; [2] includes only trips made with other travel modes than car, PT, bicycle or by foot.

Given the data requirements defined above, the used data provides rich and sufficiently representative information on Dutch mobility behaviour. The sample includes enough people and trips to identify prevailing mobility patterns. However, the number of around seven trip observations per person does not allow to detect representative trip chain complexity profiles per participant. Therefore, trip chains were aggregated for people that have similar travel behaviour (see the following section).

2.3 Research methodology

The purpose of this study is to examine the relationship between trip chain complexity and mode choice on an aggregated level, that is, between all trip chains of a person and the day-to-day mode choice behaviour. Figure 2.2 schematically illustrates the scope in the framework of activity-travel behaviour.

As we have seen in the introduction, decisions on how activities are tied together (i.e. trip chain formation) are usually made before making mode choice(s). The trip chain formation is fuelled by the out-of-home activities that a person needs to do (conceptualized in Figure 2.2 as out-of-home activity programme) and determines the complexity degree of each trip chain. Trip chain complexity, in turn, influences the mode choice. All these choices are person-dependent and translate an individual's need for activity participation into typical mode choice behaviour. For this reason, the relationship between trip chain complexity and mode choice, which is the scope of this analysis (indicated in Figure 2.2 by a black frame), should preferably be studied at the level of an individual.

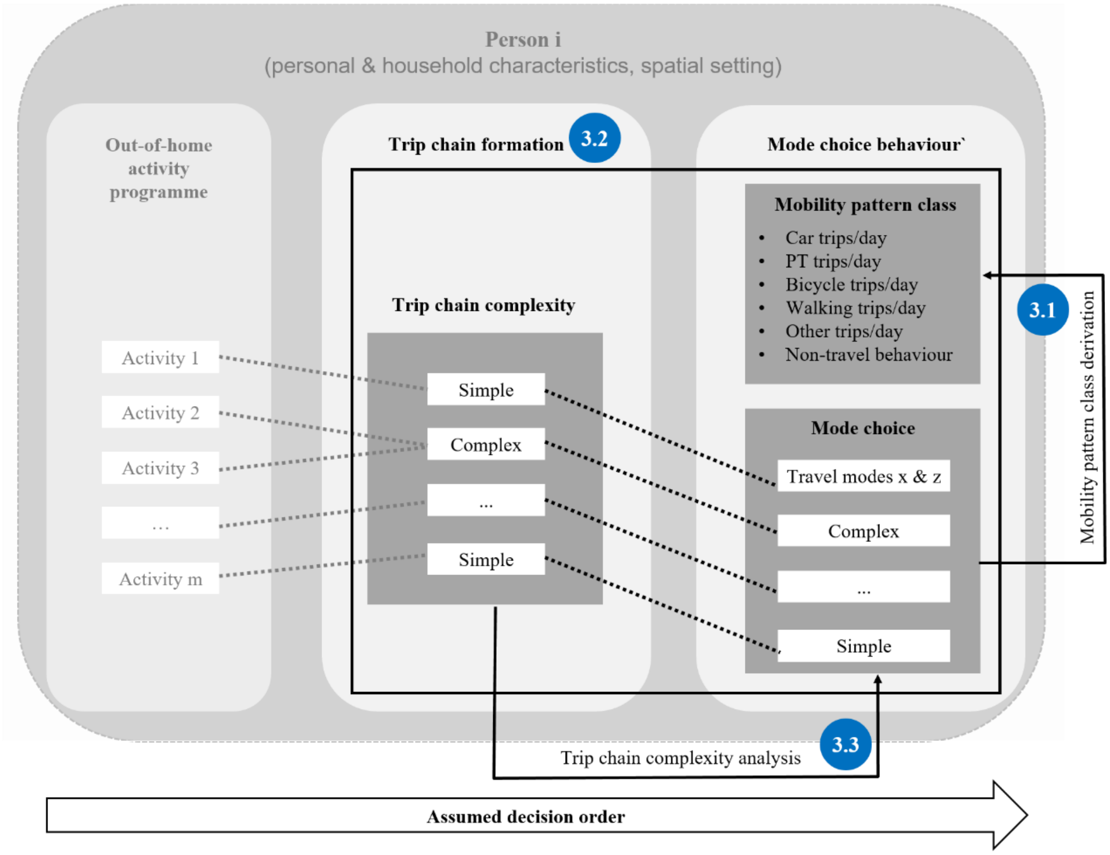


Figure 2.2 Scope of the study in the context of activity-travel behaviour.

Note: The different trip chain complexity analyses are visualised in Figure 2.3.

Due to the described characteristics of the data, however, aggregation of trip chains was necessary. In order to still capture the relationship between trip chain complexity and a person's average mode choice behaviour, we grouped trip chains of people with similar mode choice behaviour into mobility pattern classes. By doing so, every identified trip chain could be assigned to a trip chain complexity degree on the one hand, and a mobility pattern class and a travel mode category on the other hand (see section 2.3.2). This set-up allowed to analyse the relationship between trip chain complexity and mode choice at two different zoom levels, namely at the level of independently treated trip chains for the analysis between travel modes and at the level of bundled person-dependent trip chains (which theoretically includes full activity-travel patterns of people as nests) for the analysis between mobility pattern classes. In the following, the derivation of mobility pattern classes (section 2.3.1), the trip chain identification and association (section 2.3.2) and the trip chain complexity analyses (section 2.3.3) are described in detail.

2.3.1 Derivation of mobility pattern classes

In this analysis, a *mobility pattern* was used as an approximation of a person's day-to-day mode choice behaviour. It describes the average trip rates per travel mode and day. Therefore, we divided the number of reported week trips per travel mode by the number of reported weekdays. We used trip rates rather than a mode share ratio to not only indicate the composition of a person's travel mode portfolio but also the extent of mobility. In addition to the trip rates of the five defined travel mode categories, a ratio of reported non-travel behaviour (number of reported non-travel days divided by the number of reported days) was included in the mobility pattern. This measure adds valuable information on how a person's day-to-day travel behaviour is structured.

Based on this definition, a large number of individual mobility patterns is possible. Due to the explained data constraints, aggregation of mobility patterns into classes was necessary. For this cluster task, we applied a latent class cluster analysis (LCCA) using the software package *Latent Gold*. A description of this two-step cluster technique has been provided by Vermunt & Magidson (2002). The LCCA is a suitable tool because, contrary to k-means, the number of classes is not (arbitrarily) predefined by the researcher but can be specified based on statistical information criteria. Another advantage of LCCA is that no standardisation of mixed-scale indicator variables (as we have with trip rates and non-travel ratios) has to be conducted.

In a LCCA, associations between indicator variables are captured by a (categorical) latent variable in a first step. According to the definition of the mobility patterns given above, average trip rates per day and mode and the ratio of non-travel behaviour were used as indicators for the corresponding latent variable. In this analysis, the number of classes was determined by means of the Bayesian Information Criterion (BIC) and the relative reduction of log-likelihood increase (LL).

Once the optimal number of classes is found, a LCCA model predicts in a second step the class membership of every individual using exogenous variables, the so-called covariates (Vermunt & Magidson, 2002). Therefore, potential covariates were derived from the literature (age, gender, level of education, occupation, working hours, household composition and urban density; see for example De Haas et al., 2018) and tested regarding their suitability to predict the class membership of the respondents. The combination of active covariates that had led to the highest log-likelihood was included in the final model, others were kept as inactive covariates to display the composition of the classes. Respondents were assigned to the class with the highest degree of affiliation. An in-depth description of the model development can be found in Ton et al. (2019). The results of the LCCA are presented in section 2.4.1.

2.3.2 Trip chain identification and association

Trip chains were identified using the same data set as for the latent class cluster analysis. In order to be recognized as a trip chain, a sequence of at least two trips of a person had to satisfy the following conditions:

- The sequence starts and ends at the home location.
- The origin of each trip is the destination of the preceding trip (with the exception when the origin is the home location).
- All trips are reported for the same calendar day.

Subsequently, trip chains were assigned to a trip chain complexity level, a mobility pattern class and a travel mode. Trip chain complexity was categorized in simple (two trips), complex (three trips) and very complex trip chains (four or more trips). This aggregated latter category was designed in a way that it contained enough observations to conduct the analyses described in the next section (compare Figure 2.4d). The assignment of a trip chain to a mobility pattern class was made based on the class membership of the traveller. Concerning the travel mode, unimodal trip chains (i.e. trip chains where all trips were made with the same travel mode) were assigned to the categories ‘Car’, ‘Public transport’, ‘Bicycle’ and ‘Walk’. Trip chains in which the separate trips were travelled by different main travel modes (e.g. the bicycle for the trip to work and public transport for the trip back home) were associated with an additional travel mode category ‘Multimodal’. This approach is different from approaches in former studies, in which the main travel mode was assigned to the complete trip chain based on a fixed hierarchy order between travel modes (Currie & Delbosc, 2011; Frank et al., 2008; Ho & Mulley, 2013a; Yang et al, 2016; Ye et al., 2007). The proposed approach reveals, on the one hand, the proportion of multimodal trip chains. On the other hand, it discloses their trip chain complexity profile. The recognition of multimodal trip chains as a separate travel mode category reveals these aspects and avoids potential inconsistencies between seemingly unimodal trip chains and related multimodal mobility patterns. Trip chains that included trips related to the category ‘Other trips’ were filtered out. While these trips were seen as a significant element to describe a person’s mobility pattern, related trip chains were not considered in the following trip chain complexity analysis because of their unclear and possibly ambiguous interpretation. The properties of the trip chain sample are outlined in section 2.4.2.

2.3.3 Trip chain complexity analysis

This core part of the study includes three analyses of trip chain complexity that are conceptualized in Figure 2.3.

The first analysis investigated trip chain complexity between travel mode categories. Therefore, trip chains were ordered by travel modes. The purpose of this analysis is to make this study (and the underlying data) comparable to former research on the topic. In addition, the separate consideration of all defined travel mode categories provided first insights into the elements that affect trip chain complexity on the aggregated mobility pattern level, namely trip chains travelled by different travel modes.

In the second analysis, trip chain complexity was statistically compared between mobility pattern classes by analysing differences in trip chain complexity distributions (i.e. the proportions of simple, complex and very complex trip chains). Considerably different complexity distributions would lend confidence to the notion that there is a systematic relationship between the complexity degrees of people’s trip chains and their mobility patterns.

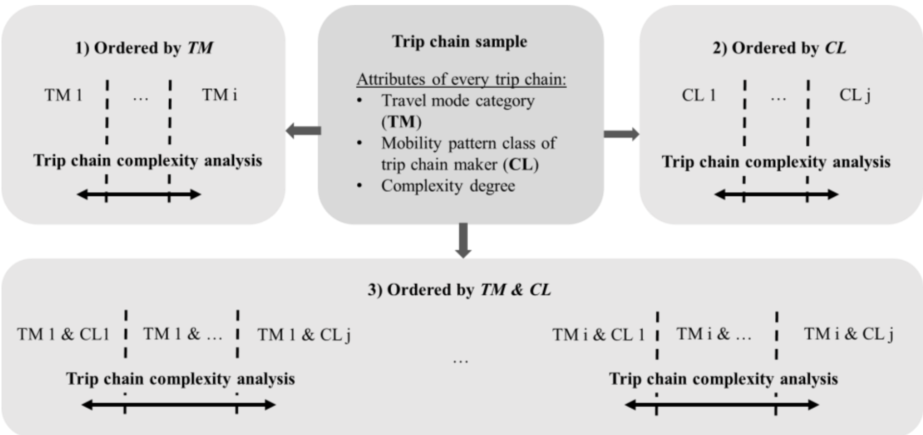


Figure 2.3 Different analyses of trip chain complexity.

The third analysis studied trip chain complexity distributions of every travel mode separately between mobility pattern classes. By doing so, we could see if trip chain complexity varies between mobility pattern classes and if such a variation correlates with the variation of another mode.

A series of descriptive and inferential statistics was applied to study differences in trip chain complexity. For the first analysis, only distributions of trip chain complexity degrees are presented as this analysis was mainly used as a benchmark. For the second and third analyses, differences in trip chain complexity were in addition interpreted by means of Pearson's chi-square tests. This test allows investigating a relationship between two categorical variables (Fisher, 1922). The first considered variable was trip chain complexity and the second a grouping variable that either refers to a mobility pattern class (second analysis) or a combination of mobility pattern class and travel mode (third analysis). The null hypothesis of each chi-square test was that trip chain complexity does not differ between the respective levels of the grouping variable. The null hypothesis was rejected in favour of the alternative hypothesis (i.e. there is a significant difference) at a 5% level of significance. In cases, in which the chi-square test could not reliably approximate the chi-square distribution due to small sample sizes, the Fisher's exact test was applied to compute the exact probability of the chi-square statistic (Fisher, 1922). This test was conducted when more than 20% of the cells in the contingency table had expected counts below five. The magnitude of the relationship between the two variables was assessed based on Cramér's V. This measure of association responds to the question concerning the extent to which trip chain complexity is different between mobility pattern classes, indicating a small effect size for values from .1 on, a medium from .3 on and a large effect for values greater than .5 (Field, 2009). For the third analysis, the study of differences additionally included the interpretation of adjusted standardized residuals to capture potential interdependencies between trip chains of different travel modes. As these residuals were converted to Z-scores, absolute values larger than 1.96 indicate that an observed frequency in the contingency table is significantly deviating from the expected counts at a .05 level of significance.

The chosen methodology is the outcome of extensive screening of data analysis techniques given the available data. The necessary aggregation of trip chains of people with similar mode choice behaviour in mobility pattern classes prevented the use of a more advanced statistical model (e.g. a multinominal logistic regression which treats the mobility pattern class as the outcome of a trip chain complexity profile and socio-demographic characteristics). However, the used analysis approach serves the main purpose of this study. That is, understanding if trip chain complexity affects day-to-day mode choice behaviour when considering dependencies between the trip chains made by the same person.

2.4 Results and discussion

Following the approach described in the methodology section, the resulting mobility pattern classes of the latent class cluster analysis are described and discussed in section 2.4.1. In section 2.4.2, the identified trip chains are outlined regarding important properties of the complete sample (i.e. their distribution on the mobility pattern classes, travel mode categories and trip chain complexity levels) to put the outcomes of the later steps into perspective. Finally, the results of the three different trip chain complexity analyses are presented in sections 2.4.3, 2.4.4 and 2.4.5.

2.4.1 Mobility pattern classes

In total, ten latent class models considering one to ten classes were compared using their BIC and log-likelihood reduction (LL). The model with the best performance distinguished five classes of daily weekday mobility patterns and included gender, education, occupation status, the number of household members and the municipal urban density level as active covariates. The classes were named and in the remainder of the paper referred to as ‘Car & bicycle’ (CB), ‘Exclusive car users’ (C), ‘Car & walk & bicycle’ (CWB), ‘Public transport+’ (PT+) and ‘Exclusive bicycle users’ (B) based on the most used travel modes they incorporate. The provided Wald statistics assess the significance of each indicator and covariate for the LCCA model (Vermunt & Magidson, 2005). The results suggest that all indicators and active covariates were significantly different between mobility pattern classes and, therefore, contribute to the postulated LCCA model. A summary of the results of the chosen model is provided in Table 2.2.

Table 2.2 shows that the 2,425 participants were unequally distributed over the mobility pattern classes. The classes ‘Car & bicycle’, ‘Exclusive car users’ and ‘Car & walk & bicycle’ were the largest, containing each around a quarter of all participants of the travel survey. The two smaller classes ‘Public transport+’ and ‘Exclusive car users’ still contained more than 200 people, and as such deserved a separate class, given their specific mobility behaviour. Car or bicycle trips were present in four classes, followed by other trips (three), and walking trips (two). Trips travelled by public transport were only present in the class ‘Public transport+’. Correspondingly, the different classes included people that potentially use five (PT+), four (CWB), three (CB) or only a single travel mode (C, B) in daily travel behaviour. This means that more than 60% of the participants were associated with multimodal day-to-day travel behaviour.

Furthermore, different averages of mobility and reported non-travel behaviour could be observed in Table 2.2. The trip rates deviated considerably from the total average of 3.3 trips per person and day (see Table 2.1). While people of the class ‘Car & walk & bicycle’ made on average 4.6 trips per day, the unimodal classes ‘Exclusive car users’ and ‘Exclusive bicycle users’ were characterised by lower numbers of trips (2.2 and 2.7 respectively). These values can be seen as a proxy for each class’s extent of out-of-home activity participation. With regard to reported non-travel behaviour, the high proportion of the unimodal class ‘Exclusive car users’ stood out. The personal and household characteristics of this group suggest that this exceptional value might be caused by a high degree of telework.

In sum, characteristic mobility pattern classes have been established that differ regarding included travel modes, mobility extent and reported non-travel behaviour as well as in their degree of multimodality. A discussion of the characteristics of each mobility pattern class, especially with respect to the active and inactive covariates, and a more detailed description of the mode development can be found in Ton et al. (2019).

Table 2.2 Results of the 5-class latent class analysis on daily weekday mobility patterns.

	Classes	**CB***	**C***	**CWB***	**PT+***	**B***
	Class size (%)	27.5	27.0	23.7	12.3	9.5
Indicators						
Car trips (Wald=2470.41, p<0.001)	Mean	1.6	2.2	1.5	0.6	0
PT trips (Wald=1178.14, p<0.001)	Mean	0	0	0	1.4	0
Bicycle trips (Wald=2081.45, p<0.001)	Mean	1.2	0.0	1.1	0.6	2.7
Walking trips (Wald=1221.83, p<0.001)	Mean	0.0	0.0	1.5	0.4	0
Other trips (Wald=743.82, p<0.001)	Mean	0.9	0	0.5	0.3	0
Share of non-travel days (Wald=298.01, p<0.001)	Mean	6%	32%	4%	6%	6%
Total trips/day	**Mean**	**3.7**	**2.2**	**4.6**	**3.3**	**2.7**
Active covariates						
Gender (Wald=15.43, ρ<0.01)	Female	55%	49%	60%	54%	58%
	Male	45%	51%	40%	46%	42%
Education (Wald=21.04, ρ<0.01)	Low	26%	22%	24%	23%	35%
	Medium	39%	42%	40%	36%	33%
	High	34%	36%	36%	41%	32%
Occupation (Wald=268.15, ρ<0.001)	Study/school	8%	3%	5%	34%	26%
	Retired	22%	12%	21%	9%	12%
	Unemployed	13%	15%	20%	4%	13%
	Employed	57%	70%	54%	53%	50%
Household members (Wald=23.72, ρ<0.01)	1	18%	15%	21%	26%	18%
	2	32%	32%	38%	26%	27%
	3 or more	50%	53%	42%	48%	54%
Urban density (Wald=32.66, ρ<0.001)	High	49%	47%	50%	62%	57%
	Medium	23%	16%	21%	17%	22%
	Low	28%	37%	29%	22%	22%
Inactive covariates						
Age	12-19	6%	2%	3%	15%	22%
	20-39	25%	34%	28%	48%	24%
	40-64	46%	52%	46%	27%	40%
	Over 64	23%	13%	23%	10%	13%
Working hours	No work	27%	20%	29%	24%	32%
	Less than 12	14%	10%	16%	17%	17%
	12-35	31%	29%	31%	24%	27%
	More than 35	28%	41%	24%	36%	24%

** CB= Car & bicycle, C= Exclusive car users, CWB= Car & walk & bicycle, PT+= Public transport+, B= Exclusive bicycle users*

2.4.2 Properties of the identified trip chains

In total, 5,121 trip chains could be extracted from the data, stemming from 2,004 persons. Figure 2.4 gives an overview of important characteristics of the total trip chain sample that helps to interpret the results of the following trip chain complexity analysis.

Figure 2.4a shows the number of trip chains that were related to each mobility pattern class. The distribution followed, in essence, the distribution that results from multiplying the class size shares by the corresponding trip rate without ‘other trips’ (see Table 2.2). While not all trips could successfully be tied together to home-based trip chains, all mobility patterns accounted for enough trip chains to perform the intended statistical procedures and tests.

Figure 2.4b presents how trip chains were distributed across travel mode categories. Trip chains were predominantly travelled by only one travel mode, though a part of around 5% included at least a second travel mode category in the course of a home-based tour. Even though the high shares of bicycle and walking trip chains might be higher than in many other places, the results suggest that research on trip chaining behaviour (which has mainly focused on the comparison between the car and public transport, e.g. Yang et al., 2016) should pay greater attention to the active modes. Furthermore, the exploration of the independent group of multimodal trip chains will add new insights to our understanding of the relationship between trip chain complexity and mode choice as, to date, these trip chains have either been assigned to the dominant travel mode or filtered out (e.g. Krygsman et al., 2007).

Figure 2.4c illustrates how trip chains of different travel mode categories composed each mobility pattern class. Besides the unimodal mobility pattern classes ‘Exclusive car users’ and ‘Exclusive bicycle users’, all mobility pattern classes included trip chains of at least three different travel mode categories.

Figure 2.4d provides the overall trip chain complexity distribution. The figure shows that the prevailing part of the trip chains contained only two trips (i.e. one activity location). Trip chains including two or three activity locations were still frequently found while more complex trip chains were rarely observed. Also in literature, simple trip chains predominate (Hensher & Reyes, 2000; Ye et al., 2007; Ho & Mulley, 2013a) but often to a lesser extent. This might be caused by differences with respect to the included travel modes, a more detailed reporting behaviour or by a different profile of the sample regarding important trip chain factors (e.g. working hours). Clear identification of the factors that explain the encountered differences in trip chain complexity was not possible due to the unavailability of thorough sample descriptions in most trip chaining papers.

This section shows the relationship between trip chain complexity and mode choice for independent trip chains. In contrast to former studies, trip chain complexity distributions were analysed for all relevant travel modes. By doing so, the knowledge gaps regarding active modes and multimodal trip chains are closed.

2.4.3 Trip chain complexity between travel modes

Figure 2.5 presents the trip chain complexity distribution for each travel mode. The figure shows that unimodal trip chains were most often complex or very complex for the car.

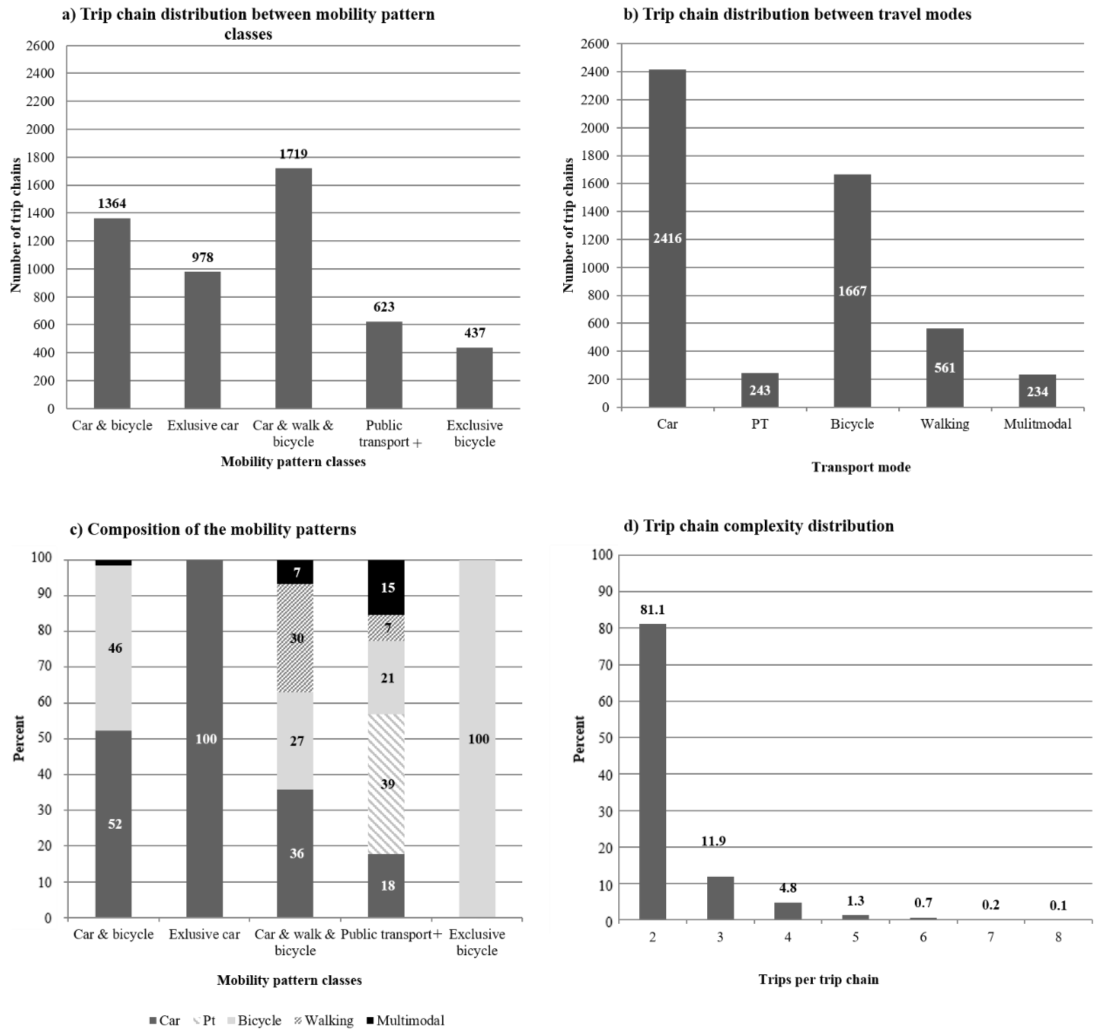


Figure 2.4 Trip chain related distributions.

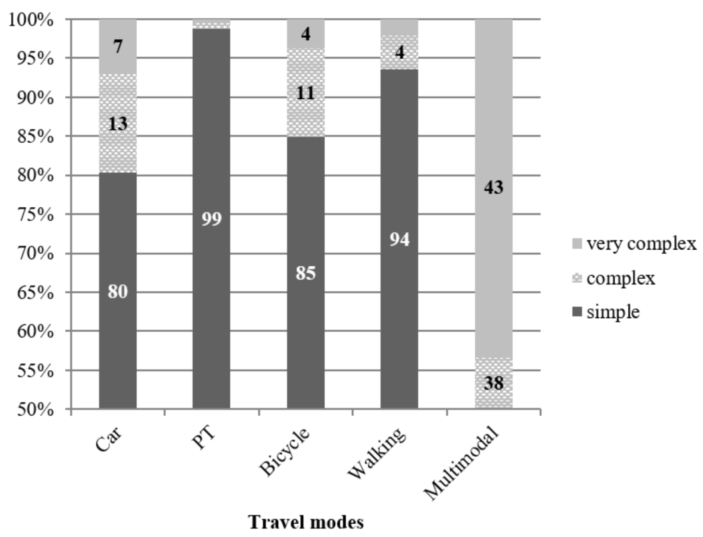


Figure 2.5 Trip chain complexity distribution between travel mode categories.

Note: The y-axis starts at 50 per cent for readability reasons.

Trip chains travelled by public transport, in contrast, were predominantly simple. These outcomes are in line with prevailing findings in the literature (e.g. Islam & Habib, 2012), yet the extreme value for public transport is surprising. This might be again related to less detailed reporting behaviour (omitting small activities at transfer hubs such as buying a coffee which, by definition, would add a further trip to the trip chain) and the high bicycle availability at both ends of the public transport leg of a trip (which entails that at least one trip of a complex trip chain will be mainly travelled by bicycle). Regarding the active modes, cycling trip chains were the second most often complex or very complex after the car while walking trip chains were mostly simple. This finding is insightful as knowledge on active mode trip chaining behaviour is still quite limited. It seems that the spatial and temporal flexibility of active modes in the Netherlands, that is being independent of a spatially restricted network and from timetables (characteristics which are particularly attributed to the car in comparison to public transport; Hensher & Reyes, 2000), facilitates that trip chains are more often complex or very complex than for public transport. Yet, the limited spatial reach might prevent from observing similar complexity degrees as for the car and possibly explains the observed differences between bicycle and walking.

A remarkable finding is that multimodal trip chains were most often complex or very complex. In former studies, this characteristic of multimodal trip chains was concealed, attributing the related trip chain complexity to an assumed main travel mode, most often the car or public transport. At first glance, the high degree of trip chain complexity is surprising as multimodal trip chains seem to require more detailed planning (similar to complex trip chains travelled by public transport). Mode changes at activity locations can entail that means of transport are not circulating in spatial, home-centred loops. For instance, using the car only for the first trip of a complex trip chain means that it will not be available at the home location for the next trip chain. An explanation for the observed shares of complex and very complex multimodal trip chains might be again the overall availability of bicycles in the Netherlands (e.g. people frequently have a second bicycle at their working location). However, multimodal trip chains are not necessarily a Dutch phenomenon. In many places, various sharing schemes such as ride-sharing and free-floating car or bicycle sharing systems in combination with public transport and walking facilitate already today to travel each trip with a different travel mode.

To summarise, this section provided a more complete picture of the relationship between trip chain complexity and mode choice for independent trip chains. The analysis revealed substantial differences in trip chain complexity between the different travel mode categories.

2.4.4 Aggregated trip chain complexity between mobility patterns

This section presents and discusses the relationship between trip chain complexity and mobility pattern classes. The analysis answers the question if differences in trip chain complexity that we found between travel modes can also be identified when all trip chains of a person are jointly considered.

Figure 2.6 illustrates the shares of simple, complex and very complex trip chains in each mobility pattern class. While simple trip chains prevailed in all mobility pattern classes, differences up to 8 percentage points could be observed. When only looking at the classes ‘Car & bicycle’, ‘Exclusive car users’, ‘Car & walk & bicycle’ and ‘Public transport+’, these differences shrank to only 4 percentage points. The similar complexity distributions of these mobility pattern classes are remarkable as they included different travel modes, of which each of them has a distinct trip chain complexity profile. This means that each mobility pattern class contained trip chains related to a more complex travel mode category (multimodal) and simpler travel mode categories (bicycle, walking, public transport) in such proportions that the resulting distribution resembled the trip chain complexity distribution of the class ‘Exclusive car users’. Consequently, car use is, contrary to the analysis of independent trip chains, not related to surpassingly complex trip chain complexity patterns on an aggregated level.

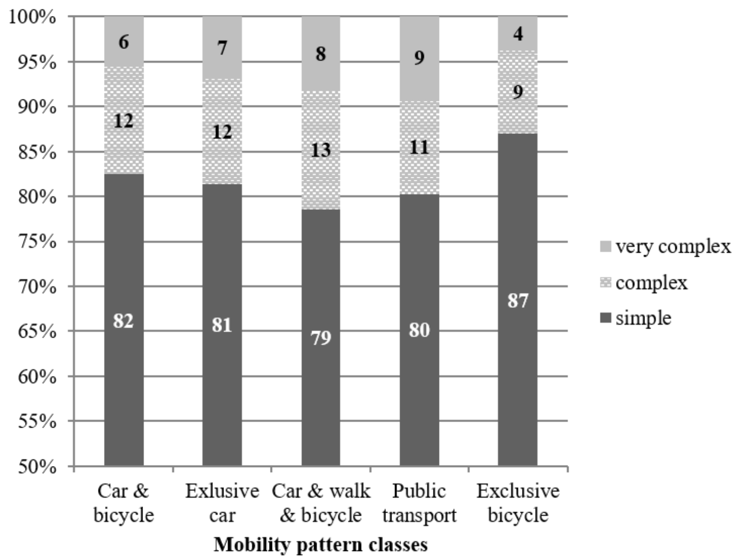


Figure 2.6 Trip chain complexity distribution between mobility pattern classes.
Note that the y-axis starts at 50 per cent for readability reasons.

The question of whether the encountered small differences between all mobility pattern classes are statistically significant was tested by means of a Pearson’s chi-squared test. The results indicate that a statistically significant association existed between trip chain complexity and mobility pattern classes ($\chi 2(8) = 28.042$, $p < 0.001$, $n = 5{,}121$). However, Cramér’s V showed that the strength of this association is negligible (Cramér’s V = 0.052, $p <.001$). Consequently, it can be concluded that although the difference in trip chain complexity between mobility pattern classes was significant, it was very small.

Considering the behavioural reasons for the similar trip chain complexity distributions, two explanations are plausible that are most likely intertwined. First, the balancing effect might happen within individuals. A simple trip chain can directly be related to a complex trip chain as both trip chains serve to implement the same activity programme. For instance, grocery purchases might not be done on a daily basis. As a result, a simple work tour on one day can directly depend on a more complex trip chain of another day (on which grocery shopping is added to the work tour). The similar trip chain complexity distributions suggest that most people do not only have simple or complex trip chains in their schedules but a combination of both (with the accompanying moderation of differences between individuals). Second, people with schedules that include different degrees of trip chain complexity might be grouped in the same mobility pattern class. For example, a busy head of a household might be associated with the same mobility pattern as a pensioner while having quite different trip chain complexities. By implication, both would have differently contributed to the trip chain complexity distribution of the same mobility pattern class.

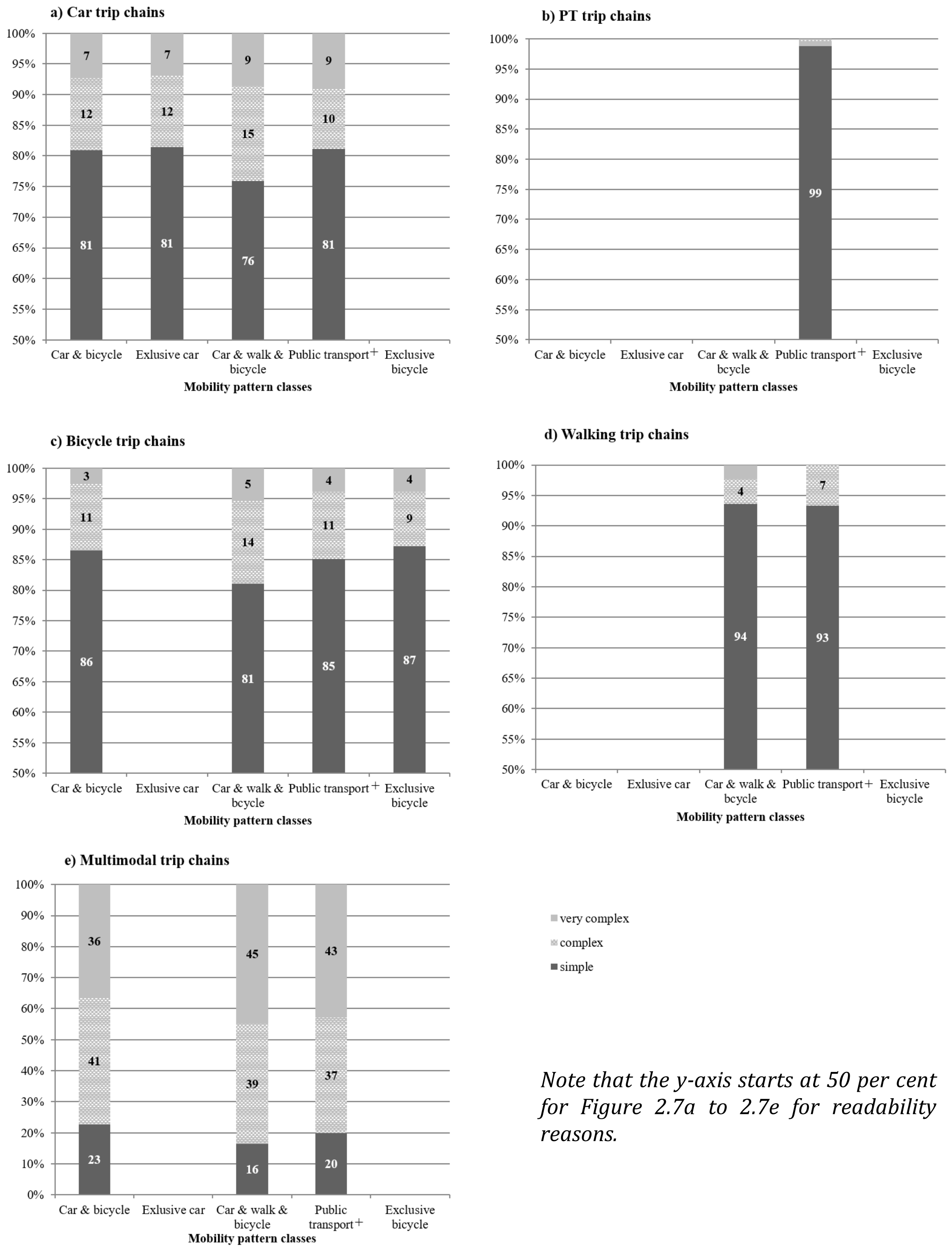
Both explanations lead credence to the conclusion that there is no obvious relationship between trip chain complexity and aggregated mode choice behaviour. This means, on the one hand, that day-to-day mode choice behaviour of a person cannot be derived from his or her trip chain complexity profile. On the other hand, the implicit notion that people with hectic schedules and, therefore, more complex trip chains, will systematically opt for the car can be rejected. While the analysis of independent trip chains suggests, in this study (see section 2.4.3) and in former research (e.g. Hensher & Reyes, 2000), that increasing complexity degrees of trip chains lead to more car use, the analysis between mobility pattern classes put the implications for a person's aggregated mode choice behaviour into perspective. The results indicate that people with more complex trip chains in their schedules did not have a salient preference for a specific travel mode, but use all kinds of different travel mode combinations. Interestingly, both highly multimodal mobility pattern classes 'Car & walk & bicycle' and 'Public transport+' had slightly more complex and very complex trip chains than the unimodal class 'Exclusive car users'. For this reason, structural car dependency cannot be seen. On the contrary, multimodal travel behaviour rather seems to be an advantageous basis to promote a mode shift to travel modes other than the car. Recent research shows that people generally have a more positive image of travel modes they already use (Ton et al., 2019).

2.4.5 Disaggregated trip chain complexity between mobility patterns

So far, we implicitly assumed that the trip chain complexity of one travel mode is stable across mobility pattern classes. This means that the trip chain complexity distributions of, for example, car trip chains are supposed to be the same regardless of the class in which they occur. However, the small deviations of the two unimodal classes (C, B) from the distributions of car and bicycle trip chains showed that this is not necessarily the case (see Figure 2.5 and Figure 2.6). As such deviations might result from insightful interdependencies between trip chains of different travel modes (i.e. a deviation that occurs in presence of another travel mode), an in-depth analysis was conducted, studying separately each travel mode's trip chain complexity across mobility pattern classes.

Figure 2.7a shows for car trip chains that complexity levels were very similar between the classes 'Car & bicycle', 'Exclusive car users' and 'Public transport+'. The class 'Car & walk & bicycle', however, had considerably more complex and very complex trip chains.

Likewise, also bicycle trip chains were least often simple in the class 'Car & walk & bicycle' (shown in Figure 2.7c). In comparison to car trip chains, more differences could be observed between the other three mobility pattern classes (CB, PT+, B), with the unimodal class 'Exclusive bicycle users' being most often simple.



Note that the y-axis starts at 50 per cent for Figure 2.7a to 2.7e for readability reasons.

Figure 2.7 Distribution of trip chain complexity for different travel mode categories between mobility pattern classes.

For multimodal trip chains, again, trip chains were least often simple in the class ‘Car & walk & bicycle’ (see Figure 2.7e) and most often simple in the class ‘Car & bicycle’. Regarding the differences in complex or very complex trip chains, an interesting observation can be made. The findings suggest that very complex trip chains are facilitated by the presence of walking and/or public transport. Both travel modes are characterised by the property that no private means of transport (car or bicycle) have to be left behind in a trip chain. The few observations of complex multimodal trip chains in the mobility pattern class ‘Car & bicycle‘ (compare Figure 2.4a, Figure 2.4c and Figure 2.7e) were most likely related to at least one trip with a free-floating sharing system such as car2go.

For walking trip chains, no noteworthy differences could be found between the two classes in which walking was present (CWB, PT+, see Figure 2.7d).

Taken together, varying degrees of trip chain complexity between mobility pattern classes were observed within trip chains related to the travel mode categories car, bicycle and multimodal. While differences within the first two modes were largest between proportions of simple trip chains, multimodal trip chains were most different regarding the share of complex and very complex trip chains. A striking outcome was that the class ‘Car & walk & bicycle’ coherently accounted for surpassingly high shares of complex and very complex trip chains. This might be explained by the outstandingly high trip rates per day in this mobility pattern class (see Table 2.2).

In Table 2.3, the encountered differences are statistically assessed using Pearson’s chi-square tests, Cramér’s V and adjusted standardised residuals. Public transport was not considered in this table, as all related trip chains are associated with only one class (‘Public transport+’), preventing from studying differences between classes. Pearson’s chi-square tests revealed that the observed differences in trip chain complexity between mobility pattern classes were non-significant for all analysed travel mode categories. This means that one cannot be sure that these differences can be reproduced on other samples of the same population. In addition, Cramér’s V indicates for all travel modes that no effects existed between trip chain complexity and mobility pattern classes. The interpretation of these outcomes is that the non-significance of the Pearson’s chi-square test was not related to too small sample size.

The adjusted standardised residuals were used to analyse interdependencies between trip chains of different travel modes. An example of such an interdependency would be the finding of significantly higher complexity degrees of car trip chains in the presence of public transport trip chains. In this case, some necessary trip chain complexity (to implement the full activity programme) might have been outsourced from public transport to the potentially more convenient car. However, the adjusted standardised residuals indicate that car trip chains did not deviate from the expected counts in the class ‘Public transport+’. Similarly, no clear trend towards more or less complex trip chains could be derived for classes in which car trip chains were jointly present with active modes. Consequently, a transfer of necessary trip chain complexity from one travel mode to a more convenient travel mode was not observed. The only significant deviations were detected for car and bicycle trip chains. While both modes had less simple and more complex or very complex trip chains in the class ‘Car & walk & bicycle’, bicycle trip chains were less often very complex in the class ‘Car & bicycle’.

Table 2.3 Relationships between trip chain complexity (in number of trips) and mobility pattern classes for different travel modes.

	Car trip chains			**Bicycle trip chains**			**Walking trip chains**			**Multimodal trip chains**		
Nr. of trips	2	3	≥ 4	2	3	≥ 4	2	3	≥ 4	2	3	≥ 4
Pearson's $\chi2$		9.271			10.576			1.304			.958	
Df		6			6			2			4	
p		.159			.102			.503[a]			.916	
Nr. of valid cases		2416			1667			561			234	
Cramér’s V		.062			.080			.055[b]			.064	
Adjusted standardised residuals												
Car & bicycle	.9	-.8	-.4	1.4	-.4	**-2.0***	-	-	-	0.6	.2	-.7
Exclusive car	1.6	-1.1	-1.0	-	-	-	-	-	-	-	-	-
Car & walk & bicycle	**-2.8****	**2.5***	1.2	**-2.8****	1.9	**2.1***	.1	-.8	1.0	-.8	.1	.5
Public transport+	.3	-.9	.6	0.1	-.1	.1	-.1	.8	-1.0	.5	-.3	-.1
Exclusive bicycle	-	-	-	1.4	-1.5	-.1	-	-	-	-	-	-

a More than 20% of cells have expected counts < 5. Therefore, the p-value of the Fisher’s exact test is indicated.

b The ρ-value of Cramér’s V (Exact significance: ρ = .449) differs from the ρ-value of Fisher’s exact test.

** Significant at .05 level of significance (|2,0|); ** Significant at .01 level of significance (|2,6|)*

In summary, no relationship could be found between trip chain complexity and mobility pattern class within the trip chains of a particular travel mode. The statistical assessment revealed that the observed differences are all non-significant. Consequently, the encountered differences in trip chain complexity between mobility pattern classes can be mainly attributed to the characteristic composition of each mobility pattern class with respect to the aggregated mode choices that it incorporates. Similarly, no consistent interdependencies could be identified between trip chains of different travel modes. However, these outcomes might be different without the undertaken aggregation of people in mobility pattern classes that potentially conceals interdependencies at the level of the individual. In addition, trip chain complexity transfers between travel modes might also occur at the household level, involving two members with different mobility patterns. Notwithstanding the non-significant results, two interesting observations can be made. First, high trip chain complexity degrees of multimodal trip chains seem to be enhanced by the use of non-private means of transport. Second, outstandingly high activity participation as for the class ‘Car & walk & bicycle’ seems to entail not only higher trip chain complexity for the car but also for other travel modes (here the bicycle).

2.5 Conclusions and future research

This paper sheds light on the relationship between trip chain complexity and mode choice in the framework of activity-travel behaviour. Using data from the Netherlands Mobility Panel, this study researched the relationship at two different levels, namely for independent trip chains and more aggregated for trip chains of people that have similar mobility patterns. The merits of this approach comprise a) a complete picture of the relationship for all relevant travel modes that are used for activity-travelling, b) a disentanglement of the trip chain complexity of intermodal trip chains and c) a straightforward interpretation of what the relationship means for the day-to-day mode choice behaviour of people that travel to perform out-of-home activities.

For the analysis, each trip chain was assigned to a travel mode category (car, public transport, bicycle, walking, multimodal), a mobility pattern class (Car & bicycle, Exclusive car users, Car & walk & bicycle, Public transport+, Exclusive bicycle) and a complexity degree (two trips – simple, three trips – complex, more than three trips – very complex). The mobility pattern was derived by means of a latent class cluster analysis, identifying five distinct mobility pattern classes that differ regarding their daily trip rates per travel mode and the proportion of reported non-travel behaviour. In the following, the most important findings of the trip chain complexity analysis are listed:

- Most trip chains in the Netherlands were simple. About 20% of the trip chains included more than one out-of-home activity location, considerably less than found in other studies.
- More than 40% of all trip chains were travelled using active modes (i.e. walking and cycling) and another 5% were multimodal - travel mode categories that have mostly been ignored in former trip chain complexity studies.
- Multimodal trip chains were considerably more often complex or very complex than unimodal trip chains. Among the unimodal trip chains, car trip chains were more often complex or very complex than bicycle trip chains, which in turn have a higher complexity degree than walking trip chains. Unimodal public transport trip chains were predominantly simple, significantly more often than in other studies.
- No substantial differences in trip chain complexity could be found between mobility patterns, regardless of the included travel modes.

- Significant differences in trip chain complexity between mobility pattern classes for trip chains of the same travel mode could not be found. Additionally, no obvious interdependencies between the trip chain complexities of different travel modes could be detected.

In conclusion, the knowledge about differences in trip chain complexity between travel modes was confirmed and, by including also the active modes, further extended. However, it is remarkable that these differences were not passed on to the aggregated level of the mobility pattern (in which all trip chains of a person were grouped together) but mitigated independently of the included travel modes. This implies that personal circumstances such as busy schedules are not systematically translated into a particular mobility pattern that is associated with higher trip chain complexity degrees. As a consequence, the interdependency between trip chain complexity and mode choice does not hold for aggregated daily mode choices of a person. Interestingly, the observed mitigation between mobility pattern classes was not the result of intramodal differences in trip chain complexity (e.g. more complex car trip chains in the presence of public transport trip chains) but of multimodal trip chains.

The findings have important policy implications. First, the results showed that the trip chain complexity profile of the bicycle is more similar to the trip chain complexity of the car than to the one of public transport. This might be related to the fact that both car and bicycle are characterised by spatial and temporal flexibility (presuming a developed bicycle network). As a consequence, the bicycle seems to have a higher potential for replacing car trip chains compared to public transport. A prerequisite, however, is that destinations can be found within bikeable distances. Second, the fact that 5% of the trip chains were already multimodal today underlines the potential of mobility-as-a-service (MaaS). In multimodal trip chains, private means of transport can often not be returned to the origin and, therefore, flexible transportation services are needed. The flexibility offered by MaaS seems to perfectly correspond to these needs. Based on the findings of this research, a good way to kick-start a MaaS scheme could be to first target people with multimodal day-to-day mode choice behaviour who have many complex trip chains in their schedules. Third and last, the results of this study put into perspective the negative outlook that some studies provided regarding the prospects of a modal shift towards non-car travel modes when trip chain patterns are becoming increasingly complex. As trip chain complexity was highest when several travel modes were included in a trip chain and people compensated for complex trip chains of one mode with less complex trip chains of another mode, structural car dependency cannot be seen. On the contrary, the observed multimodal travel behaviour rather seems to be an advantageous base for promoting the use of alternative travel modes to the car as many people are already proficient with these modes.

This paper introduced a new framework to study the relationship between trip chain complexity and mode choice that better accounts for the dependencies between trip chains of the same person. Yet, data constraints prevented to choose the individual as the scope of the analysis. Provided that enough trip chain observations per person are available to reliably derive individual trip chain complexity profiles, a purely person-centred scope would be a logical next step for future research. Such a disaggregation would allow to consistently capture dependencies between trip chains that arise from executing the same activity programme and study the precise effects on a, for instance, weekly mode choice pattern. One further, but surely challenging step could then be to also consider dependencies between trip chains of household members. These dependencies can be caused by a distribution of household tasks (e.g. grocery shopping) or the allocation of mobility tools (e.g. only one available car) among the household members and, hence, also affect mode choices.

One last direction for future research relates to findings of this study that diverge from former evidence (e.g. the low proportion of complex trip chains in the sample). While it is unclear to which extent these outcomes are caused by differences in the research design (e.g. including active modes) or by the composition of the respective samples, the results also point to differences in trip chaining behaviour between regions or countries. For instance, differences in the roles of men and women determine if gender is a trip chaining factor. For this reason, a comparative study of trip chaining behaviour across countries would be an interesting direction for future research that deserves further attention.

3. Activity hierarchies

Chapter 2 provided background knowledge on the activity-travel behaviour of cyclists. Amongst other things, it revealed typical trip chain complexities per travel mode. However, as soon as more than one destination is included in a home-based tour, the relationship between activity and travel in terms of attraction and resistance becomes unclear. In fact, we cannot directly know how much of the total tour distance relates to which of the included activities. To understand the spatial pattern of a complex trip chain, as we aim for in Chapter 4, knowledge on the organisational structure of complex trip chains is therefore necessary. That is, knowing which activity has purposed the travel (primary activities) and which activities have been added later. Due to data limitations, fixed hierarchy schemes between activity types are commonly used despite their imprecision in many cases (Doherty & Mohammadian, 2011).

In this chapter, we propose a new method to derive hierarchies between activity types in tours and assess their validity using travel diary data. Assuming that activities for which people travel further are more important and thus have a higher priority in the tour formation, we calculated relative distances of activities in home-based tours that include two different out-of-home activity types. The resulting distributions of relative distances are analysed for all available combinations of activity types regarding prevailing hierarchy patterns. The outcomes are face-validated by comparing them to activity durations, which are used in literature as an activity type independent indicator for an activity's planning horizon. In addition, the method is exemplarily applied to investigate the effect of urban density and active versus motorised travelling on activity hierarchies. As a result, this chapter reveals hierarchies between activity types based on spatial travel patterns, responding to research question 3.

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3.1 Introduction

Activity scheduling is the widely studied process that underlies observable travel patterns. In this process, activity participation and the related activity attributes (i.e., time, location, duration, company) are planned in an ongoing operation of scheduling and rescheduling that ends with the execution of the activity (Auld, Mohammadian, & Nelson, 2011; Doherty, 2005; Lee & McNally, 2006; Mohammadian & Doherty, 2006; Nijland, Arentze, Borgers, & Timmermans, 2009; Ruiz & Roorda, 2008). The part of the schedule that involves out-of-home activities is referred to as a tour (Lee & McNally, 2006). While there is general agreement in the literature that both processes, i.e. activity scheduling and tour formation, are organised around a *skeleton of anchor activities* (Cullen & Godson, 1975; Lee & McNally, 2006), the definition of a realistic and practicable priority scheme which identifies the anchor activities is still challenging.

Several approaches can be found in the literature to define a hierarchy between activities in daily schedules. An early contribution is Maslow's well known hierarchy of needs (Maslow, 1943). Departing from a psychological perspective, the author derived a hierarchy based on the importance of a particular need for human existence. Consequently, physiological needs, such as eating or sleeping, are more important than for example the desire to engage in social interactions. Similarly, Reichman (1976) proposed a classification that groups activities in three classes based on the needs to which they refer. *Subsistence and work-related activities* generate the financial resources that are necessary to engage in most other activities. *Maintenance activities or purchase and consumption of goods* satisfy the physiological needs of the household or person while *leisure activities, social, recreational and other discretionary engagements* correspond to cultural and psychological needs. Accordingly, subsistence and work-related activities are considered to be most mandatory and the group of leisure, social and recreational activities is assumed to have the most discretionary character (Akar, Clifton, & Doherty, 2011). While this approach derives hierarchies based on activity types such as work or leisure and is therefore quite practicable, there is evidence that this functional categorization alone does not sufficiently describe an activity's priority in a schedule or tour (Doherty, 2006; Doherty & Mohammadian, 2011). Several authors suggest that the priority of an activity is strongly determined by the degree of spatial and temporal flexibility, by commitments to other people and whether the activity is part of a daily routine (Cullen & Godson, 1975; Doherty, 2006). This kind of information, however, is mostly not surveyed in ordinary travel diaries. Travel diary data generally reports the revealed travel behaviour in form of consecutive trips, including in particular information on origin and destination, travel distance, timing (departure and arrival time), used travel mode and on the activity type that purposed the trip. For this reason, it seems to be reasonable to first better describe the conditions under which combinations of activity types can reliably be used to derive a hierarchy in a tour and the conditions under which additional attributes, such as company, are indispensable.

In this study, we propose a new data-driven method to derive and assess hierarchies. This method is based on the evaluation of relative distances of activities within home-based tours that include two different out-of-home activity types. We use deviations of distance positions from the tour mid-distance to determine a hierarchy between activity type pairs and to calculate a measure of hierarchy strength. In order to put our approach into perspective, we use average activity durations (a good proxy for the priority of an activity in the planning process, see (Doherty & Mohammadian, 2011)) of activity types as a benchmark. Subsequently, we exemplarily apply the method to investigate the questions if both urban density and the use of active modes (i.e. walking and cycling) have an effect on hierarchies and hierarchy strengths. The scientific contributions of this research comprise besides a new analytical approach to estimate and assess hierarchies between activity types, the link between activity hierarchies and spatial travel patterns.

In the remainder, we start with a detailed description of the theoretical framework. In section 3.3 we outline how we apply and validate the method. Subsequently, the creation and characteristics of the tour data set are explained in section 3.4. Finally, the results are presented and discussed in section 3.5 before providing some concluding comments in section 3.6.

3.2 Theoretical framework: Distance-based activity hierarchy measure

The method is developed with the aim of providing a method that reveals the activity type that purposes a tour and the activity type that is added at a later moment based on travel diary data. Considering the criticism of the use of activity type as an indicator of activity hierarchy, it is also aspired to not only determine a hierarchy as an output, but also obtain a measure of strength and consistency of this hierarchy.

The proposed method uses data of home-based tours which include two out-of-home activity types. This constellation is chosen as it represents the simplest interaction between different activity types and, therefore, allows for a straightforward interpretation. Each of the activities is associated with a distance position between 0 and 1 that relates the travelled distance to the respective activity location to the total distance of the tour. The distributions of distance positions (also named relative distances) of both activity types in a pair are used to derive the prevailing hierarchy and to give an indication of the strength of the hierarchy. In the following, we present the necessary assumptions before specifying the separate steps of the method.

The approach is based on a central behavioural assumption: The amount of travel reveals an activity’s importance. This assumption is inspired by the economic perspective on activity-travelling. In this concept, performing an activity comes with both a utility to satisfy a personal need and a disutility related to the trip (Dijst, Rietveld, & Steg, 2013). The disutility is closely linked to the resistance of the transport system and can be measured by different indicators (e.g. travel time, travel cost, effort (Annema, 2013)). In view of analysis 4 (see section 3.3), we choose travel distance as a measure because it best reflects the burden of active mode travelling, namely the physical effort for propulsion. In addition, distance allows a straightforward interpretation of the underlying spatial patterns. Based on this line of reasoning, an activity that is far away is expected to be (relatively) important because otherwise, one would not have accepted the related disutility of the trip. Consequently, an activity that is further away from home is assumed to purpose the tour and a closer activity is assumed to be opportunistically added (Lee & McNally, 2006). Therefore, we name the purposing activity primary and the added activity secondary.

In a simple home-based tour (i.e., a tour including only one out-of-home activity), the primary activity is, by nature, situated at around halfway of the total tour distance. When adding a secondary activity to the tour, the primary activity will move away from the mid-distance. However, we still assume that the primary activity stays closer to the tour mid-distance than the secondary activity. While this definition might not hold for all circumstances, we expect that the aggregation over many trip chains will reveal the prevailing hierarchy between two activity types. An example for such aggregation is illustrated in Figure 3.1. Here, activity type j is mostly concentrated around the mid-distance while activity type i is found before (a) or after (b) it. For clarity reasons, we limit further explanations in this section to case a.

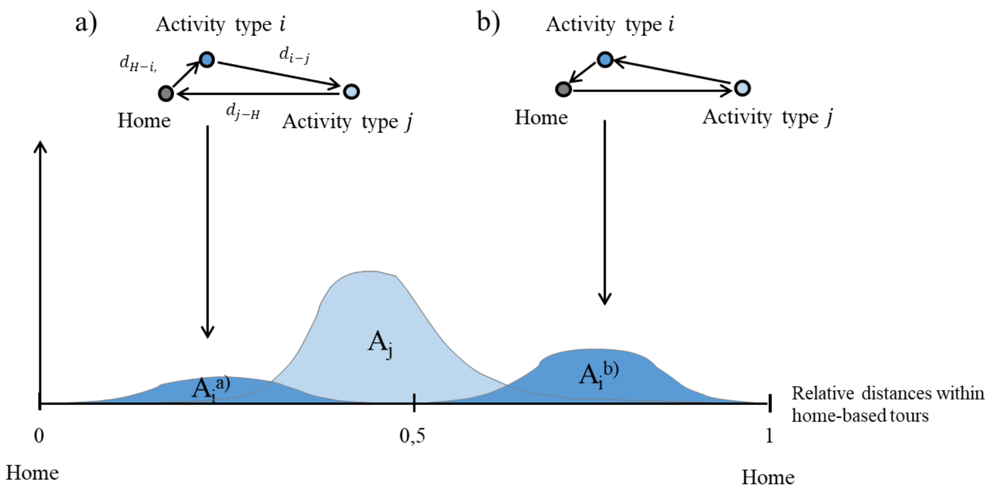


Figure 3.1 Exemplary distributions of distance positions for a pair of activity type *i* and *j*.

Distance positions of activity type j are more centred on the tour mid-distance, suggesting to be the primary activity type.

Considering now a pair of activity types i and j whose hierarchy is unknown, we have to compare the relative distance positions x_i and x_j for all tours N that include this combination. Therefore, we relate for each tour observation $n \in N$ the travel distances to both activity locations to the total travel distance of the tour:

$$x_i = \frac{d_{H-i}}{d_{H-i} + d_{i-j} + d_{j-H}} \tag{3.1}$$

$$x_j = \frac{d_{H-i} + d_{i-j}}{d_{H-i} + d_{i-j} + d_{j-H}} \tag{3.2}$$

where

d_{H-i} = distance between home and the activity of type i

d_{i-j} = distance between the activity of type i and the activity of type j

d_{j-H} = distance between home and the activity of type j

In order to measure the distance-based hierarchy, we propose to use an adjusted standard deviation that quantifies the amount of dispersion relative to the mid-distance of the tour (x = 0.5). Consequently, a mid-tour standard deviation s_i^* of activity type i can be calculated as follows:

$$s_i^* = \sqrt{\frac{\sum_{n=1}^{N}\left(x_{i,n} - 0.5\right)^2}{N - 1}} \tag{3.3}$$

where

$x_{i,n}$ = the relative distance position of the activity from type i in trip chain observation $n \in N$

The smaller s^*, the more often the respective distance positions are found close to the mid-distance. Conversely, large values can only occur when activity locations are often situated at the beginning or end of a tour. Consequently, if $s_i^* < s_j^*$, activity type i is primary and activity type j is secondary, otherwise it is the reverse. The absolute value of the difference between the two dispersions $d_{ij} = |s_i^* - s_j^*|$ gives an indication of the strength of the hierarchy. The larger d_{ij}, the more consistently one activity type is distance-wise prominent over the other. This way, d_{ij} can also be interpreted as an indication of the extent to which hierarchies between the considered pair of activity types can be predicted when only applying a fixed hierarchy order between the two respective activity types (without considering any further information such as company).

3.3 Method application: Analysis plan

This section applies the method presented above using the data described in section 3.4. The main objective is to test the hypothesis of whether hierarchies can be identified using travel distances. We approach this research goal by addressing five questions which divide the subsequent analysis into five parts. While the first three questions are mainly used for face validation of our method, the last two questions represent exemplary applications. As plausibility of the outcomes is discussed on the basis of observed behaviour, all five analyses reveal behavioural patterns.

Method validation questions:

1. To what extent are relative distance distributions different between activity types and how do these differences affect hierarchy derivation?
2. What are the hierarchies between activity types in tours derived from travel distances?
3. To what extent can these hierarchies be confirmed when being compared to hierarchies derived from activity durations?

Exemplary research questions:

4. How much do the derived hierarchies differ between people that live in high and in low urban densities?
5. What is the effect of active mode in contrast to motorised mode choice on hierarchies between activity types in tours?

The first analysis refers to question one and aims to develop an understanding for the theoretical framework and the underlying assumptions. Aggregated relative distance distributions (i.e. all tours that include a particular activity type) are provided per activity type. Differences between distributions are visually analysed and related to mid-tour standard deviations to discuss the aptitude of deriving activity hierarchies from these distributions.

The following analyses (referring to questions 2 to 5) all involve three analysis steps that are similarly performed. First, measures to determine hierarchies are calculated. For questions 2, 4 and 5, these measures are the mid-tour standard deviations s_i^* and s_j^* (see equation 3.3). For question 3, we take the proportion of each activity duration from the total out-of-home activity time in a tour and compute as a measure the average proportions for each activity type in a pair.

Second, we assume that the distributions that underlie the derivation of the pairwise hierarchies are different. Therefore, Mann-Whitney U tests are performed, hypothesizing equal distributions. The Mann-Whitney U test is chosen as it rather studies differences between distributions than differences between means. In addition, this test is known to be more robust when the assumptions of parametric statistical procedures are violated. For research questions 2, 4 and 5, the considered distributions described the distance positions x_i and x_j of activity type i and j which are mirrored at the tour mid-distance (with *mirrored* we describe a distribution that only indicates the deviation of each distance position from the tour mid-distance). We use mirrored distributions as the order of primary and secondary activity is irrelevant for hierarchy derivation and as we avoid insignificant results from the Mann-Whiney U tests due to symmetric distributions. For question 3, we studied the distributions of activity duration proportions in an activity type pair. For both measures, we tested if the hypothesis of equal distributions can be rejected at a .05 level of significance.

Third, hierarchies are derived and assessed. For questions 2, 4 and 5, hierarchies are determined by the respective smaller mid-tour standard deviation in an activity type pair (see section 3.2). The strength of the hierarchy is expressed by the difference $d_{ij} = |s_i - s_j|$. For question 3, a higher priority is determined by the larger average proportion of out-of-home activity time. The difference between both proportions is seen as an indication of the strengths of the hierarchy. For all three questions, this analysis step is only performed when the Mann-Whitney U tests revealed significant differences between both activity types in a pair.

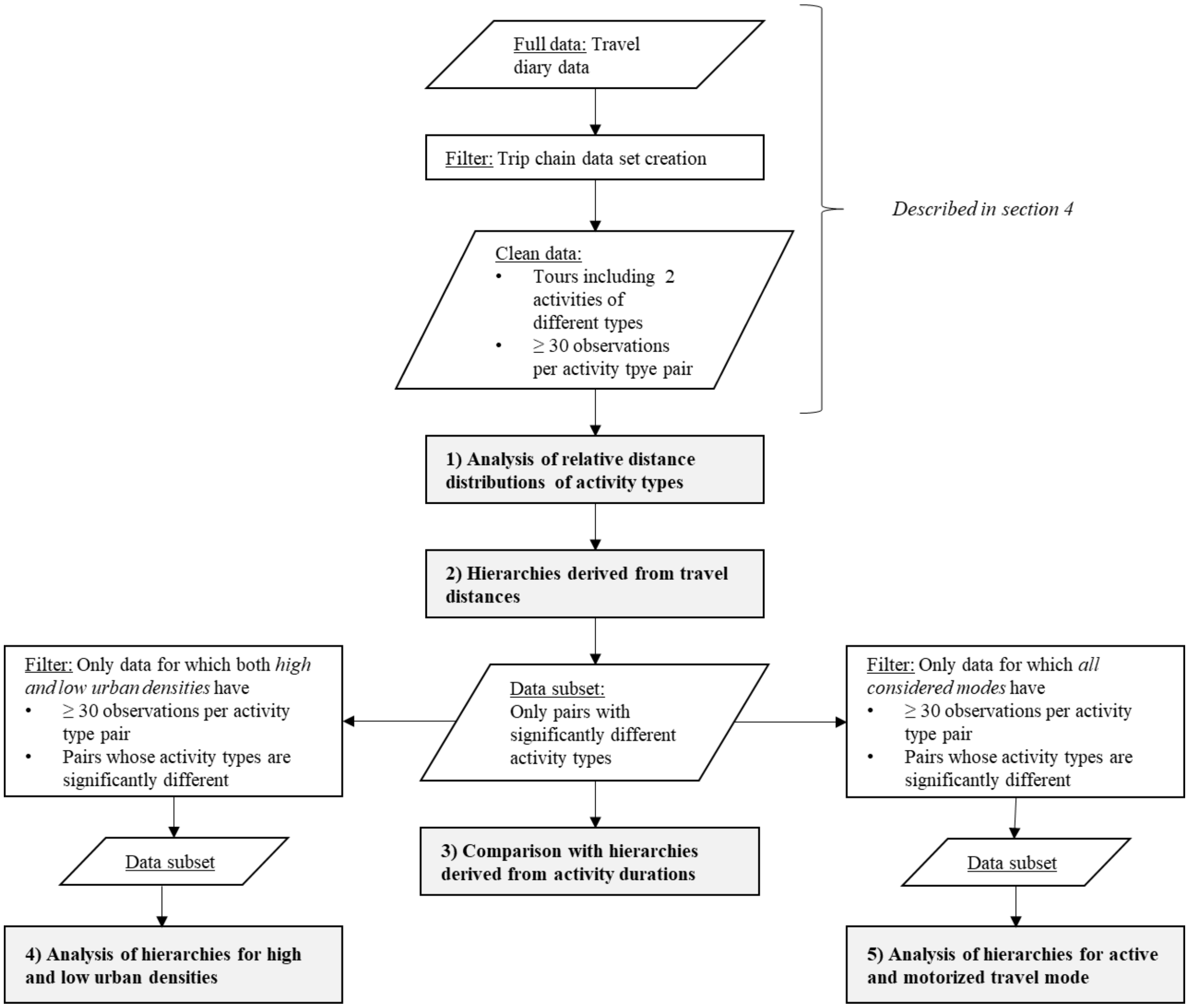


Figure 3.2 Analysis design and data flow. The five different analyses are highlighted.

The outcomes of the described analysis steps are used differently in the analysis parts 2, 3, 4 and 5. The results of each analysis step are described in more detail for analysis 2. In addition, the pairwise hierarchies and the related hierarchy strengths are synthesized into a general hierarchy scheme. In the third part of the analysis, we focus on the comparison between distance-based and duration-based hierarchies. We emphasize differences between both approaches in pairwise hierarchies as well as in hierarchy strength. In the fourth and fifth part, the three analysis steps are applied for subsets of data to study respectively the effect of the spatial environment (high versus low urban densities) and travel mode (active versus motorised) on the results. For this purpose, hierarchies and their strengths are derived separately for trip chains of travellers that live in high (≥ 2500 inhabitants/km2) and low (≤ 1000 inhabitants/km2) urban densities and for trip chains of different travel modes. The effects are investigated by comparing the outcomes between the respective subsets and by contrasting them with the outcomes of analysis part 2. Note that the data on urban densities represents the average number of people in a municipality per square kilometre of the municipal area and can give a biased impression in some cases (e.g. when the municipal area is bigger than the constructed area or when a low-density municipality is in the direct vicinity of a larger town). However, on the aggregated level of an activity type pair, the data should still provide a first notion of how different urban contexts (with for instance different accessibilities towards destinations) affect the hierarchies between activity types.

The data used for the five analysis parts is illustrated in Figure 3.2. In order to make meaningful comparisons, only activity type pairs that are statistically different in the first analysis are considered for the next analyses. The fourth and fifth analyses are only performed on activity type pairs that have at least 30 observations for high and low urban densities or, respectively, all considered travel modes. Furthermore, only pairs are taken into account whose relative distance distributions were, again, significantly different between activity types in all compared subsets.

3.4 Trip chain data set creation

The study uses data from the Netherlands Mobility Panel (MPN in Dutch). The Netherlands Mobility Panel includes a series of different surveys conducted repeatedly with the same participants, resulting in a longitudinal data set for the whole Netherlands. It has been described in more detail in Hoogendoorn-Lanser, Schaap, & Oldekalter (2015). The current analyses are based on four consecutive waves of 3-day travel diary data from the years 2013 to 2016 to have more observations available.

The analyses we aim to perform require extracting home-based tours from the travel diaries. To generate this data set, data processing on a trip and on a tour-level was necessary. Trips were assigned to one of five aggregated travel mode classes: car (driver and passengers), public transport (train, metro, tram, and bus), bicycle, walk and other modes. Additionally, activity durations were calculated by subtracting the starting time of an out-of-home activity from the starting time of the consecutive trip of the considered person on that day. Moreover, incomplete or unrealistic trip observations regarding origins and destinations and reported travel distances were discarded. Finally, only trips were considered to perform one of the following ten reported activity types (in brackets are the names of how we abbreviate the activity types):

- Work
- Dropping off/picking up people (‘escort’)
- Delivering/picking up goods (‘bring/get goods’)
- Following education/courses (‘education’)
- Shopping with the exception of grocery shopping (‘shopping’)
- Grocery shopping (‘grocery’)

- Visit
- Sport/hobby (‘sport’)
- Other leisure time activities (‘leisure’)
- Services/personal care (‘service’)

A sequence of trips of a person was identified as a trip chain when a set of conditions was satisfied. These conditions included that the sequence had to start and end at the home location, the origin of each trip had to be the destination of the precedent trip (with the exception when the origin was the home location) and the trips had to be consecutive. Only trip chains were selected that included two out-of-home activities of which each is related to a different activity type. Unimodal trip chains (i.e. trip chains where all trips were made with modes belonging to the same travel mode class) were assigned to the respective travel mode class, while trip chains incorporating travel modes of more than one class were associated to a separate multimodal class. For all trip chains, the relative distance positions x_i and x_j of the included activity pair (activity types i and j) were calculated as well as the shares of each activity duration of the total out-of-home activity time.

The resulting data set contains 7,635 trip chains stemming from 4,278 different persons. Table 3.1 shows how these trip chains are distributed over the different activity type pairs and for which pairs there are at least 30 observations related to a unimodal travel mode class. The data availability of the heterogeneous travel mode classes ‘Multimodal’ and ‘Others’ is not separately indicated since the scope of analysis 5 is the comparison between active and motorised travelling.

Table 3.1 Sample sizes of the different combinations of activity types.

	Grocery	Work	Visit	Escort	Shop	Leisure	Sport	Service	Education	Bring/get goods
Grocery		C,B*	C,B,W*	C,B,W*	C,B,W*	C,B*	C,B*	C,B,W*	B	C,B*
Work	780		C,B*	C,B*	C,B*	C,B*	C,B	C,B*	C	C
Visit	326	306		C*	C,B*	C,B*	C,B*	C	B	C
Escort	407	516	146		C,B	C	C*	C	-	C
Shop	403	192	254	146		C,B	C,B	C,B	B	C
Leisure	262	202	293	116	139		C,B*	C	-	-
Sport	243	169	210	131	124	205		C	-	-
Service	312	173	97	96	162	66	55		-	-
Education	106	85	73	42	63	55	54	54		-
Bring/get goods	138	106	65	49	92	38	32	43	9	
SUM	**2977**	**2529**	**1770**	**1649**	**1575**	**1376**	**1223**	**1058**	**541**	**572**

*The lower left half of the table contains the total counts per pair and the upper right half the travel mode classes car (C), bicycle (B), walk (W) and public transport (PT) with at least 30 observations. The green asterisk * indicates the pairs for which there are at least 30 observations available for both high and low urban densities.*

Table 3.1 shows that 44 out of 45 activity type pairs have at least 30 observations when tours of all modes are considered. In 19 pairs there were at least 30 observations available that are related to both defined urban density classes. Regarding separate travel modes, only car and bicycle tours frequently accounted for at least 30 observations. For this reason, the comparison between active and motorised modes will be limited to the comparison between car and bicycle tours. This combination was present in 22 activity type pairs.

3.5 Results and discussion

The results are presented and discussed in five subsections, following in essence the five analyses outlined in section 3.3.

3.5.1 Analysis of relative distance distributions of all activity types

The proposed theoretical framework of a distance-based hierarchy measure (see section 3.2) is based on the assumption that underlying distributions of relative distances are different between the two activity types which are paired in a tour. In order to discuss the validity of this assumption and to build up an understanding for the framework, we show cumulative relative distance distributions of all considered activity types in this section. Encountered differences between distributions are discussed against the backdrop of deriving hierarchies from them, using both a visual analysis of the distributions and a comparison of the related mid-tour standard deviations. To facilitate the interpretation, we begin with an illustration of how relative distance distribution and mid-tour standard deviation (the central measure of hierarchy derivation in this research) relate to each other using the example of work-grocery tours.

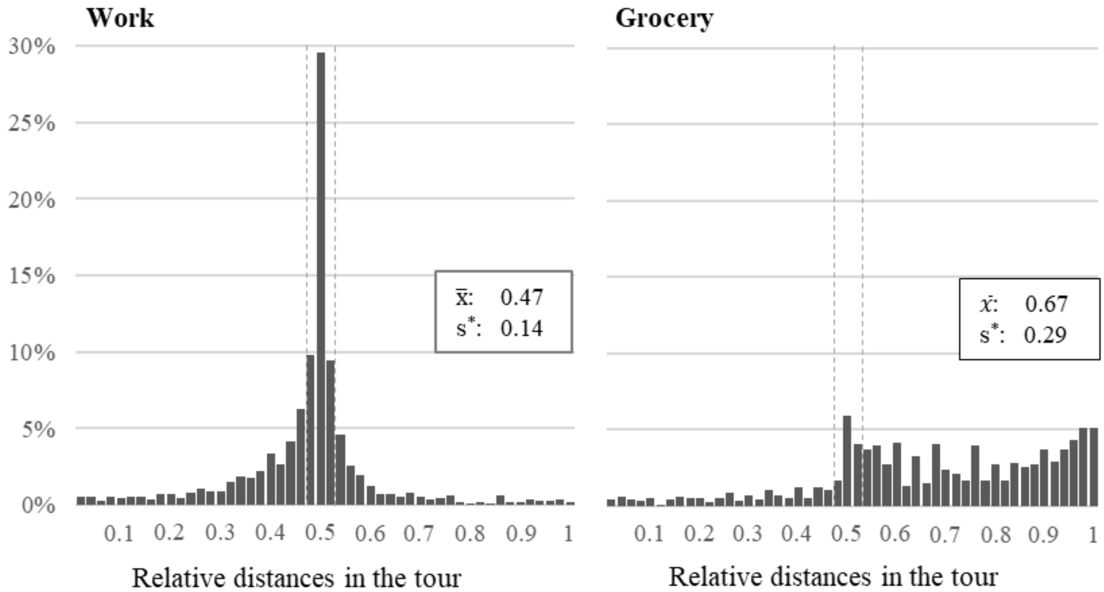


Figure 3.3 Distributions of distance positions of work and grocery shopping in tours including 2 out-of-home activities.

Figure 3.3 shows how distance positions of work and grocery shopping are proportionally distributed. Work is predominantly concentrated around the tour mid-distance in all tours that include this activity type. Almost 50% of the observations lie within a spread of only 0.02 around the mid-way of the tour and the percentage of observations continuously decreases with increasing deviations from the mid-distance. In contrast, less than 12% of the observations of grocery shopping are situated in the same span while particularly the right tail is heavily loaded. The respective mid-tour standard deviations are a condensed measure to express where distance positions are predominantly found in tours (see equation 3.3). Theoretically, mid-tour standard deviations can reach values between 0 (when all observations are exactly situated at the tour mid-distance) and very close to 0.5 (meaning that an activity location is almost at the home location). However, such extreme values are not realistic due to the heterogeneity of behaviour that can be found in a larger sample. The values of work and grocery shopping suggest that values between at least 0.15 and 0.3 can be expected.

The distributions also give insights into behavioural patterns. The symmetry of the work distribution, expressed by a mean of approximately 0.5, shows that work occurs as both first and second out-of-home activity. In contrast, the distribution of grocery shopping points to a preference to do grocery shopping as a second activity (with a mean of 0.67). Note that insights in typical activity orders are not expressed by the mid-tour standard deviations as negative (related to first activity) or positive (related to second activity) differences between a distance position and the tour mid-distance are squared in this measure.

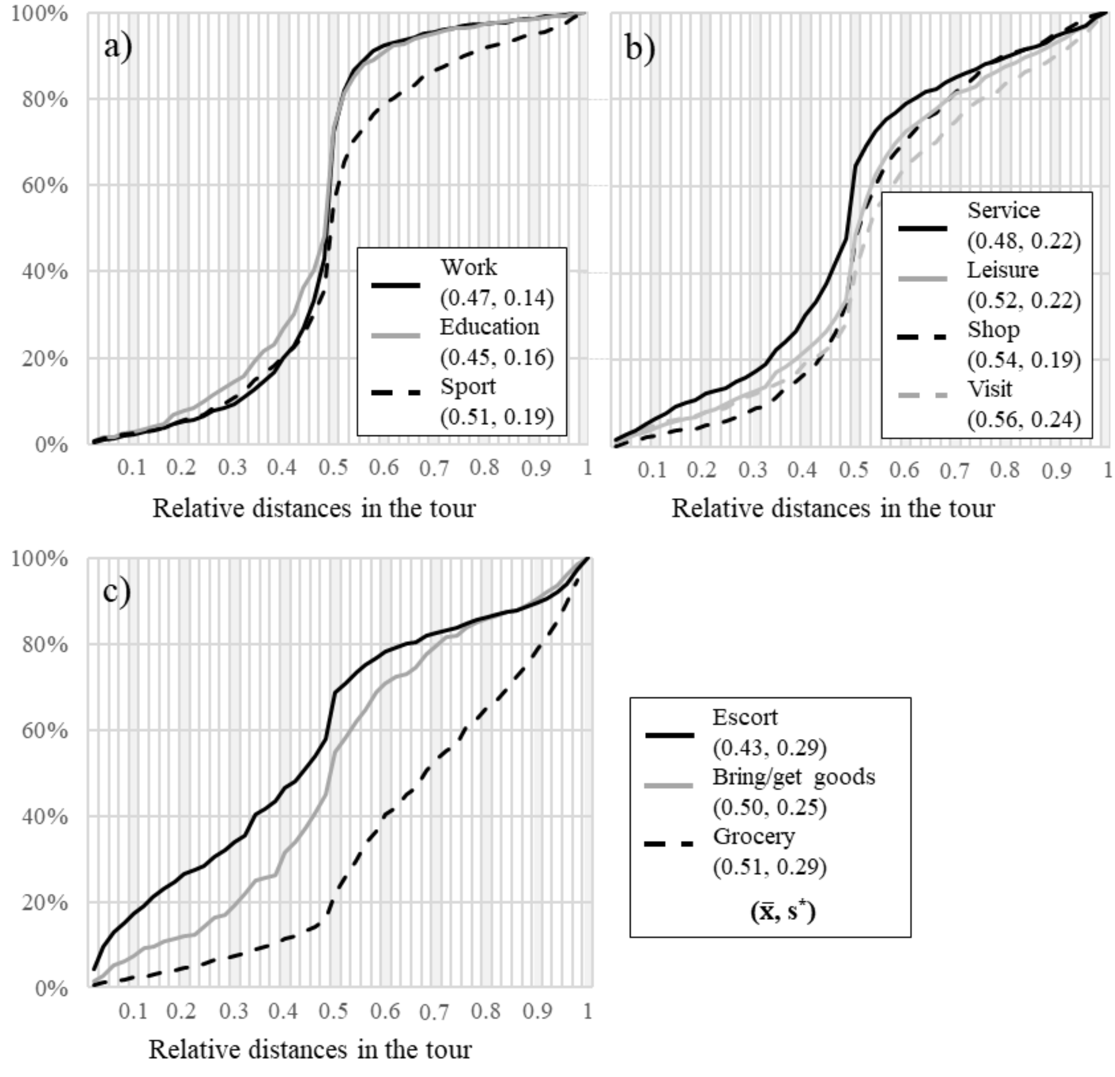


Figure 3.4 Cumulative distributions of the distance positions of all activity types in tours including 2 out-of-home activities.

Activity types are ordered and allocated to the graphs a), b) and c) depending on their mid-tour standard deviations s.*

Figure 3.4 presents the cumulative distributions of distance positions of all considered activity types. It can be seen that seven out of ten distributions have a more or less pronounced s-curved shape (see the activity types presented in the graphs a) and b) of Figure 3.4). This shape entails that the underlying distributions are approximately symmetric with a concentration of observations around the inflection point and fewer observations in the tails. As most inflection points are situated around the tour mid-way, the slopes at the inflection points and the extent of small curvature around this point primarily explain differences in related mid-tour standard deviations (ranging from 0.14 to 0.24). For instance, while the cumulative distribution of sport has a similar steepness at the inflection point to work, the latter has a much larger area of small curvature. This means that a higher percentage of work relative distances is situated close to the tour mid-way. The behavioural interpretation of an s-curved distribution is that the respective activity type is often dominating the tours (this is why there is a maximum at the tour mid-distance) but can also be found in constellations where it is added to a tour as a secondary activity. It is obvious that the more distance positions are situated close to the mid-distance, the more likely it is that this activity type is primary in a tour.

The cumulative distributions of the three remaining activity types of graph c) have distinct shapes. Grocery shopping has a relatively flat and steady slope until the mid-distance so that only around 20% of all observations are situated before the mid-distance. The continuously steeper slope on the right side of the distribution signifies that high numbers of observations are far away from the tour mid-way. Conversely, almost 70% of the observed escort services took place before the tour mid-distance. This distribution is astonishing as particularly younger children are likely to not only be dropped off but also picked up. An explanation for this outcome could be that escort services are more often chained together with another activity in the morning than in the afternoon or evening (where picking up might be organised in a separate tour). Both distributions indicate that these activity types do not often purpose tours (otherwise a more pronounced increase of observations around the tour mid-distance would be observed). The distribution of picking up or dropping off a good is unsteady across the whole relative distance range, not revealing any trend of this activity type regarding the order. Additionally, as no concentration of observations around the mid-distance can be seen, these activities seem to be rather secondary than primary activities. These findings are also reflected in mid-tour standard deviations between 0.25 and 0.29 which are lower compared to the activity types of graph a) and b).

The relative distance profiles of all activity types suggest that the profiles of some activity types are quite alike while others are clearly distinguishable. As the derivation of activity hierarchies in this research is based on aggregated differences in relative distances, it is expected that hierarchies between distinct activity profiles are more pronounced than hierarchies between similar profiles. However, the presented distributions included all possible combinations of activity types in which one specific activity type was present. Consequently, this analysis only provided a global notion of the profile of an activity type regarding its typical distance positions in tours. In order to derive hierarchies between two specific activity types, we subsequently conducted pairwise comparisons.

3.5.2 Hierarchies derived from travel distances

In this part, hierarchies were derived from relative travel distances for 44 activity type pairs for which at least 30 observations were available. First, we have a look at mid-tour standard deviations only. Next, the outcomes of the Mann-Whitney U tests are discussed. The results of the first two aspects are shown in Table 3.2. The revealed pairwise hierarchies and their strengths are presented in Table 3.3 and synthesized in a hierarchy scheme (see Figure 3.5).

Table 3.2 Pairwise comparisons of activity types.

Activity type i	Activity type j	N	s_i^*	s_j^*	U	ρ
Work	Education	85	0.280	0.169	2095.0	0.000
Work	Grocery	780	0.086	0.354	53841.0	0.000
Work	Shop	192	0.110	0.283	9112.5	0.000
Work	Service	173	0.179	0.331	7175.5	0.000
Work	Escort	516	0.128	0.381	27011.5	0.000
Work	Bring/get goods	106	0.138	0.319	2031.0	0.000
Work	Sport	169	0.172	0.269	10000.0	0.000
Work	Leisure	202	0.170	0.262	13814.0	0.000
Work	Visit	306	0.175	0.307	25718.5	0.000
Education	Grocery	106	0.101	0.328	1338.0	0.000
Education	Shop	63	0.170	0.219	1531.5	0.027
Education	Service	54	0.173	0.288	852.0	0.000
Education	Escort	42	0.144	0.313	395.5	0.000
Education	Sport	54	0.180	0.251	1246.5	0.194
Education	Leisure	55	0.192	0.244	1261.5	0.133
Education	Visit	73	0.187	0.273	1752.0	0.000
Grocery	Shop	403	0.273	0.123	37614.0	0.000
Grocery	Service	312	0.241	0.142	30303.0	0.000
Grocery	Escort	407	0.224	0.175	61411.5	0.000
Grocery	Bring/get goods	138	0.244	0.178	6766.5	0.000
Grocery	Sport	243	0.292	0.127	12037.0	0.000
Grocery	Leisure	262	0.263	0.145	18347.5	0.000
Grocery	Visit	326	0.275	0.174	32802.5	0.000
Shop	Service	162	0.187	0.198	12527.5	0.480
Shop	Escort	146	0.189	0.249	9124.0	0.033
Shop	Bring/get goods	92	0.171	0.221	3518.0	0.048
Shop	Sport	124	0.202	0.185	6216.5	0.009
Shop	Leisure	139	0.168	0.195	9414.5	0.713
Shop	Visit	254	0.209	0.227	31396.5	0.602
Service	Escort	96	0.170	0.278	2962.0	0.000
Service	Bring/get goods	43	0.164	0.267	636.5	0.013
Service	Sport	55	0.272	0.167	949.5	0.001
Service	Leisure	66	0.270	0.226	1860.0	0.147
Service	Visit	97	0.196	0.211	4088.5	0.115
Escort	Bring/get goods	49	0.200	0.231	950.0	0.075
Escort	Sport	131	0.326	0.167	3347.0	0.000
Escort	Leisure	116	0.248	0.207	6337.0	0.444

Table 3.2 continued.

Activity type *i*	Activity type *j*	*N*	s_i^*	s_j^*	*U*	*ρ*
Escort	Visit	146	0.266	0.207	8157.5	0.001
Bring/get goods	Sport	32	0.271	0.188	346.0	0.026
Bring/get goods	Leisure	38	0.252	0.170	482.0	0.013
Bring/get goods	Visit	65	0.261	0.194	1634.5	0.026
Sport	Visit	210	0.173	0.280	13788.0	0.000
Sport	Leisure	205	0.175	0.225	16379.0	0.000
Leisure	Visit	293	0.237	0.201	38397.0	0.027

Table 3.2 presens mid-tour standard deviations and the outcomes of the Mann-Whitney U tests (U and ρ) for each pair of activity type i and j. The colours situate s_i^* and s_j^* on a continuous red-green scheme in relation to the observed minimum (green) and maximum (red) deviation. Grey cells in the last column indicate there is no significant difference between the mid-tour standard deviations of both activity types (significance level 0.05).

The observed range of mid-tour standard deviations reaches from 0.086 (work in work-grocery tours) to 0.381 (escort in work-escort tours) and define the anchor values of the colour scheme in Table 3.2. The deviations of work and education are mostly red and orange, suggesting that these locations are furthest away from home in most tours. Conversely, grocery shopping consistently accounts for larger values of spread (green to yellow), emphasizing a preference to conduct the activity in the close neighbourhood. Similarly, picking up or dropping off a person or good are also performed close to the home location. A considerable number of deviations is situated relatively in the middle between the two anchor values. These deviations (illustrated in yellow) point to a large spread of relative distances, in which large deviations are balanced by small deviations. Consequently, hierarchies derived from activity pairs that include yellow cases are less consistent across observations.

The hierarchies are determined by comparing both deviations. These differences can be quite large (e.g. between work and grocery) or relatively small (e.g. between shop and service). In order to determine a hierarchy, however, it is indispensable that both activity types have distributions of distance positions relative to the mid-distance that are not equal. A series of Mann-Whitney U tests reveal that 35 out of 44 activity type pairs were differently distributed at a .05 level of significance. Regarding the insignificant results, some seem to be caused by smaller sample sizes (education – sport, education – leisure, escort – bring/get goods), while others can be explained by similar levels of spread (also see Figure 3.4). It is noteworthy that the comparisons between shop, service, leisure and visit are mostly insignificant. This is particularly interesting as these activity types are traditionally assigned to classes with different priorities (shop and service as maintenance activities compared to leisure activities, see (Reichman, 1976)). A possible explanation for this outcome is that all these activity types group activities that can have heterogeneous properties. For instance, the activity type ‘leisure’ can stand for a barbecue in a neighbouring public park or for a long-distance trip to an amusement park. Consequently, the importance of the activity in the respective tour is substantially different. The resulting hierarchies of the 35 significant activity type pairs, as well as the related hierarchy strengths, are illustrated in Table 3.3.

Table 3.3 Overview of pairwise hierarchies and hierarchy strengths.

	Grocery	Work	Visit	Escort	Shop	Leisure	Sport	Service	Education	Bring/get goods
Grocery		Work	Visit	Bring/get person	Shop	Leisure	Sport	Service	Education	Bring/get goods
Work	0.27		Work	Work	Work	Work	Work	Work	Education	Work
Visit	0.10	0.13		Visit	-	Visit	Sport		Education	Visit
Escort	0.05	0.25	0.06		Shop	-	Sport	Service	Education	-
Shop	0.15	0.17	-	0.06		-	Sport	-	Education	Shop
Leisure	0.12	0.09	0.04	-	-		Sport	-	-	Leisure
Sport	0.16	0.10	0.11	0.16	0.02	0.05		Sport	-	Sport
Service	0.10	0.15	-	0.11	-	-	0.11		Education	Service
Education	0.23	0.11	0.09	0.17	0.05	-	-	0.11		
Bring/get goods	0.07	0.18	0.07	-	0.05	0.08	0.08	0.10	-	

The primary activity is presented on the upper right half and the differences in spread on the lower left half. The colours place the differences in mid-tour standard deviations (d_{ij}) of each activity type pair on a continuous red-green scheme in relation to the observed minimum (red) and maximum (green) hierarchy strength.

The outcomes suggest that some activity types tend to be primary activities (e.g. education, work) while others are rather secondary (grocery shopping, bring/get goods). The interpretation of all pairwise hierarchies allows to establish a framework in which all activity types are ordered among each other. Education seems to be the most important activity type, followed by work and sport. On the other side of the scheme, grocery shopping is clearly the activity type that is added opportunistically to all other activity types. Also picking up or dropping off goods or a person as a joint group can consistently be placed (without establishing a hierarchy between both types though). However, in the centre of the scheme, a consistent hierarchy order cannot be derived due to the heterogeneity of relative travel distances of these activity types. The resulting hierarchy scheme is presented in Figure 3.5 in form of a pyramid, indicating a decreasing hierarchy from bottom to top.

Table 3.3 also shows that the different activity type pairs differ considerably regarding the strength of the hierarchy (d_{ij}). The greener the activity pair the more pronounced is the hierarchy between the two activity types and the more certain one can be that the hierarchy is consistent across observations. Conversely, red and orange hierarchies are not very strong, entailing that distance-wise hierarchies are likely to switch between observations. The results suggest that some activity types such as work, or grocery shopping are more often found in pairs with a strong hierarchy than others. On an aggregated level, average strengths of hierarchies for each activity type (also shown in Figure 3.5) give an indication to which extent one can be sure that the hierarchies derived from the scheme will hold. For instance, when making predictions for sport-visit tours, Figure 3.5. indicates that sport is more likely to be the primary activity. At the same time, the rather small values for both average strengths suggest that this hierarchy is not very stable and might often be inversed. This way, Figure 3.5 generalizes the more detailed findings from Table 3.2 and Table 3.3.

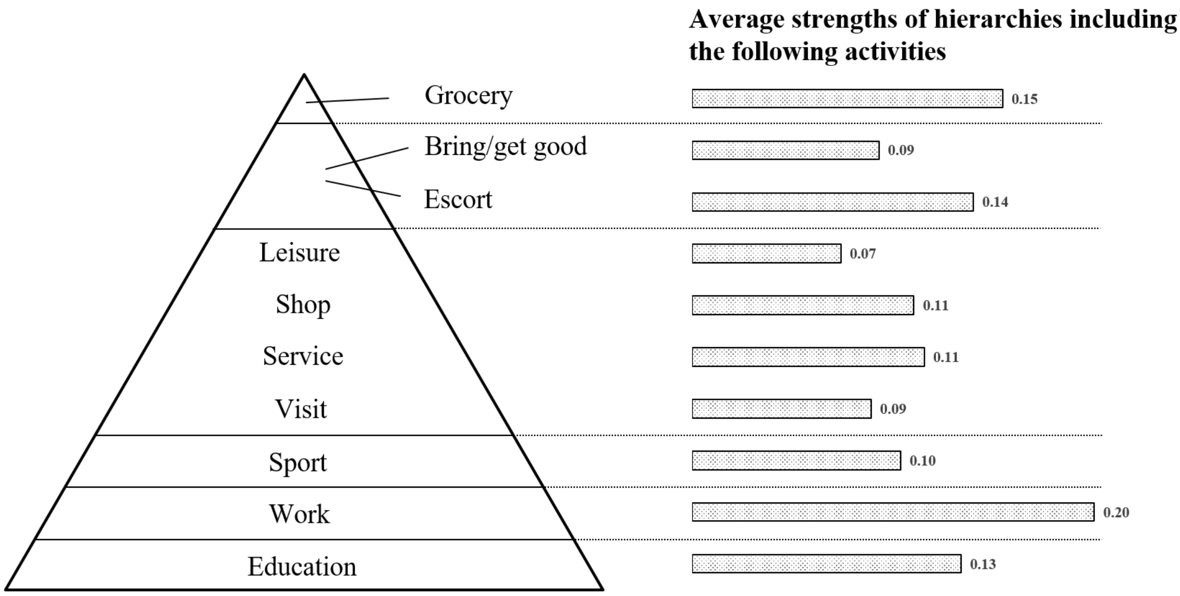


Figure 3.5 Hierarchy of activity types and related average hierarchy strengths.

Taking the hierarchy order between activity types and the related average strengths together, this scheme confirms the often-expressed criticism towards frequently used hierarchy schemes. First, this scheme is contradictory to hierarchy orders that are based on the function of each activity for human subsistence. For instance, sport as a discretionary leisure activity was found to be of higher priority than grocery shopping, a clear maintenance activity. Since sport is, as opposed to grocery shopping, more often characterized by little degrees of flexibility regarding location and timing and can include commitments to other people (particularly for team sports), we argue that this outcome makes sense. Second, the strengths of the hierarchies indicate that many activity types appear to be unstable. Consequently, the word *hierarchy* has rather to be understood as a behavioural propensity than as a deterministic decision rule.

3.5.3 Comparison with hierarchies derived from acitivty durations

In this part of the analysis, the method to derive hierarchies from travel distances was compared to the method to derive hierarchies from activity durations. Table 3.4 illustrates the average proportions of the out-of-home activity time of each activity type and the resulting pairwise hierarchy. As activity duration is used for the sake of comparison, only the activity type pairs are shown that were significantly different in Table 3.2. The statistical assessment revealed that all these 35 pairs had significantly different distributions of out-of-home activity time proportions at a .05 level of significance.

Table 3.4 shows that 31 out of 35 hierarchies derived from travel distances are confirmed by the hierarchies derived from activity durations. Regarding the four contradictions, there are different possible explanations. First, results suggest that people travel longer for education than for work, but that work takes longer. The size of this activity pair indicates that this is a rather rare combination, potentially containing both students with an additional job and workers with an education programme as a side project. Correspondingly, both hierarchies make sense. The change of dominating activity type between both approaches might be caused by the fact that student jobs are more likely to be found between home and education location than education institutions on the way to or from work. Second, hierarchies between grocery shopping and dropping off or picking up a person or, respectively, a good were contradicting. These findings are not surprising as the latter two activity types usually do not take much time. Both latter activity types, however, are often characterized by a higher degree of temporal and spatial constraints or commitments to other people than grocery shopping. Consequently, the approach based on travel distances appears to be more precise in capturing the realistic hierarchy. Last, the results suggest that people travel longer for visit activities than leisure activities but that leisure activities take longer. A closer look reveals that only a weak hierarchy was found for both approaches. Therefore, the differing derivations might simply be caused by the heterogeneity of activities that each of the two activity types include.

The difference between both proportions and the mid-tour standard deviations of each activity type pair are shown in Table 3.4 to compare the strengths of hierarchies between both methods. In order to make the measures of strength comparable, the results are again put into relation to the observed minimum (red) and maximum (green) scores of strength of each method by means of a continuous red-green colour scheme. Excluding the cases for which the hierarchy changed between both approaches, the visual interpretation of Table 3.4 suggests that most hierarchy pairs are similarly strong. However, some remarkable differences were found for pairs that included picking up or dropping of a person or good (escort – visit; bring/get goods – sport, visit, leisure). Systematically, the approach based on activity durations indicates stronger hierarchies than the method of using travel distances. As argued in the paragraph above, the importance of activity types of short activity durations seems to be underestimated. In addition, a considerable difference in hierarchy strength was observed for grocery-shop tours. In this case, activity durations were less different than the distance patterns. Since the choice of grocery shopping locations is considerably larger than the one of specialized shopping locations, grocery shopping is characterized by a higher degree of spatial flexibility. For this reason, the approach based on travel distances appears to better describe this hierarchy pair.

Table 3.4 Overview of pairwise hierarchies based on activity durations.

Activity type i	Activity type j	N	SD of activity type pair	% duration of activity type i	% duration of activity type j	|Δ| of %	$\|d_{ij}\|$
Work	Education	85	0.226	54.3%	45.7%	8.6%	0.112
Work	Grocery	780	0.107	93.1%	6.9%	86.1%	0.268
Work	Shop	192	0.166	88.3%	11.7%	76.5%	0.173
Work	Service	173	0.109	90.2%	9.8%	80.3%	0.151
Work	Escort	516	0.066	96.0%	4.0%	92.0%	0.254
Work	Bring/get goods	106	0.137	93.4%	6.6%	86.7%	0.181
Work	Sport	169	0.157	77.8%	22.2%	55.6%	0.097
Work	Leisure	202	0.214	74.2%	25.8%	48.5%	0.093
Work	Visit	306	0.186	75.9%	24.1%	51.8%	0.132
Education	Grocery	106	0.124	89.4%	10.6%	78.7%	0.227
Education	Shop	63	0.191	76.6%	23.4%	53.3%	0.050
Education	Service	54	0.133	85.1%	15.0%	70.1%	0.115
Education	Escort	42	0.152	88.7%	11.3%	77.4%	0.169
Education	Visit	73	0.196	67.0%	33.0%	33.9%	0.086
Grocery	**Shop**	403	0.223	44.1%	55.9%	11.8%	0.149
Grocery	**Service**	312	0.225	43.5%	56.5%	12.9%	0.100
Grocery	Escort	407	0.225	63.1%	37.0%	26.1%	0.049
Grocery	Bring/get goods	138	0.198	68.0%	32.0%	36.1%	0.065
Grocery	**Sport**	243	0.169	21.8%	78.2%	56.4%	0.165
Grocery	**Leisure**	262	0.227	26.1%	73.9%	47.9%	0.118
Grocery	**Visit**	326	0.193	26.5%	73.5%	46.9%	0.101
Shop	Escort	146	0.219	75.1%	24.9%	50.2%	0.060
Shop	Bring/get goods	92	0.227	68.7%	31.3%	37.4%	0.050
Shop	**Sport**	124	0.254	35.6%	65.0%	29.4%	0.018
Service	Escort	96	0.250	73.6%	26.4%	47.1%	0.108
Service	Bring/get goods	43	0.180	76.8%	23.2%	53.5%	0.103
Service	**Sport**	55	0.197	18.6%	81.4%	62.8%	0.105
Escort	**Sport**	131	0.122	10.1%	90.0%	79.9%	0.159
Escort	**Visit**	146	0.191	16.3%	83.7%	67.3%	0.059
Bring/get goods	**Sport**	32	0.222	15.6%	84.5%	68.9%	0.083
Bring/get goods	**Leisure**	38	0.216	17.2%	82.8%	65.7%	0.082
Bring/get goods	**Visit**	65	0.195	17.3%	82.7%	65.4%	0.067
Sport	Visit	210	0.229	58.5%	41.6%	16.9%	0.107
Sport	Leisure	205	0.213	57.2%	42.8%	14.4%	0.050
Leisure	Visit	293	0.234	50.4%	49.6%	0.9%	0.036

Note that only significant comparisons at a .05 level of significance are illustrated. The colours situate the |Δ| of % and d_{ij} of each activity type pair on a continuous red-green scheme in relation to the observed minimum (red) and maximum (green) hierarchy strength. The primary activity type based on activity duration is presented in bold. Grey cases indicate changing hierarchies between both methods.

3.5.4 Analysis of hierarchies for high and low urban densities

In this fourth analysis, the method is applied to investigate the effect of urban density on activity hierarchies. Different urban contexts often come along with different levels of accessibility to destinations where activities are performed. Urban density can be seen as an aggregated measure to capture these spatial structural differences, assuming that high urban densities have good accessibility to facilities and low urban densities do not. As these differences are expected to be most pronounced between high and low urban densities, the analysis focused on this contrast. Therefore, activity hierarchies are separately derived from tours that are associated to people living in high urban densities (≥ 2500 inhabitants/km2) and from tours that are associated to people living in lower urban densities (≤1000 inhabitants/km2).

In total, 19 activity type pairs accounted for at least 30 observations for both defined urban density categories (see Table 3.1), of which 18 had significantly different relative distance distributions in analysis 2 (see Table 3.2). Out of these 18 pairs, Mann-Whitney U tests revealed for 11 activity type pairs that relative distance distributions were significantly different within both urban density categories. For these activity type pairs, the mid-tour standard deviations, the corresponding hierarchy strength as well as the deviations of these strengths from the hierarchy strength of the complete sample are shown for both urban density categories in Table 3.5.

The results of Table 3.5 indicate that hierarchies are stable across both urban density categories for all studied activity type pairs. This means that independently of the urban structure, the same activity type seems to predominantly purpose a tour. However, due to data constraints, activity type pairs were analysed that are related to rather strong hierarchies (see Figure 3.5). Therefore, hierarchy changes due to different urban densities cannot generally be excluded.

A closer look at the hierarchy strengths of both urban densities and their deviations from the total hierarchy strength reveals more clearly the effect of urban density on pairwise hierarchies. In general, travel distances in high urban densities are expected to be shorter since high urban densities are typically related to a high density of destinations. However, as this higher level of accessibility potentially affects both activity types, relative distances (and thus hierarchy strengths) do not necessarily change across urban densities. Against this backdrop, it is instructive to see that hierarchies of five activity type pairs are more pronounced in areas of high urban density than in areas of low urban density. Since all these pairs include grocery shopping, the results suggest that particularly these distances are disproportionately short due to a large choice of accessible activity locations. This means that people seem to have a preference to generally do grocery shopping very close to the home location (if they can) and not, for instance, close to the work location.

In contrast to the five mentioned activity type pairs, three other pairs have stronger hierarchies in a less dense urban environment. These pairs are related to tours that combine work and escort or visit and to sport-escort tours. The interpretation of these results is that commute distances are longer in comparison to people that live in areas of high urban densities while day-care facilities or schools can still be found in the neighbourhood. In addition, social ties within the neighbourhood might be stronger, entailing more short distance visits than in high-density environments.

Table 3.5 Overview of pairwise hierarchies between two activity types and corresponding hierarchy strengths for high and low urban densities.

Density	Activity type *i*	Activity type *j*	*N*	s_i^*	s_j^*	$d_{ij,\,density}$	$d_{ij,\,density} - d_{ij}$
High	**Work**	Grocery	246	0.077	0.367	0.290	0.022
Low	**Work**	Grocery	154	0.095	0.327	0.232	-0.036
High	**Work**	Shop	44	0.109	0.281	0.172	-0.001
Low	**Work**	Shop	45	0.109	0.265	0.156	-0.017
High	**Work**	Service	34	0.215	0.316	0.101	-0.050
Low	**Work**	Service	40	0.192	0.300	0.108	-0.043
High	**Work**	Escort	76	0.144	0.371	0.227	-0.027
Low	**Work**	Escort	177	0.103	0.397	0.294	0.040
High	**Work**	Visit	72	0.202	0.311	0.109	-0.023
Low	**Work**	Visit	81	0.156	0.327	0.172	0.040
High	Grocery	**Shop**	84	0.296	0.120	0.176	0.027
Low	Grocery	**Shop**	103	0.227	0.120	0.106	-0.043
High	Grocery	**Sport**	60	0.336	0.099	0.237	0.072
Low	Grocery	**Sport**	66	0.265	0.139	0.126	-0.039
High	Grocery	**Leisure**	71	0.296	0.123	0.173	0.055
Low	Grocery	**Leisure**	61	0.220	0.143	0.077	-0.041
High	Grocery	**Visit**	38	0.303	0.162	0.140	0.039
Low	Grocery	**Visit**	99	0.268	0.181	0.088	-0.014
High	Escort	**Sport**	32	0.310	0.190	0.120	-0.039
Low	Escort	**Sport**	30	0.333	0.164	0.169	0.010
High	**Sport**	Visit	53	0.166	0.250	0.084	-0.023
Low	**Sport**	Visit	49	0.150	0.254	0.105	-0.003

The primary activity type is indicated in bold. The colours place the differences in hierarchy strength between both urban densities ($d_{ij,density}$) and the total sample (d_{ij}) on a continuous red-green scheme in relation to the observed minimum (red) and maximum (green).

Finally, three activity type pairs indicate that hierarchies are less pronounced in both urban environments in comparison to the total sample. This necessarily means that tours of people living in intermediate urban densities account for higher strengths. This somewhat surprising finding can be explained by different increase (or decrease) rates of travel distances between the two involved activity types across urban densities. For instance, work distances might increase faster with decreasing urban densities than service distances, entailing that hierarchies are strongest in intermediate urban densities.

The encountered differences in hierarchy strengths of up to 0.07 (what is considerable in proportion to a range of possible values that is only 0.5) point to the importance of urban spatial structure on the results of this distance-based activity hierarchy measure. The instability of the outcomes across urban densities can be seen as a limitation of the method. We argue, though, that the results reflect realistic behavioural adaption to different spatial environments. Section 3 has shown that the flexibility of an activity strongly affects its priority in the planning process. The urban environment determines (at least) the spatial flexibility of an activity and in consequence, its ease of planning. For this matter, varying hierarchies across different spatial environments make perfect sense and reveal notable behavioural patterns (such as the preference of people to do the grocery shopping close to the home location).

3.5.5 Analysis of hierarchies for active and motorised travel modes

In the last part of the analysis, the influence of travel mode on hierarchies and hierarchy strengths was studied. Table 3.6 presents 12 activity type pairs for which the distributions of distance positions relative to the mid-distance of both activity types were significantly different in both, car and bicycle tours. These values show how the strength of the hierarchy pair evolves when only car or bicycle tours are analysed.

Table 3.6 Overview of pairwise hierarchies separately for car and bicycle.

Mode	Activity type *i*	Activity type *j*	*N*	s_i^*	s_j^*	$d_{ij, mode}$	$d_{ij, mode} - d_{ij}$
Significant comparisons (at .05 level of significance)							
Car	**Work**	Grocery	360	0.077	0.372	0.295	0.03
Bike	**Work**	Grocery	283	0.078	0.315	0.236	-0.03
Car	**Work**	Shop	116	0.107	0.303	0.197	0.02
Bike	**Work**	Shop	56	0.109	0.246	0.137	-0.04
Car	**Work**	Escort	375	0.122	0.383	0.260	0.01
Bike	**Work**	Escort	76	0.122	0.348	0.227	-0.03
Car	**Work**	Leisure	92	0.166	0.278	0.112	0.02
Bike	**Work**	Leisure	41	0.137	0.245	0.108	0.01
Car	**Work**	Visit	216	0.163	0.312	0.150	0.02
Bike	**Work**	Visit	35	0.179	0.245	0.066	-0.07
Car	Grocery	**Shop**	228	0.293	0.126	0.167	0.02
Bike	Grocery	**Shop**	95	0.244	0.137	0.107	-0.04
Car	Grocery	**Service**	131	0.270	0.161	0.108	0.01
Bike	Grocery	**Service**	111	0.227	0.136	0.091	-0.01
Car	Grocery	**Escort**	194	0.256	0.174	0.082	0.03
Bike	Grocery	**Escort**	146	0.197	0.173	0.024	-0.03
Car	Grocery	**Sport**	119	0.317	0.100	0.217	0.05
Bike	Grocery	**Sport**	85	0.268	0.121	0.147	-0.02
Car	Grocery	**Leisure**	104	0.287	0.151	0.136	0.02
Bike	Grocery	**Leisure**	99	0.230	0.134	0.095	-0.02
Car	Grocery	**Visit**	170	0.298	0.171	0.127	0.03
Bike	Grocery	**Visit**	97	0.236	0.165	0.071	-0.03
Car	Visit	**Sport**	115	0.256	0.173	0.083	-0.02
Bike	Visit	**Sport**	49	0.252	0.169	0.082	-0.02

This Table presents mid-tour standard deviations, the resulting differences in spread and deviations from Table 3.3. The colours situate d_{ij}*, mode -* d_{ij} *of each activity type pair on a continuous red-green scheme in relation to the observed minimum (red) and maximum (green) hierarchy strength. The primary activity type is indicated in bold letters.*

The results indicate that the separate consideration of car or bicycle tours did not cause any changes in the hierarchies. However, it seems that travel mode has an influence on *the strength of the hierarchy*. In 11 of the 12 activity type pairs, hierarchy strength was more pronounced for car tours and less strong for bicycle tours. A possible explanation for this phenomenon is that long distances to the primary activity are likely to influence the tour mode choice in favour of the car. Tours by bicycle, on the contrary, are generally shorter so that differences in relative distances become smaller (since minimum distances to secondary activities such as grocery are fixed by the spatial structure of the area). The exception was (again) observed for visit – sport tours, an activity type pair, in which a substantial share of strongly hierarchic multimodal tours was present. Consequently, these findings have to be interpreted with some caution, as possible interactions with other travel mode categories were not yet considered and since the analysis was mostly limited to tours related to work and grocery shopping.

3.6 Conclusions and recommendations

In this study, we proposed a method to derive and assess hierarchies between different activity types from travel diary data. The method is based on the assumption that travel distance reveals the importance of an activity. Using the scope of home-based tours that include exactly two different out-of-home activity types, we conduct pairwise comparisons regarding the relative distance distributions of both activity types in tours. The deviations of these relative distances from the tour mid-distance were used to determine hierarchies and corresponding hierarchy strengths.

Our findings generally support the assumption that travel distance is an indicator for the importance of an activity and can be used to derive hierarchies between activity type pairs. The analysis of relative distance distributions between activity types revealed different distribution shapes, suggesting that some types are rather primary and others secondary activity in a tour. Hierarchies between activity types could successfully be derived and their strengths could be quantified. Both, the hierarchies themselves as well as their strengths are in congruence with intuitive expectations. Furthermore, most hierarchies were confirmed by the outcomes of the activity duration analysis or, conversely, revealed more credibly an activity’s priority in the tour formation process. For instance, a pronounced hierarchy was found between shopping and grocery in tours (which reflects the different degrees of spatial flexibility between both activity types) while activity durations were similar. Two exemplary analyses showed how the method can be applied to study the effect of a particular factor (here urban density and active versus motorised travel mode) on activity hierarchies.

The findings also confirm the often-expressed criticism towards activity type as an indicator of hierarchies. Similar relative distances distributions of some activity types pointed to the heterogeneity of activity profiles (and hence, of people’s behaviour) and resulted in low hierarchy strengths or, in few cases, even prevented from hierarchy derivation at all. For this reason, the proposed hierarchy scheme should by no means be interpreted deterministically. On the contrary, it rather reveals a trend towards one or the other activity type that can be more or less pronounced. As such, it gives a notion in which cases further activity attributes (activity duration, company, regularity, etc.) are necessary to estimate the hierarchy with some degree of certainty. For instance, the results suggest that one can be quite sure that work is the primary activity in work-grocery tours but that the primary activity in sport-shop tours varies on a case-by-case basis.

The positives of the approach encompass the possibility to use travel diary data (which is easy to collect and therefore widely available) and to determine not only hierarchies between activity types but also their strengths. This allows to use activity type as a measure to define hierarchies between activities more consciously (e.g. in activity-based travel demand models). As such, it is a considerable improvement over the approach in which a fixed hierarchy is applied (typically mandatory over maintenance over discretionary activity types). Moreover, the disclosure of spatial (travel) patterns is noteworthy. For instance, the findings reveal that day-care centres, kindergartens or primary schools are rather chosen close to the home than to the work location. Consequently, this method can be recommended for more extensive applications.

The simplicity of the method comes with a limitation, of which one should be aware. The interpretation of spatial patterns only might not sufficiently capture other factors that determine activity hierarchies, such as commitments to other people (particularly when they are systematic as for escort services). For this reason, a direction for further research is the development of a method that derives hierarchies from a bundle of available variables in travel diaries. These variables preferably include activity type, (relative) travel distances, activity durations and maybe even information on travel company. By implication, such an advancement potentially allows to establish a more disaggregated (and thus more consistent) hierarchy scheme.

4. Spatial trip chaining behaviour

In Chapter 2, typical mode-related trip chaining behaviour was revealed based on trip chain complexities of home-based tours. Complex trip chaining is particularly interesting since it is an efficient way of implementing an activity programme (Duncan, 2016). To explore the relationship between activity participation and travel in complex trip chains also spatially, knowledge is necessary about which activity purposed a tour and which has been added later. Therefore, we identified hierarchies between activity types in Chapter 3, allowing us to make robust assumptions about primary and secondary activities in complex trip chains using travel diary data.

Based on these grounds, this chapter studies spatial trip chaining behaviour of cyclists. Chapter 2 revealed that the bicycle accounted for a lower proportion of complex trip chains than the car. It seemed that this lower proportion is linked to the smaller spatial reach of the bicycle. From a spatial perspective, the question of whether there is an opportunity for complex trip chaining depends on the spatial proximity of a secondary activity from the activity programme to the route between home and primary activity. To better understand spatial arrangements between destinations that facilitate complex trip chaining by bicycle and car, we compare the detours that people make by both modes to include a secondary activity. We do this for commute tours since work turned out to be the most consistent primary activity across observations in Chapter 3. Influence factors on these detours are identified and related effects are compared between the two travel modes to reveal behavioural peculiarities of bicycle travel, responding to research question 4. Regarding the research objective of the thesis, Chapter 4 addresses the spatial dimension of activity-travelling by bicycle for complex trip chains (the spatial features of simple tours will be investigated in Chapter 5).

This chapter is currently under review for journal publication: *Schneider, F., Daamen, W., Hoogendoorn, S. Trip chaining of bicycle and car commuters: An empirical analysis of detours to secondary activities. Transportmetrica A: Transport Science (2019).*

4.1 Introduction

Activity participation and the reduction of travel-related impacts are often two contradictory objectives of policy-makers. People mainly travel to perform activities that satisfy their personal needs, such as going to work, buying food in a supermarket or bringing their child to a day-care centre. While this activity participation is crucial for the functioning of modern society, the related (and predominantly motorised) mobility causes a long list of environmental and societal problems, such as air pollution or congestion. To mitigate these conflicting goals, many cities aim for increasing the mode share of cycling at the expense of the car. However, such a mode shift requires that urban environments support activity-travelling by bicycle. A largely overlooked aspect in this context is trip chaining.

Trip chaining is an efficient way of activity participation regarding necessary travel. A home-based trip chain or tour is a sequence of trips that starts and ends at the home location (Primerano et al., 2008). By tying trips to several activity locations together, fewer trips and, typically, less travel resistance in terms of time or distance has to be overcome to implement a person's out-of-home activity programme. As a consequence, the mode-dependent capability of visiting several destinations within a tour can become an important mode choice factor (Ho & Mulley, 2013a).

The capability of forming complex trip chains (i.e. trip chains which include at least two destinations) by bicycle largely depends on the distances between activity locations. Several studies concluded that differences in trip chain complexity between car and public transport are largely caused by varying degrees of spatial and temporal flexibility (Duncan, 2016). In line with these outcomes, recent research found that trip chains related to the bicycle (which is temporally and spatially flexible but restrained by the physical effort of locomotion) include more often two or more different activity locations than public transport trip chains but less often than car trip chains (Schneider et al., 2020). Reducing the constraint induced by the limited reach through intelligent urban planning makes the bicycle more competitive for complex trip chaining and, by implication, increases its mode share. To design such urban environments, empirical knowledge on spatial trip chaining behaviour of cyclists is required. However, this information is, to our knowledge, largely lacking. This paper aims to fill this gap.

When we analyse the spatial relationship between activity locations that facilitate trip chaining, a basic understanding of activity planning is necessary. Former research suggests that activity planning is a dynamic process in time that is organised around a skeleton of anchor activities (Cullen & Godson, 1975; Lee & McNally, 2006). These anchor or primary activities appear to be the activities in a trip chain that are furthest away while less distant (secondary) activities are added opportunistically (Lee & McNally, 2003). An opportunistic situation can be assumed once the detour related to the inclusion of a secondary activity from the need list entails some efficiency gain in terms of travel distance or time. In practical terms, this is usually the case when the location of the secondary activity is close to the route between home and primary activity. The identification of primary activity types from travel diary data, however, is not trivial (Doherty 2006; Doherty and Mohammadian 2011). Research has shown that work seems to be the activity type that stably structures tours in time and space (Schneider, Daamen, Hoogendoorn-Lanser, et al., n.d.).

This is why this paper used commute tours as a reference to analyse the spatial arrangements of activity locations that result in complex trip chains. More precisely, we investigated how much people extend simple commute tours (i.e. tours involving only one destination) to include different types of secondary activities by bicycle and car. The comparison with the car as a spatially and temporally flexible travel mode (and main competitor) was chosen to identify bicycle-specific peculiarities of trip chaining behaviour. Using Dutch travel diary data, a linear regression model was developed, in which the distance extension of a tour was used as dependent variable and travel mode, type of secondary activity and several control variables as independent variables. As the effect of a variable can be mode-dependent (e.g. age might only affect bicycle travel but not car travel), all independent variables were additionally interacted with both travel modes.

The results give urban planners indications of how residential areas, companies and other destinations should be arranged to stimulate bicycle trip chaining. A further contribution of this study is the disclosure of some behavioural principles related to cycling that differ from car travel behaviour.

In the remainder of this paper, we first introduce the theoretical reflections that underlie this analysis. Then, we explain the commute tour data set in section 4.3. Subsequently, the employed statistical model is described in section 4.4. Finally, the results are shown and discussed in section 4.5, before drawing conclusions in section 4.6.

4.2 Theoretical framework of the study

The objective of this study is to reveal spatial arrangements of activity locations that facilitate bicycle and car trip chaining. The scope is commute tours to which another out-of-home activity is added.

The relationship between activities and travel can be described by a physical model, in which activities attract people to change locations while the related travel represents a resistance (Annema, 2013). Following this conceptualization, we can think of the commute tour formation as a hierarchical attraction-resistance problem. The hierarchy refers to the priorities in the activity planning process in which work is assumed to be the primary activity and another activity to be the secondary purpose of the tour. This means that the importance of work causes a person to accept the resistance that is related to the travel distance from home to work and from work to home. In this research, travel distance designates the actually covered distance of a person who travelled from a point A (e.g. home) to a point B (e.g. work) in a network. When adding another activity to the commute tour, its attraction only has to be in equilibrium with the travel distance that is related to the detour. For the event that several options would meet this requirement, we make the explicit assumption that the traveller picks the alternative that maximises his or her utility (i.e. the alternative for which, conceptually, the difference between attraction and travel resistance is largest).

Travel distance is only one measurement of travel resistance. In the literature, more factors are known that are linked to travel resistance. Annema (2013), for instance, divides travel resistance into the components travel time, travel costs and efforts. As a consequence, the same travel distance with a particular mode can entail different travel resistances depending on traffic conditions, the features of the respective road network (e.g. the allowed travel speed or the perceived safety) or the fitness of the traveller. In light of the spatial focus of this research, however, we make the simplified assumption that travel distance approximates the mode-specific travel resistance at the aggregated level of a sample (which includes data from different people, traffic states, networks, etc…).

Consequently, spatial arrangements of activity locations that lead to complex commute tours can be described by the travel distance extension e that can be calculated by comparing the tour distance of an observed complex commute tour $D_{complex}$ with the tour distance of its simple hypothetical counterpart D_{simple} (see Figure 4.1). In mathematical terms, the extension e for each tour observation $n \in N$ was calculated as follows:

$$e = D_{complex} - D_{simple} = (d_{Work} + d_{Sec} + d_{Home}) - (2 * d_{Work}) \qquad (4.1)$$

where

d_{Work} = distance from home (or the secondary) to the work location

d_{Sec} = distance from work (or home) to the activity location of the secondary activity

d_{Home} = distance from secondary activity (or work) to the home location.

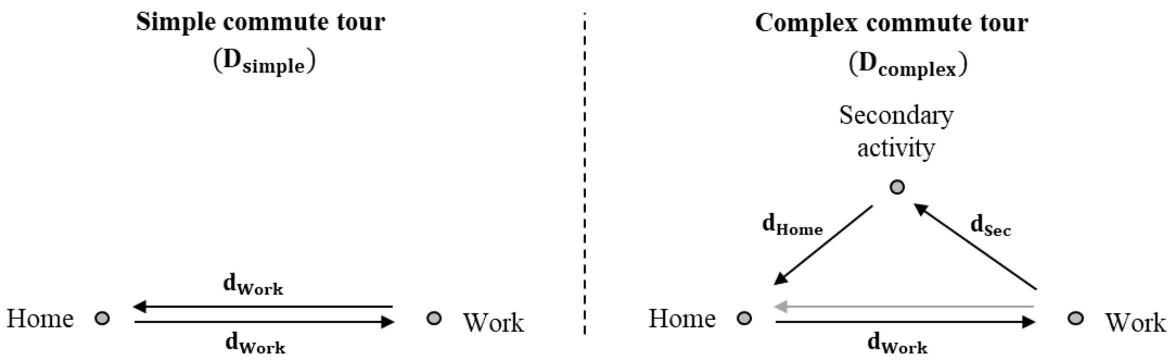


Figure 4.1 Tour distances in simple (D_{simple}) and complex ($D_{complex}$) commute tours.

To reveal spatial relationships between home, work and secondary activity locations that stimulate complex commute tours, it is useful to group secondary activities into types (e.g. leisure or grocery shopping) and relate these types to typical distance extensions. Furthermore, the effect of travel mode on these extensions should be isolated to gain knowledge that can be used for mode-specific spatial planning. Therefore, we addressed the following two research questions:

1. How much do people extend commute tour distances to accommodate secondary activities of different types?
2. What is the effect of bicycle compared to car travel on these extensions?

These research questions refer to two major elements that relate to commute tour extensions, that is, *secondary activity type* and *travel mode*. In Figure 4.2, we put forward a conceptual model that illustrates the assumed relationships. Below, we elaborate on the different elements of Figure 4.2.

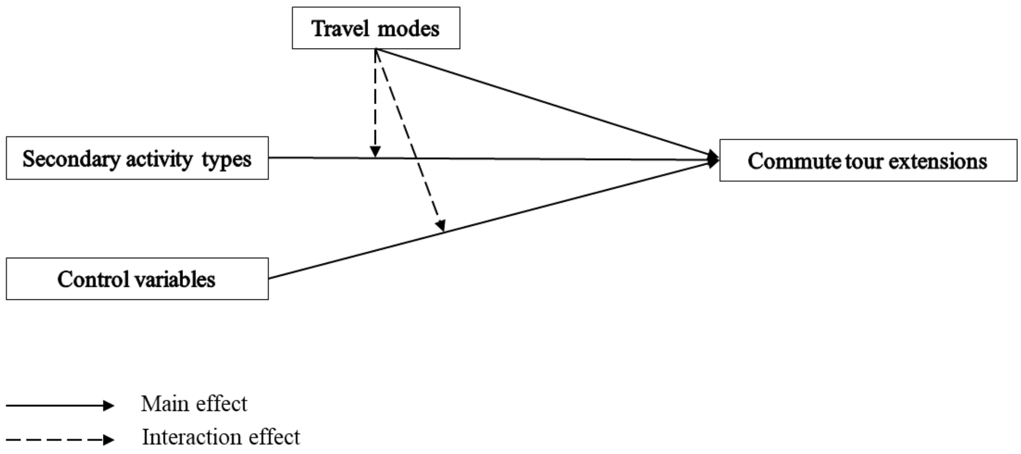


Figure 4.2 Conceptual model of commute tour extensions

First, *secondary activity type* influences observed commute tour extensions. By definition, the secondary activity causes the extension. On the one hand, we assume that the question of whether a secondary activity is added to a commute tour depends on its importance (or attraction potential). Accordingly, some activity types will only be added when they are close by. On the other hand, the detours to include a secondary activity also depend on spatial availability. In this case, observed extensions thus do not necessarily reflect the importance of the secondary activities. For instance, one would expect that extensions for grocery shopping will generally be shorter than those for visiting a language school. In sum, we expect that different activity types have on average distinct tour extension ranges.

Second, *travel mode* relates to observed commute tour extensions. While travel resistance increases with the length of the detour, it is perceived differently between bicycle and car travellers. For example, an extension by five kilometres represents a major barrier by bicycle, but an effortless extension by car. Considering the different travel resistance perceptions, we isolated the effect of travel mode on commute tour extensions from the effect of the secondary activity type. We did so by considering both a main effect that shows how much bicycle and car tour extensions are different in scale and an interaction effect that specifies the effect of the secondary activity type depending on the used travel mode (see Figure 4.2).

Third, a series of control variables are expected to affect commute tour extensions. Therefore, a list of potential control variables was identified based on the literature. Note, though, that not all variables of the list were available in our data set (see section 4.3 for the data description and section 4.4.1 for the variable selection). The list included commonly used socio-demographic variables (age, gender) as well as variables that represent the built environment and related availability constraints (urban density, land-use (Susilo & Maat, 2007; van Acker & Witlox, 2011)). Furthermore, a set of variables that capture space-time constraints (time of the day, simple tour distance, work duration (Brunow & Gründer, 2013; Kondo & Kitamura, 1987; Krygsman et al., 2007; van Acker & Witlox, 2011)) and the importance of the secondary activity (activity duration (Doherty and Mohammadian 2011; Schneider, Daamen, et al., n.d.)) were added to the list. Similarly to secondary activity type, these control variables might also have different effects on tour extensions dependent on the used travel mode. As mentioned above, age might not affect commute tour extensions by car, but it might affect commute tour extensions by bicycle. For this reason, we also interacted available control variables with the travel modes (see Figure 4.2).

4.3 Trip chain data set

The study was based on data from the Netherlands Mobility Panel (MPN in Dutch), a longitudinal panel that covers the whole Netherlands. The MPN consists (among other things) of a 3-day travel diary, a personal survey and a household survey. All three surveys are conducted yearly with around 4,000 participants. The MPN has been described in more detail in (Hoogendoorn-Lanser et al., 2015). The current analyses employed data from the years 2013 to 2016 to increase the number of observed commute tours.

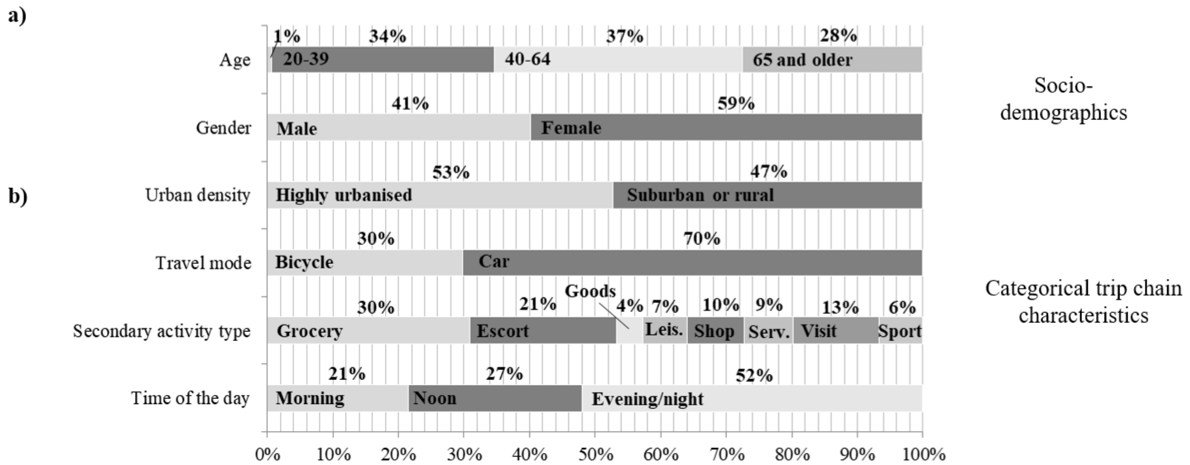
To derive commute tours from travel diary data, some data processing on both trip and tour-level was conducted. First, incomplete observations concerning trip origins and destinations, and observations with unrealistic reported travel distances were excluded. Second, trip purposes that did not lead to a fixed activity location (e.g. strolling, professional driving) were discarded. Third, trips were assigned to one of the three aggregated travel modes *car* (driver and passengers), *bicycle* and *other modes* based on the reported main mode of the trip. Fourth, activity durations were calculated by subtracting the ending time of a trip from the starting time of the consecutive trip of the same person. And last, commute tours that include a secondary activity were derived from travel diary data. Therefore, the following set of conditions was imposed:

- A sequence of consecutive trips had to start and end on the (same) home location.
- The origin of each trip had to be the destination of the previous trip.
- One of the two included activity types had to be work.

The trip chain data set contained information on several trip chain properties. Each trip chain was associated with a travel mode based on the travel mode(s) of the composing trips. Only unimodal trip chains, where all trips were travelled by bicycle or by car were considered for this research. Each trip chain was attributed to activity type, activity durations and time category (morning, noon, evening) of the secondary activity. In addition, we calculated for each trip chain both simple tour distance D_{simple} (which is d_{Work} times two) and travel distance extension e based on the reported distances of all related trips (see section 4.2). And finally, information pertaining to the traveller (age, gender) was connected with all trip chains.
Further filtering of the resulting trip chain data set was necessary in consideration of the proposed analysis framework. A tour extension e is supposed to be a positive value, however, some observations accounted for negative extensions. While these observations can be plausible, they are problematic to interpret and were therefore discarded. Furthermore, the longitudinal character of the data can result in multiple observations per person. To mitigate dependency between observations, we discarded duplicates of a person (i.e. tours that were travelled by the same travel mode to the identic destination). Lastly, tours were excluded in which work appeared to be clearly the secondary activity. We assumed this case once i) the simple tour distance D_{simple} was shorter than the tour extension e, ii) work duration was simultaneously shorter than the duration of the secondary activity (Doherty and Mohammadian 2011) and iii) when the secondary activity was *education* (Schneider, Daamen, Hoogendoorn-Lanser, et al., n.d.). The trip chain data set included 1,488 trip chains that were travelled by 1,424 different persons.

Figure 4.3 provides information on the sample composition regarding the explanatory variables that were considered for the analysis. Under a), socio-demographic features of the sample are presented. Most commute tours were as expected made by working-age people. While few commute tours were observed for people under 20 years, people who are usually still in education, a surprisingly large number of commute tours was related to people in retirement age. This indicates that many people continue to work (part-time) even after reaching the official retirement age (i.e. 65 by 2016 in the Netherlands). Another interesting feature of the sample was the high share of trip chains of women. This was partly caused by the composition of the underlying data set (women were more likely to fill in the questionnaires and diaries). In addition, former findings suggest that complex trip chains are more often formed by women than men (Islam & Habib, 2012).

Concerning the categorical trip chain characteristics presented in Figure 4.3b), the majority of the trip chains were travelled by *car* but also the *bicycle* accounted for a sufficiently large number of observations to perform statistical analyses. With regard to the urban density at the municipality level, a similar proportion of trip chains was related to people living in highly urbanised areas than those residing in suburban or rural environments. The cut-off point between both urban density categories was chosen 1,500 inhabitants per square kilometre. Figure 4.3b) also shows the sample composition for the secondary activity types. While *grocery*, *escort* and *visit* were often included in commute tours, *pick up/drop off goods* were rarely observed. The variable *time of the day* refers to the moment in which the secondary activity is performed. In this sample, smaller shares of the secondary activities were performed in the *morning* (6h00-10h59) and during *noon* (11h00-15h59), while the majority of secondary activities was conducted in the *evening* (and few observations also in the night). This can be explained by less temporal constraints after work than before work (Krygsman et al., 2007).



c)

	Mean	SD
Simple tour distance [km]	36.14	45.83
Duration of secondary activity [h]	0.77	1.08
Duration of primary activity (work) [h]	7.02	2.73

Continuous trip chain characteristics

d)

Sec. activity	Grocery	Escort	Goods	Leisure	Shop	Service	Visit	Sport
Mean [h]	0.33	0.22	0.20	2.04	0.42	0.64	2.03	1.85
SD	0.28	0.26	0.27	1.64	0.55	0.52	1.41	1.30

Durations of secondary activities per activity type

Figure 4.3 Sample description regarding all considered explanatory variables.

Next, mean values and standard deviations are provided for *simple tour distances* and the *durations of work* and the *secondary activity* in Figure 4.3c). The standard deviations of *simple tour distance* and *duration of secondary activity* indicate that there was large variation regarding how far people commute and how long secondary activities last. This means that the sample covered commuters whose work is situated close to their residence as well as long-distance commuters. Similarly, secondary activity durations ranged from activities of a few minutes to activities that last several hours. Conversely, the heterogeneity of work durations was rather small.

Finally, Figure 4.3d) indicates mean durations per type of secondary activity and related standard deviations. Activity duration is a proxy for activity attraction (Doherty & Mohammadian, 2011) and, therefore, useful information to interpret the model results. The figure shows that the different activity types had different duration profiles, both with regard to mean durations as well as concerning the spread. For instance, *sport* activities seemed to be consistently long while *grocery* activities were predominantly short. In contrast, *picking up or dropping of goods* or *shopping* durations accounted for a lot of variation.

4.4 Model development

This section describes how the postulated conceptual model (see Figure 4.2) was translated into a statistical model that reveals the effect of a set of explanatory variables on calculated commute tour extensions. First, we specify the included explanatory variables in section 4.4.1. Then, we explain how these variables are coded in section 4.4.2. And finally, we describe the chosen statistical procedure to estimate the effect of each explanatory variable.

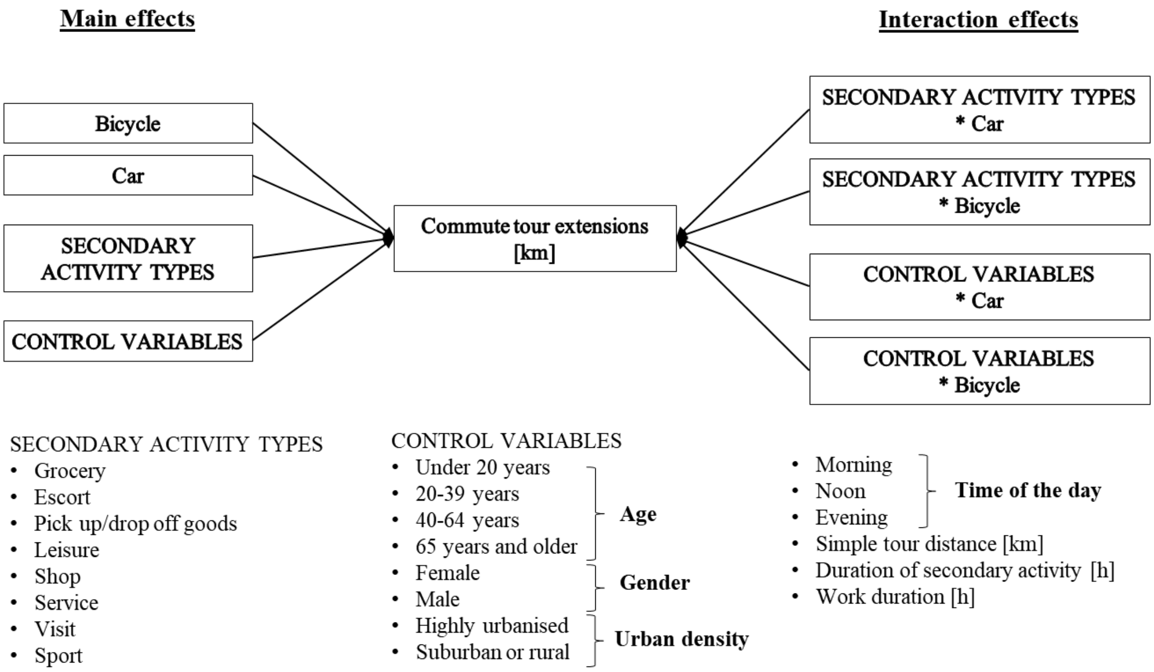


Figure 4.4 Composition of the statistical model of commute tour extensions.

4.4.1 Variable selection

In light of the addressed research questions, the following variables were considered in the model. The comparison between travel modes includes *bicycle* and *car* commute tours. With respect to secondary activity types, *grocery, escort, drop off/pick up goods, leisure, shop, service, visit* and *sport* were taken into account. This selection comprises all available activity types in the data set except activities that do not lead to a specific activity location (e.g. strolling) and *education*. This latter activity type was discarded since former research found that the (rare) combination between *work* and *education* is predominantly representing situations in which *work* is the secondary activity (Schneider, Daamen, Hoogendoorn-Lanser, et al., n.d.). Concerning the selection of control variables, the factors derived from the literature (see section

4.2) were mostly included in the final model. The exception were the variables that represent the built environment and related availability constraints. Due to data constraints, only urban density at a relatively aggregated level were suitable for inclusion. The reasoning behind the non-consideration was the suitability of available information in our data set. The resulting variable selection of the statistical model is presented in Figure 4.4.

4.4.2 Variable coding

The postulated model included a series of categorical variables. Categorical variables can be entered in a statistical model using coding techniques, such as *dummy coding* or *effect coding*. Both techniques build upon a transformation of variable categories into so-called dummy variables. A technical description of these transformations can be found in (Alkharusi, 2012). Differences between dummy coding and effect coding arise regarding the point of reference to which they pertain. While dummy-coded estimates indicate the effect of a category relative to an omitted reference category (whose effect is expressed by the constant of the model), effect-coded estimates refer to the *grand mean* (average of the estimated means of all categories) (te Grotenhuis et al., 2017b). Consequently, there is no confounding of reference categories in the constant using effect-coding. This is an important property given the large number of categorical variables in our analysis. Another advantage of effect coding is that estimated parameter values are stable regardless of the omitted category. This allows estimating the effects of all categories by employing two (main effects only) or four complementary models (main effects and interaction effects) and merging the results afterwards.

In this study we used *weighted effect coding* since the categories of our categorical variables did not account for equal numbers of observations (resulting in different values for *grand mean* and *sample mean*). As the *grand mean* weighs a category with few observations equally as a category with many observations, it is not suitable to display the central tendency of unbalanced data. By using *weighted effect coding*, all estimates relate to the *sample mean*. We coded the categorical variables following the procedure described in (te Grotenhuis et al., 2017b), the interaction terms between two categorical variables as defined in (te Grotenhuis et al., 2017a) and the interaction terms between categorical and continuous variables using the method explained in (Nieuwenhuis, Grotenhuis, & Pelzer, 2019). In addition, explanatory variables with a continuous measurement level were mean-cantered.

4.4.3 Parameter estimation

The statistical model estimating the effects of the variables from Figure 4.4 should ideally satisfy the following requirements. First, the model should allow estimating not only the main effects but also interaction effects. In this context, limited data as a consequence of interacting a variable category that contains few observations with the less frequently used bicycle should not systematically result in statistical insignificance for interaction terms. Next, the model should be a generalised linear model (GLM), as this is a requirement for the use of effect coding (te Grotenhuis et al., 2017a). Furthermore, the estimates should be easily understandable given the relevance of the research for practice. This condition entails that linear models are preferred in general, and GLM models with an identity link and non-transformed data in particular. And last, the model should not only allow inferring behavioural insights but also predicting beyond the limits of the sample.

In light of these requirements, we used a Bayesian linear regression model to estimate the mean effect of each variable on the outcome variable (Wakefield, 2013). Bayesian methods can be used to estimate the parameters of GLM models and can, hence, treat weighted effect coded variables. The reason to prefer Bayesian interference over frequentist interference (such as ordinary least square regression (OLS)) was its advantageous properties when having to deal with small samples (Depaoli & van de Schoot, 2014). This has to do with the way how each method treats the uncertainty arising out of few observations. The frequentist approach assumes that there is only one true parameter value, which holds for the whole population. Since statistical significance indicates how sure one can be that the estimated parameter corresponds to this true value, small sample sizes easily lead to insignificant effects. In contrast, the Bayesian approach conceptually assumes that parameter values follow a probability distribution, which is characterised by a mean and a measure of spread. In this context, more uncertainty leads to a flatter probability distribution of the parameter but does not prevent from interpreting the effects (Depaoli & van de Schoot, 2014).

Having said that, we did estimate an accordant OLS model to enrich Bayesian estimates with information on statistical significance and to attain a simple measure of goodness of fit (R squared as a reference to assess the quality of the model). Both models are based on the following equation:

$$Y = X\beta + \varepsilon \tag{4.2}$$

where

Y = vector of observed commute tour extensions [in km]

X = design matrix that includes the values of selected variables

β = vector of parameters

ε = vector of errors

We estimated the Bayesian regression models using the *stan_glm* function from the R r*stanarm* package and OLS regression models running the basic R function *lm*. As our research problem has (to our knowledge) never been studied before in a comparable setting, no suitable prior knowledge exists to construct the prior distribution for the Bayesian estimation. As a consequence, we used the uninformative prior of the *stan_glm* function (which is also the default setting). This entails that all parameter values are equally likely to be estimated before considering the data. We applied 10,000 iterations to estimate the posterior distributions. This means that interference is only made based on the assumed model and the available data. An exploration of the assumptions of linear regression models revealed that the residuals of the proposed model were neither normally distributed nor homoscedastic. This means that we could not, as aimed for, generalise findings beyond the sample of observed values (Field, 2009).

To determine the effects of all main and interaction effects, four models were estimated in which we omitted different categories of each categorical variable (see Table 4.1)). This entails four different design matrices X_1 to X_4. In model 1, for instance, the dummy variables for the main effects of *bicycle*, *grocery*, *older than 65 years*, *female*, *suburban/rural* and *evening* were omitted. Accordingly, model 2 estimated these main effects by omitting a complementary category of the respective categorical variables. As interaction terms could only be calculated for the travel mode that is included in the respective model, model 3 and 4 were necessary to estimate missing interaction effects.

Table 4.1 Omitted categories in the different models where applicable.

Variable	Model 1 Main effect	Model 1 Interaction effect	Model 2 Main effect	Model 2 Interaction effect	Model 3 Main effect	Model 3 Interaction effect	Model 4 Main effect	Model 4 Interaction effect
Travel mode	Bicycle	n.a.	Car	n.a.	Bicycle	n.a.	Car	n.a.
Secondary activity type	Grocery	Grocery *Car	Sport	Sport * Bicycle	Sport	Sport *Car	Grocery	Grocery *Bicycle
Age	≥65 years	≥65 years *Car	< 20 years	< 20 years *Bicycle	< 20 years	< 20 years *Car	≥65 years	≥65 years *Bicycle
Gender	Female	Female *Car	Male	Male *Bicycle	Male	Male *Car	Female	Female *Bicycle
Urban density	Suburban/ rural	Suburban/ rural *Car	Urban	Urban* Bicycle	Urban	Urban*Car	Suburban/ rural	Suburban/rural *Bicycle
Time of the day	Evening	Morning *Car	Morning	Evening *Bicycle	Morning	Evening *Car	Evening	Morning *Bicycle
Simple tour distance (DIST)	n.a.	DIST *Bicycle	n.a.	DIST *Car	n.a.	DIST *Bicycle	n.a.	DIST* Car
Duration of secondary activity (DURSEC)	n.a.	DURSEC *Bicycle	n.a.	DURSEC *Car	n.a.	DURSEC *Bicycle	n.a.	DURSEC *Car
Duration of work (DURWORK)	n.a.	DURWORK *Bicycle	n.a.	DURWORK *Car	n.a.	DURWORK *Bicycle	n.a.	DURWORK *Car

Note that no omission is needed for continuous variables which are hence indicated by n.a.

To determine the effects of all main and interaction effects, four models were estimated in which we omitted different categories of each categorical variable (see Table 4.1)). This entails four different design matrices X_1 to X_4. In model 1, for instance, the dummy variables for the main effects of *bicycle*, *grocery*, *older than 65 years*, *female*, *suburban/rural* and *evening* were omitted. Accordingly, model 2 estimated these main effects by omitting a complementary category of the respective categorical variables. As interaction terms could only be calculated for the travel mode that is included in the respective model, model 3 and 4 were necessary to estimate missing interaction effects.

The applied effect coding scheme allowed to merge the results of all four models into a single results table since parameters do not depend on the omitted category. The reported results comprised the mean, standard deviation and 95% credible interval of each posterior distribution. In addition, we augmented the results by highlighting the effects that were statistically significant at a 0.05 level in the OLS model.

4.5 Results and discussion

This section discusses the results in the following three subsections. Section 4.5.1 provides descriptive statistics of commute tour extensions for travel modes and secondary activity types. Subsequently, section 4.5.2 presents the results of the regression model explained in section 4.4 before discussing the outcomes in section 4.5.3.

4.5.1 Descriptive statistics of commute tour extensions

Table 4.2 provides mean commute tour extensions for car and bicycle and secondary activity types. Extensions of commute tours travelled by car accounted for on average 7.4 kilometres whereas extensions by bicycle were considerably shorter with a mean value of approximately 1.3 kilometres. The coefficient of variation (which is a standardised measure of spread) revealed that the distance extension of *car* tours were quite heterogeneous compared to the bicycle. This means that even though 7.4 kilometres was the mean of car extensions, both considerably shorter and longer extensions frequently occurred. In contrast, *bicycle* trip chains seem to have more limited distance extension ranges.

The different secondary activity types entail quite different distance extensions. *Grocery* and other *shopping* detours were generally very short, reflecting the good spatial distribution of supermarkets and stores in the Netherlands. Dutch planning policies, as opposed to those of many other countries in Northern America and Western Europe, rejected the concentration of retail activities in large-scale shopping centres on the outskirts of cities in favour of integrated locations in city centres and residential areas (Nijkamp, Klamer, & Gorter, 2003; Wagenaar, 2015). While *grocery* and other *shopping* are characterised by some extent of spatial flexibility, *visit* is much more constrained (a person cannot choose e.g. the place where the parents live). This means that a person is either willing to accept the resulting detour or the *visit* is not included in a commute tour. Interestingly, *escort* is the activity type that accounts for most (standardised) spread regarding observed tour extensions. These outcomes suggest that some people bring their children to the closest available location while others choose dedicated locations (e.g. an institution associated to a specific religious group), which are further away. The spread could also be related to different urban environments.

Table 4.2 Descriptive statistics of extensions in kilometres per travel mode and activity type.

Variable	**N** (N by bicycle)	**Mean**	**SD**	**CV**	**95 percentile**
Car	1053	7.37	18.49	2.50	36.00
Bike	435	1.28	2.14	1.67	5.62
Grocery	452 (194)	1.17	2.33	1.99	4.33
Escort	314 (56)	5.38	15.97	2.97	19.78
Pick up/drop off goods	66 (13)	4.65	10.41	2.24	20.51
Leisure	102 (32)	8.40	14.99	1.78	46.7
Shop	142 (48)	4.13	7.12	1.72	20.70
Service	126 (34)	8.60	16.41	1.91	47.20
Visit	193 (30)	12.81	29.00	2.26	60.00
Sport	93 (28)	8.53	20.02	2.35	40.60
Complete sample	**1488**	**5.59**	**15.57**	**2.79**	**25.00**

Overall, we identified different average commute tour extensions by travel mode and secondary activity type. What is missing is the disclosure of the effects of both aspects (travel mode and secondary type) at the same time while considering other control variables as well, such as the age of the traveller or the distance of the simple commute tour. This is done in the next section.

4.5.2 Results of regression model

This section shows and discusses the results of the postulated Bayesian and OLS regression models (see section 4.4). Table 4.3 presents the estimated coefficients of the posterior distributions of all main and interaction effects. The posterior distribution represents the uncertainty regarding the effect of a particular variable. The provided lower and upper bounds indicate the values of the 95% credible interval for each value. This means that there is a 95% probability, given the prior and the data, that the population parameter of a particular explanatory variable on the outcome variable lies within this credible interval (Depaoli & van de Schoot, 2014). Since we used an uninformative prior, the posterior distribution only depends on the data. As a result, the mean of each posterior distribution approximates the regression coefficient that was estimated with the OLS regression model (see section 4.4.3). The convergence statistics of the *stan_glm* function indicated that chain convergence was reached for all 4 estimated models. The R squared of the OLS models were 0.16. The estimated main effects in Table 4.3 refer to the sample mean, which is expressed via the constant. Conversely, the interaction terms pertain to the corresponding main effect (Nieuwenhuis et al., 2019; te Grotenhuis et al., 2017a). Note that the presented features of the posterior distributions represent the average values of all four estimated models in case that small deviations occurred (e.g. the mean of the posterior distribution of *visit* varied between 0.84 and 0.86).

Gender

We interpret in detail the effect of gender (which is with only two categories an easy example) on commute tour extensions to show how to interpret the estimates of Table 4.3. The estimated mean value of the main effect of each gender indicates the deviation from the sample mean. The estimated mean distance extension of *women* was hence 5.59 – 1.19 = 4.40 kilometres and the mean distance extension of *men* 5.59 + 1.76 = 7.35 kilometres. The difference between both genders can directly be calculated by subtracting the mean values of the main effects. Consequently, the model results suggest that *female* extensions were on average 2.95 kilometres shorter than those of *men* (-1.19 – 1.76 = -2.95 kilometres). The main effects of gender were statistically significant in the OLS model. When we are interested in the effect of bicycle commute tour extensions of *women*, we have to take into account two main effects (travel mode and gender) and the corresponding interaction term. This means that bicycle commute tours by *women* were on average extended by 5.59 (sample mean) – 1.19 (female main effect) – 2.26 (bicycle main effect) + 0.74 (female*bicycle interaction effect) = 2.88 kilometres. To calculate the differences between *male* and *female* extensions of bicycle commute tours, we can omit constant and bicycle main effect. Hence, the difference results from the sum of main and interaction effect for each gender and then subtracting the two sums: (1.76 + (-1.71) – (-1.19 + 0.74)) = 0.50 kilometres. The difference between estimated average *male* and *female* car commute tour extensions was 3.82 kilometres. However, the interaction effects were both insignificant in the OLS model. In conclusion, the model results propose that *male* tour extensions were considerably longer than *female* tour extensions. This finding might be related by a (still) different distribution of household tasks (e.g. more grocery shopping of women) or longer simple commute tour distances of men (compare the description of respective effects below). The gender effect was considerably more pronounced for car than for bicycle trip chains.

Travel mode

The model results suggest that the isolated effect of travel mode on commute tour extensions was large. Estimated mean extensions by car were 6.53 kilometres and those by bicycle 3.33 kilometres. Both main effects were statistically significant in the OLS model. These outcomes are not surprising considering typical travel speeds of both modes and the different mean extensions presented in Table 4.2.

Table 4.3 Bayesian linear regression.

Main effect	Interaction effect	Mean	Standard deviation	Lower bound**	Upper bound**
Constant (= sample mean)		5.59*	0.38	4.85	6.34
TRAVEL MODE					
Bike		-2.26*	0.68	-3.60	-0.92
Car		0.94*	0.28	0.39	1.49
SECONDARY ACTIVITY TYPE					
Grocery		-1.97*	0.66	-3.26	-0.68
	Bicycle	0.79	0.70	-0.59	2.15
	Car	-0.60	0.53	-1.65	0.44
Escort		2.22*	0.89	0.49	3.95
	Bicycle	-2.82	1.91	-6.59	0.85
	Car	0.61	0.41	-0.19	1.42
Drop off/pick up goods		0.99	1.80	-2.53	4.49
	Bicycle	-1.14	3.66	-8.31	6.05
	Car	0.29	0.90	-1.48	2.04
Leisure		-2.64	1.55	-5.72	0.40
	Bicycle	2.05	2.30	-2.46	6.56
	Car	-0.94	1.06	-3.01	1.12
Shop		-0.31	1.21	-2.68	2.06
	Bicycle	0.11	1.68	-3.18	3.36
	Car	-0.05	0.87	-1.75	1.65
Service		3.53*	1.27	1.05	6.01
	Bicycle	-1.79	2.08	-5.89	2.29
	Car	0.67	0.78	-0.85	2.19
Visit		0.85	1.18	-1.47	3.15
	Bicycle	-1.09	2.65	-6.33	4.08
	Car	0.21	0.49	-0.76	1.16
Sport		-1.77	1.59	-4.88	1.34
	Bicycle	1.55	2.41	-3.19	6.29
	Car	-0.68	1.05	-2.75	1.38
AGE [years]					
Under 20		1.43	4.70	-7.82	10.57
	Bicycle	0.41	3.81	-7.08	7.83
	Car	-0.56	5.71	-11.70	10.58
20-39		-0.69	0.56	-1.77	0.39
	Bicycle	0.93	0.85	-0.73	2.59
	Car	-0.41	0.37	-1.14	0.32
40-64		0.62	0.50	-0.37	1.60
	Bicycle	-0.88	0.80	-2.45	0.68
	Car	0.36	0.33	-0.28	1.01
65 and older		-0.04	0.62	-1.26	1.18
	Bicycle	-0.01	1.03	-2.03	1.98
	Car	0.00	0.38	-0.73	0.74
GENDER					
Female		-1.19*	0.33	-1.85	-0.54
	Bicycle	0.74	0.41	-0.08	1.54
	Car	-0.39	0.21	-0.80	0.04
Male		1.76*	0.49	0.79	2.70
	Bicycle	-1.71	0.95	-3.59	0.17
	Car	0.48	0.27	-0.05	1.00

Table 4.3 Continued.

Main effect	Interaction effect	Mean	Standard deviation	Lower bound**	Upper bound**
URBAN DENSITY					
Highly urbanised		0.26	0.38	-0.49	1.00
	Bicycle	-0.20	0.42	-1.01	0.63
	Car	0.12	0.27	-0.40	0.65
Suburban or rural		-0.29	0.42	-1.12	0.55
	Bicycle	0.45	0.95	-1.42	2.31
	Car	-0.10	0.22	-0.55	0.33
TIME OF THE DAY					
Morning		-0.57	0.85	-2.23	1.09
	Bicycle	0.36	1.34	-2.24	3.01
	Car	-0.14	0.53	-1.18	0.91
Noon		0.28	0.72	-1.13	1.70
	Bicycle	-0.22	1.05	-2.27	1.81
	Car	0.11	0.50	-0.88	1.08
Evening		0.09	0.44	-0.77	0.94
	Bicycle	-0.01	0.72	-1.42	1.40
	Car	0.00	0.28	-0.55	0.56
SIMPLE TOUR DISTANCE [km]					
Distance		0.03*	0.01	0.01	0.05
	Bicycle	-0.01	0.11	-0.23	0.20
	Car	0.00	0.00	0.00	0.00
DURATION SECONDARY ACTIVITY [h]					
Duration		4.22*	0.49	3.27	5.17
	Bicycle	-3.82*	0.97	-5.72	-1.93
	Car	0.91*	0.23	0.46	1.37
DURATION WORK [h]					
Duration		-0.19	0.17	-0.52	0.15
	Bicycle	0.13	0.24	-0.34	0.61
	Car	-0.07	0.13	-0.33	0.18

** Statistically significant effect at 5% level of significance in OLS regression model; ** Lower and upper bound of 95% Credible Interval*

Secondary activity type

The model estimates propose that different activity types entail considerably different commute tour extensions. *Leisure*, *sport*, *grocery* and *shop* were all related to shorter extensions than the sample mean while *visit*, *drop off/pick up goods*, *escort* and *service* were associated with longer extensions. In this context, *leisure* had the smallest effect on tour distances with an estimated 2.95 kilometres detour, whereas *service* entailed the longest mean extensions with 9.12 kilometres. Interestingly, the estimated effects of the model did not always correspond to the means presented in Table 4.2. This signifies that the presented means of Table 4.2 confound several features of tours that also affect commute tour extensions. For instance, the mean of *escort* extensions shown in Table 4.2 appeared to be relatively small but it might have accounted for short activity durations and a high proportion of tours conducted by women at the same time (see the discussion of these specific effects below). As a consequence, the isolated effect of *escort* was larger. The OLS model revealed that the main effects of *grocery*, *escort* and *service* were all statistically significant.

The effect of secondary activity type on bicycle commute tour extensions ranged from 1.18 kilometres below cycling average extension (i.e. 3.33 kilometres) for *grocery* shopping to 1.75 kilometres above cycling average for *service*. This was a considerably lower spread than for those of car tours, for which *leisure* was 3.58 kilometres below and *service* 20.4 kilometres above the average of 6.53 kilometres. This finding indicates that differences between secondary activity types are smaller for bicycle commute tours than for car commute tours as both travel modes have different operational distance ranges.

Some of the estimated effects of the model deserve further discussion. Interestingly, *escort* and *picking up or dropping off goods* had inversed estimated effects on the mode-specific means. More specifically, both activity types had positive effects on car detours and negative effects on bicycle commute tour extensions. It can be hypothesised that the inconvenience of transporting people and goods lead to these inversed effects.

Another remarkable outcome is related to *leisure* and *sport*. While both main effects were negative for the whole sample with 2.64 and 1.77 kilometres respectively, the negative effects of car were considerably more pronounced. As a result, the estimated mean commute tour extensions of both modes approached each other and deviated the least among all considered secondary activity types (0.21 kilometres for *leisure* and 0.97 kilometres for *sport*). This finding is noteworthy against the backdrop that both activity types are recreational. In this context, it can be speculated that the disutility of travel might be reduced by a utility that potentially arises from bicycle use. Former research found that people often perceive cycling as a travel mode that is outstandingly ‘fun’ and ‘relaxing’ (Ton et al., 2019). This potential of the bicycle might particularly take effect when the utility of bicycle use (recreation, physical exercise) is in line with the purpose of the related activity.

Age classes

The model results suggest that commute tour extensions of the age group of *under 20 years* were longest with 7.02 kilometres and shortest for the age group of *20 to 39 years* with 4.90 kilometres. The age group of people aged *40 to 64* accounted for a small positive effect for the whole sample (extensions of around 6.21 kilometres), while the *oldest age group* did not considerably deviate from the sample mean. When looking separately at the effects for car and bicycle tours, an interesting observation can be made. While the younger age groups were related to larger and the older to smaller tour extensions than average for the bicycle, no clear relationship could be found for the car. At first glance, this finding suggests for bicycle travel that the physical effort related to extending a commute tour becomes an increasing barrier with age. However, the deviations of in particular the *oldest age group* with only 0.05 were surprisingly small. This unexpected outcome could be explained by the increasing number of e-bikes in the Netherlands (Kroesen, 2017), which are assumed to be more used by elderly people. Moreover, the estimates of the youngest age group are highly uncertain (indicated by the large 95 per cent credible interval) due to the small group size. All main and interaction terms were statistically insignificant, indicating that age was no major factor to explain trip chaining behaviour of commuters.

Urban density

The outcomes of the model propose that commute tour extensions relating to *highly urbanised* municipalities are 0.53 kilometres longer than those of *suburban or rural* municipalities. This result is counterintuitive. Since high urban densities usually coincide with a higher supply of services, one would rather expect a negative relationship. Interestingly, the positive effect for the whole sample seems to be caused by car commute tours. According to the model estimates, corresponding extensions were 0.77 kilometres longer in highly urbanised municipalities than in suburban or rural municipalities. In contrast, bicycle commute tour extensions were, as expected, slightly longer in the suburban or rural context (by estimated 0.10 kilometres). An explanation of the surprising car estimates could be that car travellers residing in highly urbanised environments have access to more specialised services (e.g. an organic supermarket), for which they are willing to travel further. Their counterparts from suburban and rural areas as well as cyclist commuters, however, do not have these choices and go for the closest available destination. While this explanation is speculation, main and interaction effects related to *urban density* were both insignificant in the OLS model.

A caveat to the surprising car estimates in particular and all estimates in general is a feature of the variable *urban density*. As this variable refers to the municipality of residence in the MPN data set, it is more informative for commute tours that start and end in the same municipality than for tours that involve further (unknown) municipalities. This latter case is more likely to occur for car commuters, who travel on average 24 kilometres to work in our data set as compared to four kilometres by bicycle.

Time of the day

Commute tour extensions for secondary activities that took place in the *morning* (and hence before work) were estimated more than half a kilometre shorter than those in the *evening*. This finding is in line with former evidence, revealing that the *morning* is characterised by stronger time constraints (Kondo & Kitamura, 1987; Krygsman et al., 2007). Interestingly, the model results further suggest that the longest commute tour extensions occurred during *noon*. This finding might be related to people that work part-time (as *noon* was defined as the time span from 11 a.m. to 4 p.m.). These people potentially have fewer time constraints (as they have the afternoon available) what might allow them to make longer detours to include a secondary activity. While the difference between detours during *noon* and *morning* was 0.85 kilometres, all main effects were non-significant in the OLS model. When we look at the effects for bicycle commute tours only, the differences between *morning*, *noon* and *evening* were trivial. Conversely, differences in car commute tour extensions were more pronounced and accounted for up to 1.1 kilometres between *morning* and *noon*. This contrast suggests that observed car commute tour extensions are more constrained by available time than detour distance while it is the other way round for bicycle commute tour extensions. However, also the (car) interaction effects were statistically insignificant.

Simple tour distance

The model results propose for the complete sample that commute tour extensions slightly increase with increasing distances of the simple commute tour. This mode-independent outcome is surprising as longer distances to work come along with higher time constraints for the inclusion of a secondary activity, suggesting hence a negative effect on commute tour extensions. An explanation behind the unexpected (and statistically significant) trend could be that longer commute distances reduce the perceived travel resistance of the detour since the ratio between simple commute tour and detour is decreasing. Having said this, the positive effect of simple commute tour distances does not seem to be very important for both modes. For example, a simple commute tour distance of 50 kilometres by car would relate to a 1.50 kilometres detour and a simple commute tour distance of 10 kilometres by bicycle an extension of only 0.20 kilometres.

Duration of secondary activity

The findings reveal a strong effect of the activity duration of the secondary activity on commute tour extensions, which is also statistically significant for both main and interaction effects. The model results propose that the commute tour extensions are increasing by 4.22 kilometres per hour of activity duration. This finding is expected as activity duration is often a proxy for the importance (attraction potential) of an activity (Doherty and Mohammadian 2011). In addition, longer durations also justify longer travel distances, and thereby, longer travel times since the so-called travel time ratio (which relates travel time to the sum of travel and activity time) remains stable (Dijst & Vidakovic, 2000; Schwanen & Dijst, 2002). The model further suggests that extensions differ substantially between car and bicycle commute tours. Car tours are extended by 5.13 and bicycle tours by 0.40 kilometres per marginal unit. An explanation of this finding could be that a linear relationship between activity duration and commute tour extension only exists up to an acceptable total commute tour distance is reached. This boundary is likely to be smaller for cyclists than for car drivers as it is not only determined by time and cost constraints but also by the fitness of the cyclist. Once the boundary is passed, cyclists will not extend tour distances anymore regardless of the activity duration, entailing that a smaller overall effect is estimated.

Duration of work

The model suggests that commute tour extensions are decreasing by 0.19 kilometres per hour of work. This negative relationship is expected based on time-geography (Hägerstrand, 1970). Since longer working time is reducing the available time for both travel and performing a secondary activity, also accessible space is limited. This notion seems to be mode-independent. While car commute tour extensions decrease by 0.26 kilometres per working hour, bicycle commute tour extensions decrease by 0.06 kilometres. Applied to an eight-hour working day, the effects add up to 2.08 kilometres by car and 0.48 kilometres by bicycle. The values roughly represent the difference of commute tour extensions in scale between both modes. Since both main and interaction effects were non-significant in the OLS model, the activity duration of work does not seem to be an important predictor of commute tour extensions.

4.5.3 Discussion

To sum up the results, the presented model outcomes revealed the effects of different factors on commute tour extensions that were related to the inclusion of a secondary activity in the tour. Obviously, the choice of travel mode had the biggest effect on the extent of such detours: bicycle commute tours were considerably less extended than car commute tours. In addition, large differences were observed between types of secondary activities. Moreover, considerable differences in tour extensions were found between men and women. Furthermore, the simple commute tour distance had a small effect on detour lengths. Last but not least, tour extensions were strongly related to the duration of the secondary activity. Besides these statistically significant effects, the work duration and time of the day had noteworthy effects on commute tour extensions. Surprisingly, the age of the traveller was not related to any consistent influence on trip chain extensions. Finally, the effect of urban density was marginal. However, this latter effect should be interpreted with caution due to potentially missing density information around the work location. In the following, we discuss the implications of our findings for research and policy.

The comparison between car and bicycle trip chains provided some signals of the manner in which trip chaining behaviour of both travel modes is different. First, bicycle trip chaining seems to be less influenced by available time or the importance of the secondary activity than car trip chaining. In contrast to car tours, extensions were similarly long independent of the time of the day, and activity duration was only related to moderate tour extensions. While car trip chains seemed to be more constrained by time availability, bicycle travel behaviour appeared to be more subject to distance restrictions. These findings raise the question if there is something like a travel distance budget that acts (similarly to the concept of travel time budget) as a regulative principle of bicycle travel behaviour. And second, we found an indication that the concept of travel resistance (or disutility in econometric terms) has to be carefully used for bicycle travel. The effects of commute tour extensions related to leisure and sport suggest that bicycle travel is not only a necessary burden to reach activity destinations but can partly have a utility in its own.

The findings of this research are policy-relevant in several respects. First, the research revealed the types of secondary activities that frequently can be found in commute tours. These types often seem to be in reach and appear to be functionally combinable with the features of work travel. Land-use planning that increases the spatial availability of these activity types between residence and work locations would facilitate trip chaining and could thereby increase the efficiency of the transport system. In particular, the locations of supermarkets, shops, medical and day-care centres, primary schools or sports facilities can be placed accordingly by the urban planner. Second, the results of the model directly give guiding values for the design of such trip chaining-friendly environments. For instance, urban planners could run a four step travel demand model only for bicycle commute trips and optimise the locations of secondary activities in such a way that they are within realistic detours for a maximum number of bicycle commuters. By facilitating the formation of complex trip chains by bicycle, there are also good prospects that the bicycle mode share increases. And third, the behavioural insights of active mode travel that emerged from this analysis may have implications for several policy tools. Travel time, often expressed in monetary terms via the value of time, is a central factor of many transport applications (e.g. mode choice models or cost-benefit-analyses). The findings of this research, however, challenge that time is the principal driver of active mode travel behaviour. Similarly, the notion that active mode travel might come along with some utility, as opposed to the motorised travel modes, might require a review of choice models and appraisal methods. Having said this, more knowledge is needed to clearly disentangle the complex interrelationship between travel time and travel distance and to better understand the trade-off between utility and disutility in active mode travel.

4.6 Summary, conclusions and future research

In this study, we investigated distance extensions of simple commute tours to accommodate a second activity in the tour for both bicycle and car trip chains. We conducted a regression analysis, in which commute tour extensions were used as the dependent variable and travel mode, secondary activity type, age, gender, urban density, time of the day, simple commute tour distance and duration of work and secondary activity were employed as the independent variables. In addition, all independent variables were interacted with both travel modes to reveal mode-specific effects.

The results comprise the disclosure of typical distance extensions by car and by bicycle to reach different types of destinations. The model outcomes suggest that commute tour extensions depend first and foremost on the travel mode. While average bicycle tours were extended by 3.33 kilometres, car tours accounted on average by 6.53 kilometres. Besides the travel mode, commute tour extensions also differed considerably depending on the type of secondary activity. For instance, the accommodation of specific *services*, such as a visit to the doctor, was related to 3.5 kilometres longer detours compared to the average commute tour extension in the sample. Conversely, the effect of the secondary activity types *leisure*, *sport* and *grocery* were estimated to be around 2 kilometres shorter than average. The estimated interaction terms, however, revealed that these effects are mode-dependent. In general, much larger effects were found for car travel than for bicycle travel. In addition, some effects on the mode-specific means were even inversed between bicycle and car. For instance, the model results suggest that the secondary activities *escort* and *pick up or drop off goods* have a negative effect on the length of the extension when travelling by bicycle but a positive effect when the travel mode is the car.

The findings of this paper are of interest for both transportation scientists and practitioners. The identified behavioural differences between active and motorised travel behaviour have implications for example for the space-time prism concept, in which space should not only be restricted by available time for active mode travellers, but also by a measure of physical capacity. Furthermore, the interpretation that cycling can be related to positive utility challenges the foundations of current econometric choice modelling practice. Urban planners can use the outcomes to develop dedicated urban environments that stimulate trip chaining behaviour in general or bicycle trip chaining in particular. The estimated mean extensions can be used to identify hot spot areas between residential zones and jobs in which further destinations such as day-care centres, supermarkets, other shops and further services (e.g. surgeries) could be concentrated. Such areas could additionally be accompanied by bicycle-friendly policies such as providing safe and accessible bicycle parking facilities, publicly available lockers to store purchases or charging stations for electric bicycles.

As the data did not meet the parametric assumptions of the used regression models, caution is needed when transferring the results to data with a considerably different sample composition. In this context, we recommend interpreting the estimates of this model rather as an upper limit of distance extensions that enable trip chaining. Further research should address this limitation by employing more robust regression techniques. In addition, we advise to include more variables that capture the urban context in which the commute tour takes place. Moreover, we recommend to further explore the role of utility and disutility in active mode travel decisions. And finally, we suggest reviewing various concepts in transportation which are built around travel time, such as *travel time budget* or *travel time ratio* for active mode travel.

5. Bicycle accessibility

In Chapter 2, we identified the roles that the bicycle can play for daily-life activity-travelling of different classes of cyclists. Furthermore, we revealed how typical activity-travel patterns by bicycle and other modes look like in terms of the number of activities included in home-based tours (i.e. the so-called trip chain complexity). In Chapters 4 and 5, the relationship between activity participation and related travel is studied with regard to its spatial features. More specifically, Chapter 4 analysed complex trip chain patterns whereas the current Chapter investigates the spatial characteristics of simple trip chains. As such, Chapter 5 completes the necessary understanding of spatial activity-travel behaviour of cyclists to attain the overall research objective of this thesis.

In this chapter, we study cycling distances to destinations in an accessibility framework. Bicycle accessibility of destinations is a key requirement for any activity-travelling by bicycle. A measure of accessibility is the distance from an origin to a destination (Vale, Saraiva, & Pereira, 2016). To understand how far people typically cycle to different types of destinations, we analyse travel distances of outbound trips in simple home-based tours. Since observed travel distances always reflect local realities with regard to land-use and transport system, we employ data from three different bicycle-friendly regions, namely the Netherlands, the Copenhagen Metropolitan Area and the Freiburg Region in Germany. We relate cycling distances to activity types and a broad set of explanatory variables. Moreover, the effects of influence factors are disaggregated for the three considered regions, indicating behavioural differences between those three cycling cultures. Chapter 5 answers research question 5, inquiring typical cycling distances to daily-life destinations and their determinants.

This chapter is currently under review for journal publication: *Schneider, F., Jensen, A.F., Daamen, W., Hoogendoorn, S. Bicycle accessibility: What can we learn from best-practice examples? Transport Geography (2020).*

5.1 Introduction

For many reasons, cities want to provide good bicycle accessibility to jobs, shops and other services. Road traffic is increasingly associated with serious environmental (Ouis, 2001; Pérez et al., 2010) and societal problems (Hine, 2003; Sauter & Huettenmoser, 2008), particularly in growing urban areas. One way to reduce these travel-related problems while still enabling people to move to destinations where they can engage in various types of activities is to travel more by bicycle. Cycling is known to have visually no environmental impacts, to be affordable for the user and both space and cost-efficient for the city. However, a prerequisite for the use of the bicycle in daily life travelling is that typical destinations such as the workplace or shops are accessible.

Accessibility can be defined as ‘the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s) at various times of the day’ (Geurs & van Wee, 2013, p. 208). Assuming that the temporal dimension of this definition due to congestion is not (yet) a major concern for bicycle traffic, bicycle accessibility essentially depends on the land-use and transport system and the characteristics of the traveller. According to the aforementioned authors, the land-use component primarily describes the spatial distribution of demand (i.e. the places where people live who need activities) and offer (i.e. destinations which offer these services). The transport system component captures the resistance that is attributed to overcoming the space between origins and destinations in a given area. When travelling by bicycle, this resistance can for example arise from physical (related to active locomotion) and psychological (due to unsafe feelings) efforts (Annema, 2013). This means that bicycle accessibility depends on an attractive and safe cycling network to reduce the resistance of space, but, more importantly, on activity locations that are available within cycling distances.

Urban planners have several levers to ensure that distances to destinations are in reach. In particular high urban densities combined with mixed land-use zonings, as embodied in the concept of the *compact city* (Dieleman & Wegener, 2003), increase the probability that the desired destinations can be found in the vicinity. Clearly, not all origin-destination (OD) relations can be influenced by the planner (e.g. where friends live), but land-use plans still allow to determine for instance (minimum) distances between residential areas and the locations of schools, supermarkets and other services. What is still missing are benchmark values for planners to assess existing urban structures and optimise new urban developments with respect to bicycle accessibility.

In this research, we aim to provide this knowledge by looking at actual cycling distances in best-practice environments. For this purpose, we created a unique data set that combines travel diary data from three of Europe’s most bicycle-friendly regions, namely the Netherlands, the Copenhagen Metropolitan area in Denmark and the Freiburg Region in south-west Germany (Buehler & Pucher, 2011; Nielsen, Skov-Petersen, & Agervig Carstensen, 2013; Pucher & Buehler, 2008). Using both quantile regression and ordinary least square (OLS) regression techniques, we relate a rich set of contextual variables to observed cycling distances to identify benchmark distances to typical destinations.

Besides the identification of important factors on cycling trip distances, this paper comprises two major contributions. First of all, the quantile regression results indicate the effects of different types of activities not only on median cycling distances but also on other meaningful statistics of the bicycle trip distance distribution. And second of all, the employed OLS model reveals due to integrated interaction terms important differences in cycling behaviour across the three considered regions.

In the remainder of this paper, we first outline how we investigate bicycle accessibility in section 5.2. Subsequently, we present the study areas and the data used in the analysis in section 5.3. Next, we describe the statistical analyses performed in section 5.4. Finally, the results are presented and put into perspective in sections 5.5 and 5.6 before providing some concluding comments in section 5.7.

5.2 Research approach

The aim of this study is to empirically underpin theoretical conceptualizations of cycle-friendly land-use systems by providing benchmark values from best-practice environments for typical distances to destinations. More precisely, we intend to investigate how far people cycle from home to typical daily-life destinations in environments that are supposed to have already outstanding bicycle accessibility today. Moreover, we want to identify factors other than the type of activity performed at the destination that play a role in explaining observed (or revealed) cycling distances.

Distance is an often used operational measure of bicycle accessibility (Vale et al., 2016). According to the definition of accessibility provided in the introduction, this measure is compounded of the land-use system (determining the distances between origins and destinations) and the transport system (i.e. the cycling network, the cycling facilities and the bicycle itself) and the joint evaluation of both features by the traveller. Consequently, every revealed bicycle trip can be interpreted as a data point of existing (subjective) bicycle accessibility (otherwise the trip would not have taken place by bicycle).

From an urban planning perspective, it would be of interest to completely separate the land-use system from the other components of bicycle accessibility (in particular the subjectivity induced by the profile of the traveller). This isolation would allow to derive useful parameters of cycle-friendly land-use systems, for instance, expectable catchment areas for particular destinations (e.g. a shopping centre). To do so, activity-travel data would be required that include besides the personal characteristics of the traveller trajectory data of the trip and related information on network features and facility types. However, such highly detailed data is in practice not (yet) available. Therefore, we have to make an assumption concerning the transport system. In a best-practice environment, a good cycling network and adequate bicycle facilities are expected to be largely in place. Consequently, observed cycling distances would only depend on the land-use component, the characteristics of the traveller and the type of bicycle.

Based on these reflections, we put forward the conceptual model illustrated in Figure 5.1. We treat observed cycling distances as a dependent variable, which is explained by the different components of bicycle accessibility and a few control variables. The land-use component refers to the type of activity at the destination that purposed the tour. To avoid any ambiguity, we only look at outbound trips in home-based tours that include a single out-of-home activity. Recent research suggests that this scope covers most activity-travelling by bicycle (Schneider et al., 2020). As argued before, the transport system component has been reduced to the type of bicycle by the choice of bicycle-friendly environments. Personal characteristics comprise features of the traveller and his or her social environment and were chosen based on available data (see section 5.4).

The considered control variables monitor different aspects. Activity duration is a proxy for the importance of an activity (Schneider, Daamen, Hoogendoorn-Lanser, et al., n.d.), expecting that longer durations entail longer distances. Additional daily cycling distances which go beyond the regarded tour (that is the distance to the considered destination and back home) capture the influence of physical constraints. Urban density relates to the land-use system and provides us with a notion to what extent an expected contrast regarding spatial availability of destinations affects observed cycling distances. And finally, a variable referring to the included regions tests, if the non-included features of the transport system (characteristics of cycling network and bicycle facilities) are indeed no factor to explain observed cycling distances at the aggregated level of a best-practice region. Furthermore, we check the culture-dependency of the outcomes by interacting all variables with the different regions.

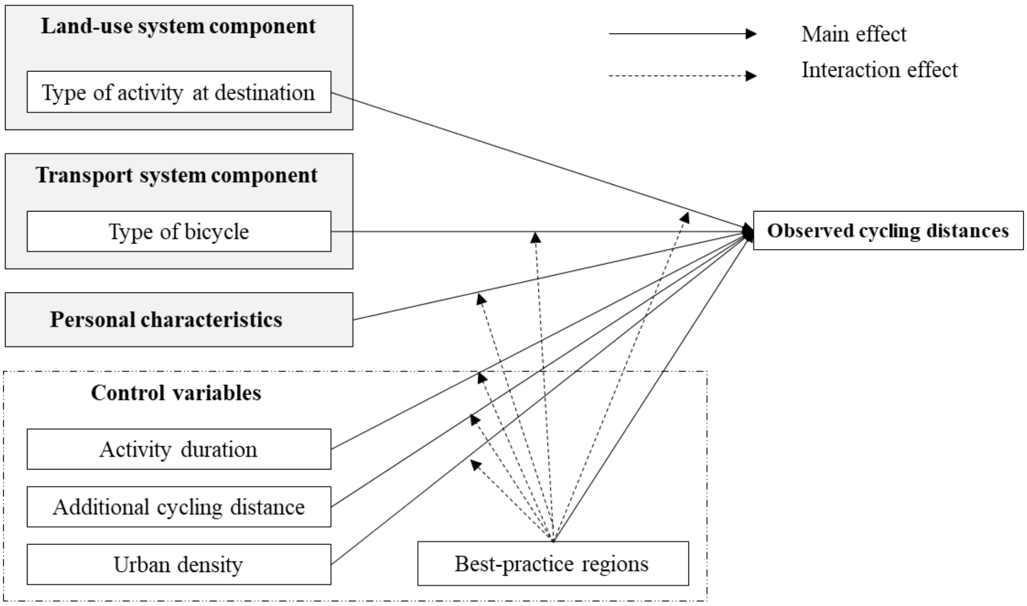


Figure 5.1 Conceptual model of the analysis of observed cycling distances.

Considering the probability of having many trips in the data that are much shorter than what travellers would have accepted to cycle, we do not only look at mean effects but also at other parts of the cycling distance distribution (e.g. at the 25 per cent longest trips). This provides us with a better understanding of which trip purposes entail longer cycling distances and which type of people can be expected to have higher personal boundaries of acceptable cycling distances.

5.3 Study areas

In this section, we first introduce indicators of good bicycle accessibility at the aggregated level of a region and discuss the three studied regions (the Netherlands, the Copenhagen Metropolitan Area and the Freiburg Region) with regard to these indicators. Subsequently, we outline the cycling conditions of each region in section 5.3.2. Finally, we describe the employed data and discuss the features of the sample in sections 5.3.3 and 5.3.4 respectively.

5.3.1 Introduction to best-practice bicycle accessibility

Based on the accessibility definition from the introduction, we can identify areas with an overall good level of bicycle accessibility by looking at two indicators. First, a high mode share of the bicycle is an indication that both land-use and transport systems enable people to reach many destinations by bicycle. And second, a similar activity participation by bicycle compared to the total out-of-home activity participation demonstrates that bicycle use is not restricted to a few activity types only (e.g. leisure) but that all kind of activities that people perform can often be reached by bicycle. In the following, we present the three studied regions and analyse how suitable these three areas are with respect to these indicators.

In this study, we employed travel diary data from the Netherlands, the Freiburg region in South-West Germany and the Copenhagen Metropolitan area (as defined by the Organisation for Economic Cooperation and Development (OECD, 2009)) in Eastern Denmark. All three European regions are forerunners in bicycle transportation (Buehler & Pucher, 2011; Nielsen et al., 2013; Pucher & Buehler, 2008). The chosen geographical outlines presented in Figure 5.2 are the result of making the regions comparable in terms of average urban density and the proportion of observations associated to a highly urbanised or suburban/rural setting given the available data.

	Population	Urban density [inh./km²]
The Netherlands	17.1 millions	411
Copenhagen Metropolitan Area	2.6 millions	266
Freiburg Region	0.7 millions	295

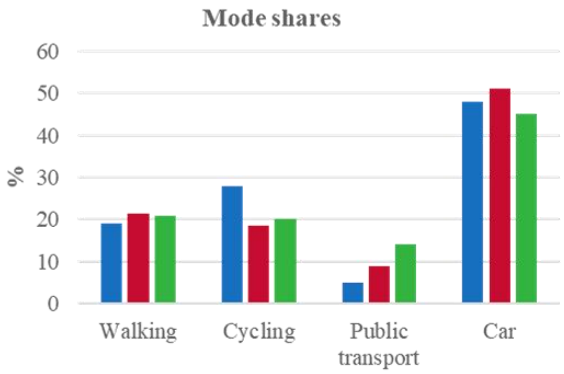


Figure 5.2 Key features of the study areas.

All figures refer to data from 2016 respectively from 2014-2019 (mode share of the Copenhagen Metropolitan Area). Calculated based on data from: Statistics Netherlands (CBS, 2016), Danish National Travel Survey, Danish Ministry of social affairs and the interior (Social og indenrigsministeriet, 2016), City of Freiburg (PTV Group, 2017), Statistical state office Baden-Württemberg (Statistisches Landesamt Baden-Württemberg, 2016). Map modified based on (San Jose, 2006).

With regard to the first indicator of good bicycle accessibility described above, Figure 5.2 shows the mode shares of all three considered regions. In international comparison, these values are outstandingly high in the Western world, in particular when considering that they do not only refer to urban but also rural zones (Pucher & Buehler, 2008).

Concerning the second above-mentioned indicator, Figure 5.3 presents the shares of different activity types for the three considered regions in single-stop tours. The overall share of activity types (including all travel modes) in dark grey can be seen as a proxy for the average need of out-of-home activity participation (even though small deviations were found when also considering multi-stop tours). Unlike the example of public transport (illustrated in light grey), the share of activity types by bicycle roughly follows the distribution of all travel modes. This finding indicates that the combination of transport system and land-use context in these three regions often enables people in the study areas to reach all kinds of destinations by bicycle (in contrast to public transport).

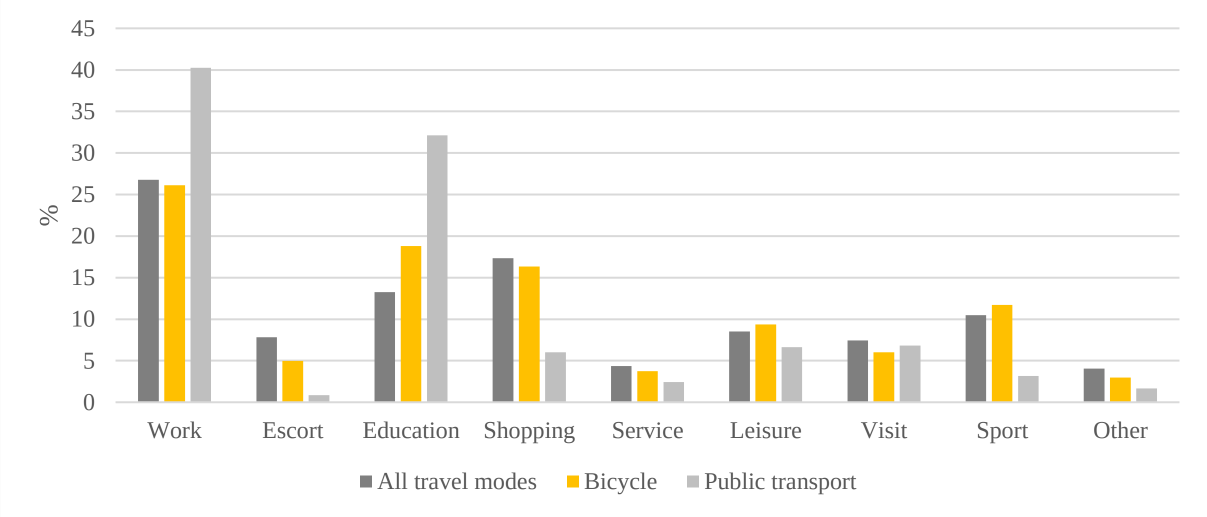


Figure 5.3 Weekday activity participation in simple tours.

Note that percentages add up to 100 per cent within each travel mode category. Sources: Netherlands Mobility Panel (2016), National Danish travel survey (2014-2019), Travel survey Freiburg Region (2016).

5.3.2 Bicycle conditions in the three regions

In order to understand similarities and differences between the Netherlands (NL), the Copenhagen Metropolitan Area (CPN) and the Freiburg region (FRG), we shortly compare the bicycle environments.

Geography and land-use structure

The Netherlands are a mostly flat and highly urbanised country, with large areas resembling a poly-centric metropolitan area. In our data set (described in section 5.3.3), for instance, 50 per cent of all home locations were situated within less than 12 kilometres as the crow flies from the next urban centre. This outcome can be linked to a tradition of space-efficient land-use practices that goes back to the seventies, aiming for both compactness and multifunctional land-use (Dieleman & Wegener, 2003). The Copenhagen Metropolitan area comprises mainly the Danish island of Zealand and some smaller neighbouring islands and is relatively flat. The city of Copenhagen itself accounts for around 730,000 inhabitants (including Frederiksberg municipality) and is situated in the densely populated *Capital region*. Urbanisation in this area has strongly been influenced by the so-called finger plan from 1947, a plan that concentrated the emerging sub-urbanisation along five axes (OECD, 2009). The western and southern parts of the Metropolitan area have a mostly rural character with low urban densities and only few urban settlements. The Freiburg Region is an area in south-west Germany which consists of the three districts *City of Freiburg*, *Emmendingen* and *Breisgau-Hochschwarzwald*. It extends from the river Rhine in the west (which also is the border to France) into the *Black Forest* mountain range in the east and is situated between 20 to 70 kilometres in the north of the Swiss border. The city of Freiburg, which accounts for around 230,000 inhabitants, is the major city of the region, while the remaining area is mostly rural. Freiburg is often considered to be Germany's leading city regarding sustainability, including sustainable transportation (Buehler & Pucher, 2011; Fitzroy & Smith, 1998) and bicycle-friendly land-use development (Broaddus, 2010; Ryan & Throgmorton, 2003).

Mode share

It is not overstated to call the Netherlands the leading bicycle country in the world. The country accounts for the highest nation-wide mode share with 27 per cent of all trips travelled by bicycle, followed at some distance by Denmark and Germany (Buehler & Pucher, 2012; Harms & Kansen, 2018). All three regions have in common that policies to inverse the decline of bicycle use after the second world war have been implemented from the early 1970s onwards (Buehler & Pucher, 2011; Haustein, Koglin, Nielsen, & Svensson, 2019; Trine & Anne-Katrin, 2012). Some smaller Dutch cities, such as Zwolle or Groningen, now reach mode shares of more than 45% of all inner-urban trips. But also some rather rural areas in the East of the Netherlands outnumber the Dutch average, while Rotterdam, the second largest Dutch city, stays with 22 per cent below it (Harms & Kansen, 2018). In the Copenhagen Metropolitan Area, a considerable gradient can be observed in bicycle use between the city of Copenhagen itself (29 per cent of all trips were made by bicycle in 2017), the Capital region (accounting for around 21 per cent in 2016) and the distant rural periphery, where cycling levels seem to be considerably lower (Capital Region of Denmark, 2016; City of Copenhagen, 2017; Thomas A.S. Nielsen, Mulalic, & Christiansen, 2016; Thomas Alexander Sick Nielsen, Olafsson, Carstensen, & Skov-Petersen, 2013). Similarly, the bicycle mode share of trips within each of the three districts of the Freiburg region in 2016 was with 34 per cent much higher in the city itself than in the surrounding districts, accounting for 19 and 12 per cent respectively (PTV Group, 2017).

Cycling network

In all three study regions, dense cycling networks exist which are particularly in the highly urbanised zones denser than those of cars due to *filtered permeability* (Melia, 2012). These networks mainly consist of traffic-calmed streets and bicycle lanes or paths. In this context, some differences can be observed between the regions. Traffic calming seems to be more applied in the Netherlands and in the Freiburg Region than in the Copenhagen Metropolitan Area. By 2008, 85 per cent of the Dutch street network within built-up areas was traffic-calmed and in Freiburg, 90 per cent of the citizens lived in traffic-calmed streets (Buehler & Pucher, 2011; Schepers et al., 2017). Since these streets are restricted to 30 kilometres per hour or lower, speeds between cyclists and cars are similar and, therefore, no separation of both travel modes is usually designed (Schepers et al., 2017). Along streets with higher speed limits, dedicated bicycle facilities are extensively available in all three study areas but with different designs. In both, the Netherlands and Copenhagen physically separated bicycle paths prevail while in Germany, on-road bicycle lanes are preferred (Gössling, 2013; Schepers et al., 2017; Stadt Freiburg im Breisgau, 2002). All three regions have introduced a hierarchy to their cycling networks by developing a category of routes (named ‘Fietssnelweg’ (NL), ‘Supercykelstier’ (CPN) and ‘Radvorrangroute’ (FRG)) which is especially designed for attractive travel times by avoiding or minimising waiting times at intersections (Capital Region of Denmark, 2016; Govenment of the Netherlands, 2018; Stadt Freiburg im Breisgau, 2002). Another common feature of all three regions is that cycling networks do not end at the municipal borders of Copenhagen, Freiburg and the Dutch cities but also extend to the surroundings. However, while a consistent cycling network exits between cities in the Netherlands and a growing network of *cycle superhighways* connects most municipalities in the *Capital Region of Denmark*, the development of a utilitarian inter-urban network just started in the Freiburg Region (Ministerium für Verkehr und Infrastruktur, 2016).

5.3.3 Data set preparation

The analysis employed travel diary data from the Netherlands, Denmark and the Freiburg Region (see Table 5.1). Considering the scope of the analysis, only outbound trips within simple home-based tours (i.e. tours that include a single out-of-home activity only) by bicycle were selected. Cases with missing information on the variables used in the regression analyses or implausible observations were discarded. Since reported travel distances were not available in the travel survey from the Freiburg Region (ZRF), bicycle travel distances had to be calculated using *Distance Matrix API* from *Google*. In this context, an exploratory analysis of the impact of the different data collection methods was conducted for the Netherlands Mobility Panel (MPN), revealing more or less normally distributed deviations which are not expected to bias our analyses. We removed cycling trip distances larger than 20 kilometres in all data sets based on an outlier analysis of the most affected ZRF data (20 kilometres corresponded to the mean cycling distance plus three times the standard deviation). These outliers initially entailed that trends across the three regions were reversed when comparing mean to median cycling distances. Furthermore, observations that occurred more than once for the same person (e.g. identical work trip observations) were filtered out. Data processing of the Danish National travel survey (*Transportvaneundersøgelsen* (TU)) additionally involved the selection of trips that corresponded to geographical boundaries of the Copenhagen Metropolitan area and the calculation of urban densities on a municipality level based on population data from 2016 (Social og indenrigsministeriet, 2016).

Table 5.1 Key features of the employed travel diaries.

	The Netherlands	**Copenhagen Metropolitan Area**	**Freiburg Region**
Data set name	Netherlands Mobility Panel (MPN)	Danish National Travel Survey (TU)	Travel survey Freiburg Region (ZRF)
Year(s)	2016	2014 – 2019	2016
Survey duration	3 days	1 day	1 day
Season of data collection	Autumn	All year	Summer/autumn
Weekday/weekend	both	Both	Weekday only
Age of participants	>11	>5	>5
Business trips	yes	Yes	no
Travel distances	Reported	Reported	Calculated using google Distance Matrix API
Further information	Hoogendoorn-Lanser et al., 2015	Christiansen & Skougaard, 2015	-

Finally, further processing was conducted to make all three data sets comparable and to merge them into a single data file. In this context, weekend data and business trips (i.e. trips during working hours) were removed. In addition, variables were renamed and recoded into comparable categories across data sets.

5.3.4 Sample description

The final data set contains 5,965 bicycle trips stemming from 4,674 different travellers. The composition of the sample with regard to the variables employed in the regression analyses (see section 5.4) is shown in Table 5.2. In the following, we discuss some remarkable features of the sample that should be considered when analysing the model results.

Since TU travel surveys are collected throughout the whole year, the data from the Copenhagen Metropolitan area account for somewhat higher shares of mandatory activities (*work* and *education*), whose frequency drops less during winter (Nielsen et al., 2016). Remarkably are also the shares of *education* and *shop* trips in the Dutch subset. The lower share of *education* trips in the Netherlands (and likewise, trips of the youngest age class *Under 20*) seems to be related to the fact that the MPN only includes children from 12 years onwards while this boundary is lower in the TU and ZRF data (6 years). A follow-up analysis, however, revealed that the lack of younger children does not seem to be accountable for the outstandingly long *education* trips in the Netherlands compared to the other two regions. The high share of *shop* observations in the Netherlands could be, again, related to the age composition in this subset since shopping is expected to be more an adult task in the household. Another interesting feature is the consistent preponderance of *female* travellers across all regions, which is in line with former evidence from cycling-friendly areas that women cycle more often (Haustein et al., 2019). A striking outcome are the differences regarding *car availability*. While we can only speculate about the limited car availability of the Danish sub-sample, boundary conditions such as outstandingly high car registration taxes (Haustein et al., 2019) (which might primarily discourage people from buying a car for who the bicycle is a viable alternative) certainly play a role. A last note on the sample composition concerns the few e-bike observations, which are mostly related to the Dutch subsample. While there are indications from e-bike sales that the Netherlands is the leading country in terms of bicycle use, data on e-bike mode shares across countries is still missing.

5.4 Quantile and ordinary least square regression models

The conceptual model, in which a continuous outcome (observed cycling distances) is explained by a set of explanatory variables, is a typical use case of multivariate regression analysis (Wakefield, 2013). The postulated research goals from section 5.2 require to use more than one regression technique. First, we are interested in exploring the effects of explanatory variables on other parts than only the mean of the cycling distance distribution (e.g. on the 25 per cent longest trips). And second, we want to investigate a rich set of independent variables and related interaction terms, resulting in a large number of (mostly categorical) explanatory variables.

The first goal can be achieved using quantile regression (Koenker & Bassett, 1978). This regression technique allows for estimating the parameters of the explanatory variables for any quantile of interest. Another advantage of quantile regression is that there are no underlying parametric assumptions regarding the residuals (homoscedasticity and normally distributed residuals). Yet, quantile regression results are difficult to interpret when confronted with a large number of categorical variables (as we intend to do here). In such a case, all reference categories of dummy-coded categorical variables are confounded in the intercept, representing a meaningless benchmark group for the estimates of dummy-coded categories.

For this reason, the second goal can be better attained using ordinary least square regression (OLS) in combination with weighted effect coding. In weighted effect coding, estimated effects do not refer to an omitted category but to the sample mean (te Grotenhuis et al., 2017b). This coding technique entails that estimated regression coefficients remain stable regardless of the omitted category. By estimating models with complementary omitted categories, all effects can be isolated and merged to a single results table (consult Schneider, Daamen, & Hoogendoorn, n.d.) for a more detailed explanation). While weighted effect coding can be applied in combination with any generalised linear model (te Grotenhuis et al., 2017b), its design around the sample mean makes it incompatible with quantile regression.

Table 5.2 Sample composition with descriptive statistics.

	Total		NL		CPN		FRG	
	N (%)	Mean	N (%)	Mean	N (%)	Mean	N (%)	Mean
Activity type [km]								
Work	1557 (26)	4.68	492 (23)	4.46	628 (30)	4.90	437 (25)	4.63
Escort	298 (5)	1.48	119 (5)	1.61	79 (4)	1.38	100 (6)	1.40
Education	1121 (19)	3.17	286 (13)	4.75	466 (22)	2.48	369 (22)	2.83
Shop	972 (16)	1.73	453 (21)	1.88	273 (13)	1.87	246 (14)	1.31
Service	224 (4)	2.25	100 (5)	2.20	29 (2)	2.36	95 (5)	2.27
Leisure	560 (9)	2.69	190 (9)	2.50	171 (8)	3.02	199 (12)	2.60
Visit	358 (6)	2.88	130 (6)	2.92	147 (7)	2.92	81 (5)	2.75
Sport	697 (12)	2.30	315 (14)	2.33	225 (11)	2.34	157 (9)	2.20
Other	178 (3)	2.18	88 (4)	2.38	62 (3)	2.03	28 (2)	1.90
Gender [km]								
Female	3266 (55)	2.68	1271 (59)	2.69	1088 (52)	2.90	907 (53)	2.41
Male	2699 (45)	3.43	902 (41)	3.54	992 (48)	3.38	805 (47)	3.35
Age classes [km]								
Under 20	1439 (24)	2.67	355 (16)	3.97	574 (28)	1.97	510 (30)	2.55
20-39	1590 (27)	3.36	603 (28)	2.98	651 (31)	3.70	336 (20)	3.40
40-64	2137 (36)	3.25	800 (37)	3.03	632 (30)	3.84	705 (41)	2.96
65+	799 (13)	2.36	415 (19)	2.37	223 (11)	2.48	161 (9)	2.18
Education [km]								
Non-academic	3806 (64)	2.83	1497 (69)	2.99	1211 (58)	2.71	1098 (64)	2.75
Academic	2159 (36)	3.35	676 (31)	3.16	869 (42)	3.72	614 (36)	3.03
Household members [km]								
1	844 (14)	2.96	397 (18)	2.65	339 (16)	3.40	108 (6)	2.76
2	1665 (28)	3.08	606 (28)	2.72	639 (31)	3.52	410 (24)	2.93
3	1014 (17)	3.01	306 (14)	3.06	359 (17)	3.18	349 (21)	2.79
4 or more	2452 (41)	3.00	864 (40)	3.44	743 (36)	2.66	845 (49)	2.85
Car availability [km]								
No car availability	2567 (43)	2.91	642 (30)	3.42	1235 (59)	2.83	376 (40)	2.56
Requires planning*	1658 (28)	3.39	587 (27)	3.09	621 (30)	3.71	683 (26)	3.17
High car availability	1740 (29)	2.82	944 (43)	2.76	224 (11)	3.22	653 (34)	2.69
Land-use context [km]								
Suburban/rural	2491 (42)	2.87	984 (45)	3.02	843 (41)	2.51	664 (39)	3.11
Highly urbanised**	3474 (58)	3.12	1189 (55)	3.06	1237 (59)	3.56	1048 (61)	2.69
Type of bike [km]								
Normal bicycle	5493 (92)	2.94	1786 (82)	2.86	2037 (98)	3.12	1670 (97)	2.81
E-bike	472 (8)	3.91	387 (18)	3.87	43 (2)	3.77	42 (3)	4.41
Activity duration [h]	5965	3.74	2173	3.06	2080	4.56	1712	3.60
Additional bicycle distance [km]	5965	3.23	2173	3.21	2080	2.48	1712	4.17

** Refers to car sharing within household (number of people with driving license > number of cars in the household), among friends or commercial car sharing*

*** Refers to urban densities larger than 1500 inhabitants/km² on a municipality level for the Netherlands and Copenhagen Metropolitan area, includes only the core-city of Freiburg (excluding villages that administratively belong to the municipality) for the Freiburg Region.*

<u>Quantile regression</u>

Considering the elaborated difficulties of interpreting quantile regression models with many categorical variables, we opted for a parsimonious model. Obviously, such a model has to include the *type of activity* since this is the primary research interest. In addition, we added *gender* and *age* as typical control variables. Furthermore, we also included the *type of bicycle* since e-bike distances are expected to be considerably longer (Kroesen, 2017). We estimated the effects of these variables on three different quantiles, namely the 50th (median), 75th and 90th quantiles. The reasoning for investigating more the effects on the right-tail of the cycling distribution is that we expect more insightful differences between the included explanatory variables when distances are getting longer. For parameter estimation, we used the R package *quantreg* (Koenker, 2018). To link quantiles straightforward to cycling distances, we provide an empirical cumulative density distribution (CDF) of the cycling distances in the sample.

<u>OLS regression</u>

The purpose of the OLS regression models is to exploit the full potential of the data set with regard to relationships between explanatory variables and observed cycling distances. We selected the specified explanatory variables from the conceptual model (Figure 5.1) and interacted them with the three regions. In this context, we included the categorical variables *activity type*, *gender*, *age classes*, *education*, *number of household members*, *car availability*, *land-use context* and *type of bicycle* (see Table 5.2). Furthermore, the continuous variables *activity duration* and *additional bicycle distance* were considered. All categorical variables were weighted effect coded using the R package *wec* (Nieuwenhuis et al., 2019) and continuous variables were mean-centred. The same R package was employed to code the interaction terms between all explanatory variables and the three regions (te Grotenhuis et al., 2017a). The OLS regression models were estimated using the R package *stats* (R Core Team, 2013).

In OLS regression, a prerequisite for reliable estimates is that the residuals are normally distributed and homoscedastic (Field, 2009). In our data, these assumptions are violated, leading to biased standard errors and, as a consequence, to potentially wrong significance values for the regression coefficients. A generalisation of the results beyond the sample is therefore problematic and the results from the OLS regression will only be used to highlight further factors that are potentially important to assess bicycle accessibility. In contrast, the estimates of the quantile regression should refer to the underlying population.

5.5 Results and discussion

In this section, we describe the outcomes of the analysis. We show and discuss the cumulative distance distribution of cycling trips and the results of the quantile regression analysis in sections 5.5.1 and 5.5.2 respectively. The results of the OLS regression analysis are presented in section 5.5.3. A critical discussion follows in section 5.5.4.

5.5.1 Cumulative distance distribution

Figure 5.4 shows the empirical cumulative cycling distance distributions (CDF) of all three considered regions. Since the MPN and TU data sets included reported travel distances (as opposed to calculated travel distances in the ZRF data set) which are often rounded (Witlox, 2007), visible steps occur every 0.5 kilometres. Nonetheless, all three curves are quite similar, emphasizing the notion that (at least) in bicycle-friendly environments cycling distances follow a characteristic distance distribution. The (mostly) positive curvature of the CDF confirms that bicycle-friendly land-use schemes are in place in all three regions since 50 per cent of the trips are shorter or equal to only two kilometres. Interestingly, the graphs also show that there seems to be a lower threshold distance for cycling as few observations are recorded for distances shorter than 500 metres. In this distance range, many people might rather walk than cycle.

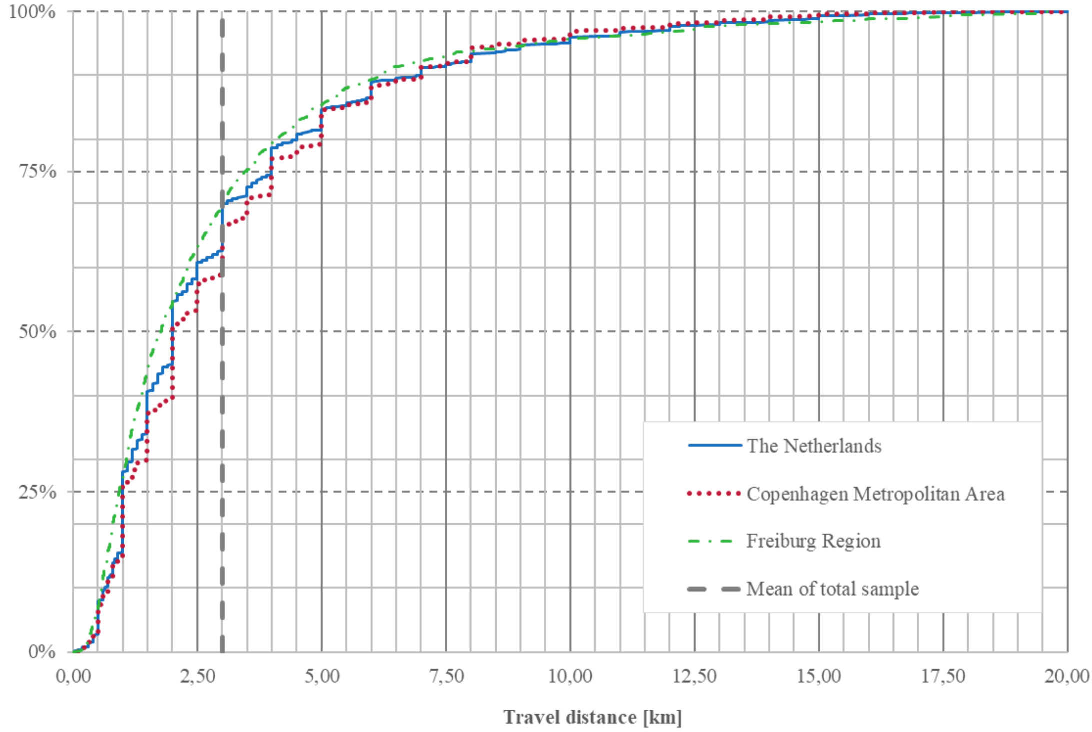


Figure 5.4 Empirical cumulative distribution of cycling trip distances towards a destination

5.5.2 Quantile regression model

Table 5.3 shows the estimated parameters of the three quantile regression models. It can be seen that most estimates are highly significant. This means that given the sample data we can be sure that the observed effects are also present in the population. The estimates of the different variables relate to the reference group expressed by the intercept, which shows estimated cycling distances for the three considered quantiles of *male commuters* aged *40-64* who use a *conventional bicycle*. Compared to this reference group, most estimates gradually decrease when moving from the Q50 to the Q90 model. As a consequence, it can be concluded that the reference group is a major driver of longer cycling trips.

The results suggest that *trip purpose* has a much stronger effect on observed cycling distances than all included control variables, regardless of the considered quantile. In particular, *escort*, *shop* and *service* trips seems to be much shorter than the *work* trips of the reference group. As a consequence, the related destinations (day-care, elementary school, grocery shops, medical centres, etc.) should be placed close to (or within) residential zones. On the contrary, *education* was the trip purpose that deviated least from *work* cycling distances. This means that also for education, people often travel longer distances. While there is an increasing gap between *female* and *male* cyclists when distances are getting longer, a similar effect was not found for age. Only the *youngest age class* was accounting for an increasingly negative effect compared to the reference group across the three quantiles. An explanation for the surprisingly insignificant estimates of the *oldest age class* could be that older people are more likely to own and use an e-bike (Kroesen, 2017), a factor which might offset to some extent lower physical capabilities. More importantly, however, seems to be the scarcity of data associated with this age class in the tails of the distribution. The positive and increasing estimates of the *e-bike* across the considered quantiles show that electrification has the potential to extend the bicycle range considerably.

Table 5.3 Parameter estimates of the quantile regression models for the 50th, 75th and 90th quantiles

	Effects on quantiles		
	Q50	Q75	Q90
	Estimate (p-value)	*Estimate (p-value)*	*Estimate (p-value)*
(Intercept)	**3.71** (p<.001)	**6.25** (p<.001)	**9.90** (p<.001)
Work is reference			
Escort	**-2.57** (p<.001)	**-4.34** (p<.001)	**-6.25** (p<.001)
Education	**-1.01** (p<.001)	**-1.44** (p<.001)	**-1.90** (p<.001)
Shop	**-2.35** (p<.001)	**-3.84** (p<.001)	**-5.80** (p<.001)
Service	**-2.02** (p<.001)	**-3.14** (p<.001)	**-5.00** (p<.001)
Leisure	**-1.61** (p<.001)	**-2.44** (p<.001)	**-3.90** (p<.001)
Visit	**-1.61** (p<.001)	**-2.26** (p<.001)	**-3.40** (p<.001)
Sport	**-1.71** (p<.001)	**-2.84** (p<.001)	**-4.80** (p<.001)
Other	**-2.18** (p<.001)	**-3.34** (p<.001)	**-4.70** (p<.001)
Male is reference			
Female	**-0.36** (p<.001)	**-0.60** (p<.001)	**-1.20** (p<.001)
Age40-64 is reference			
Age< 20	**-0.35** (p<.001)	**-0.80** (p<.001)	**-0.90** (p<.001)
Age20-39	**0.26** (p<.001)	0.20 (p=.068)	0.10 (p=.546)
Age65+	-0.07 (p=.155)	-0.23 (p=.127)	0.00 (p=1.000)
Normal bicycle is reference			
E-Bike	**0.84** (p<.001)	**1.43** (p<.001)	**2.50** (p<.001)

5.5.3 Linear regression model

Table 5.4 presents the main and interaction effects of the OLS models described in section 5.4. Due to weighted effect-coded categorical variables and the mean-centred continuous variables, all four estimated models could be merged into one single results table. The adjusted R squared of the models was 0.22. This is an acceptable value for an exploratory analysis, considering that the data stems from three different data sets. In the following, we highlight and discuss relevant main and interaction effects with regard to bicycle accessibility.

Table 5.4 Parameter estimates of the OLS regression models.

	Main effect	Interaction effects		
		NL	CPN	FRG
	Estimate (p-value)	*Estimate (p-value)*	*Estimate (p-value)*	*Estimate (p-value)*
Intercept (= sample mean)	**3.02** (p<.001)	**-**	**-**	**-**
NL	**0.11** (p=.026)	-	-	-
FRG	-0.06 (p=.282)	-	-	-
CPN	-0.06 (p=.276)	-	-	-
Work	**0.60** (p<.001)	**-0.59** (p<.001)	**0.42** (p<.001)	0.06 (p=.697)
Escort	**-0.91** (p<.001)	0.37 (p=.069)	**-0.69** (p=.016)	0.10 (p=.679)
Education	0.17 (p=.086)	**0.70** (p<.001)	-0.02 (p=.543)	**-0.45** (p=.001)
Shop	**-0.58** (p<.001)	**0.26** (p=.014)	**-0.39** (p=.0211)	-0.04 (p=.800)
Service	-0.09 (p=.637)	-0.08 (p=.710)	-0.60 (p=.200)	0.26 (p=.219)
Leisure	0.00 (p=.970)	**-0.39** (p=.012)	0.09 (p=.616)	**0.30** (p=.049)
Visit	0.04 (p=.779)	0.01 (p=.968)	-0.15 (p=.378)	0.25 (p=.326)
Sport	**-0.29** (p=.005)	-0.04 (p=.716)	-0.09 (p=.575)	0.20 (p=.288)
Other	**-0.43** (p=.036)	0.22 (p=.279)	-0.41 (p=.143)	0.21 (p=.650)
Activity duration [h]	**0.24** (p<.001)	**0.09** (p<.001)	**-0.13** (p<.001)	**0.06** (p=.041)
Female	**-0.22** (p<.001)	-0.03 (p=.479)	0.04 (p=.426)	0.00 (p=.936)
Male	**0.28** (p<.001)	-0.04 (p=.479)	-0.04 (p=.426)	0.00 (p=.936)
Age< 20	**-0.46** (p<.001)	**0.52** (p=.006)	**-0.55** (p<.001)	0.26 (p=.074)
Age20-39	**0.22** (p<.001)	**-0.18** (p=.026)	0.10 (p=.206)	0.14 (p=.251)
Age40-64	**0.14** (p=.020)	-0.01 (p=.833)	**0.32** (p<.001)	**-0.27** (p=.002)
Age65+	0.01 (p=.956)	-0.15 (p=.170)	0.22 (p=.207)	0.04 (p=.840)
No e-bike	**-0.12** (p<.001)	-0.02 (p=.143)	**0.02** (p=.011)	0.24 (p=.549)
E-bike	**1.44** (p<.001)	0.08 (p=.143)	**-0.99** (p=.011)	-0.01 (p=.549)
Non-academic	**-0.09** (p=.005)	-0.07 (p=.058)	0.03 (p=.468)	0.06 (p=.224)
Academic	**0.15** (p=.005)	0.15 (p=.058)	-0.04 (p=.525)	-0.11 (p=.224)
1 pers. Household	-0.08 (p=.403)	-0.04 (p=.706)	0.03 (p=.802)	0.05 (p=.852)
2 pers. Household	-0.06 (p=.378)	-0.09 (p=.268)	0.04 (p=.657)	0.08 (p=.462)
3 pers. Household	-0.07 (p=.385)	-0.10 (p=.402)	0.06 (p=.539)	0.02 (p=.838)
4 or more pers. household	0.10 (p=.063)	0.12 (p=.083)	-0.08 (p=.344)	-0.06 (p=.382)
No car availability	-0.04 (p=.496)	0.16 (p=.093)	-0.04 (p=.419)	-0.09 (p=.358)
Requires planning	0.11 (p=.073)	-0.15 (p=.064)	0.06 (p=.475)	0.12 (p=.270)
High car availability	-0.05 (p=.439)	0.01 (p=.788)	0.06 (p=.871)	0.01 (p=.876)
Highly urbanised	-0.01 (p=.682)	0.01 (p=.840)	**0.15** (p<.001)	**-0.18** (p<.001)
Suburban or rural	0.02 (p=.682)	-0.01 (p=.840)	**-0.22** (p<.001)	**0.29** (p<.001)
Additional bike distance [km]	**0.01** (p=.022)	-0.02 (p=.055)	0.00 (p=.687)	**0.01** (p=.031)

The intercept represents the mean distance of the total sample (around three kilometres) to which all main effects refer. In contrast, the interaction terms are related to the respective main effect and show, how this effect differs between the three included regions. In general, cycling distances from the Dutch data set were significantly longer, yet, the estimated effect of 110 metres is negligible. This outcome is in line with the similar CDFs presented in Figure 5.4, suggesting that overall cycling behaviour is quite similar in all three regions.
Work trips were related to the longest estimated mean distances with around 3.6 kilometres. Interestingly, this value deviates significantly by around one kilometre between NL and CPN. The particular long estimated commute distances for the Danish context can be linked to a focus of local cycling policies on commuters, for whom the network is optimised (Capital Region of Denmark, 2016; Gössling, 2013). *Escort* and *shop* trips accounted for the shortest estimated mean distances among all considered activity types. Both the estimated 2.1 kilometres for escort trips and the estimated 2.4 kilometres for shop trips seems to be strongly influenced by the significantly shorter trips in CPN, suggesting that related destinations are more densely distributed. While *education* trips did not significantly differ from the sample mean, the positive interaction effect related to the Dutch data is outstanding. This result is in line with former evidence, showing that trips to more distant secondary schools (further away than three kilometres) are largely travelled by bicycle in the Netherlands (van Goeverden & de Boer, 2013). With regard to other activity types that can be subject to urban planning, *sport* trips are slightly shorter than the sample mean while *service* trips did not significantly deviate from it.
All estimated mean distances of the different activity types have to be interpreted together with the estimate of *activity duration*. The model results suggest that per hour of activity duration an extra 0.24 kilometres have to be added. As a consequence, the gap in cycling distances between typically short activities, for instance, *escort* and longer activities such as *work*, increases. Interestingly, this relationship between an activity's importance and the related effort in terms of cycling distance is significantly less pronounced in CPN, while it is even stronger in the other two regions. Assuming stable travel time ratios (Dijst & Vidakovic, 2000), this outcome would indicate considerably higher cycling speeds in CPN than in the other two regions. This finding might be related to green waves in the City of Copenhagen, which are designed for speeds of 20 kilometres per hour (Gössling, 2013).

Average cycling distances of *male* cyclists were estimated to be 0.5 kilometres longer than those of *female* cyclists and no significant deviation was found for any of the regions. This gender difference is supported by former research (Heinen et al., 2010).

With regard to the effect of *age* on cycling distances, the negative main effect of the *youngest age group* is most remarkable. It results from a large discrepancy in this age class between the overall positive effect of Dutch cyclists and the strongly negative effect of Danish cyclists. This observation might be linked to typical infrastructure features, which result in different levels of exposure to motorised traffic. While Copenhagen guidelines promote separation at sections by (only) a kerbstone and mixed zones at intersections (City of Copenhagen, 2013), the Dutch counterparts advocate more physical separation along main roads and complete segregation at (busy) intersections (CROW, 2017). Both features of Dutch infrastructure design are particularly in favour of more vulnerable (including young) cyclists.

Similar to the outcomes of the quantile regression, the use of the e-bike is related to the longest average cycling distances. While this outcome is not surprising, it is remarkable that the effect is much larger in both the Netherlands and the Freiburg Region than in the Copenhagen Metropolitan Area. This finding might in parts be explained by the relatively little data available for CPN and FRG. Yet, the magnitude of the effect of one kilometre raises the question, if there are different e-bike user groups (e.g. commuters compared to pensioners) and if the cycling infrastructure accommodates the needs of e-bike users differently.

Concerning the additional control variables used in the OLS model, several interesting findings came to light. Cyclists with an academic background cycle on average an estimated 0.24 kilometres longer than cyclists with a non-academic education. This outcome might be linked to different lifestyles and the respective role of the bicycle in them (the bicycle as being a part of a healthy lifestyle versus being simply a mobility tool). Another explanation could be that job opportunities for highly specialised persons are often further away from home.
While urban density was not related to any significant deviation from the sample mean at the level of the whole sample, a significant difference was identified between the Copenhagen Metropolitan Area and the Freiburg Region. For the former, estimated distances were longer in municipalities with high urban densities and shorter in suburban or rural environments. In contrast, the inversed relationship was found for the Freiburg region. A follow-up analysis revealed that due to the smaller city size, particularly *work* and *education* trips towards Freiburg were longer than those within it. Conversely, the city of Copenhagen is considerably larger and many surrounding municipalities still account for high urban densities according to the definition employed in this research (i.e. more than 1,500 inhabitants per square kilometre). Yet, all trip purposes besides *leisure* accounted for longer mean distances in the urbanised than in the suburban and rural municipalities, suggesting that the bicycle facilities in the urban setting are considerably better.

Finally, the variable *additional cycling distance* regarded the influence of additional cycling beyond the considered cycling distance (and the related trip distance to get back home). The result suggests that this additional physical effort is only little affecting the observed cycling distances. However, since many people do not make more than two trips a day (Schneider et al., 2020), entailing that no additional cycling distance has been covered, it has to be questioned how conclusive this result is.

5.5.4 Limitations

While our approach to look at observed cycling distances in best-practice environments provided valuable insights, it comes with three limitations. First of all, we do not have data of cases, in which destinations were not accessible by bicycle due to distance or inappropriate infrastructure. As a consequence, there is a risk of overestimating critical distance values of bicycle accessibility. However, we argue, that by choosing regions with high mode shares of the bicycle, we ensure that observed cycling distances are not restricted to few types of (sporty and fearless) cyclists only (Dill & McNeil, 2013), but represent the whole cycling population. Consequently, the risk of overestimating accessible distances due to the profile of the sample is reduced.

Second of all, the existing bicycle-friendly land-use systems in the three considered regions entail that observed cycling distances are often very short and do not provide information about how much further a person would have cycled if necessary. By implication, the benchmarks values of this analysis are conservative estimates of distance ranges within which destinations should be placed. Yet, while too long distances are an exclusion criterion for bicycle use, an underestimation is less problematic.

And finally, all results from the analysis relate to the cycling networks and bicycle facilities available in the three regions. Since these are of higher standards than what can be found in many other places (see section 5.3), one has to be cautious to transfer the results to another context.

5.6 Implications for urban planning and policy-making

Based on the conducted analysis, three lessons can be learnt. The first lesson refers to the question of how to define bicycle accessibility in practical terms. In theory, a destination is accessible for a person as long as it lies within the range of what he or she is willing and capable to cycle given the features of the transport system. From an efficiency point of view (i.e. not imposing more than the necessary requirements on land-use planning), one might therefore be tempted to approximate boundary values and set these values as thresholds of bicycle accessibility. The results from the three regions, however, suggest orientating bicycle-friendly planning at lower values. For all three regions, the CDF of cycling distances showed that a high concentration of observed trips had only very short distances. Considering that high mode shares can only be reached if a large part of the cycling population (i.e. all people for whom cycling is in principle an option) has access to their daily-life destinations by bicycle, accessibility should be ensured for the less performing cyclists, regardless whether the majority of the cycling population is willing to cycle further. As a positive side-effect, accessibility for pedestrians at the land-use level might be achieved at the same time.

Second, the outcomes of the conducted analyses suggest adjusting critical cycling distances to the type of activity performed at the destination and the profile of a destination's target group rather than using a universal value. All models highlighted the importance of the type of activity at the destination. In addition, if younger people are a target group, distances should be adapted in accordance with the estimates of this age class. In this context, we recommend to use the estimates from the median quantile regression model as a benchmark for catchment areas of a destination. This model displays effects on average behaviour instead of on mean distances (which are naturally more affected by more performant cyclists and outlier observations).

A third observation from the analysis is that even in cycling-friendly areas, some features of the transport system can make a substantial difference in terms of accessibility. Not surprisingly, the e-bike has the potential to extend the reach of the bicycle considerably. This is particularly true for user groups that are more subject to physical constraints such as pensioners or maybe also cargo bike users. In addition, differences between the three regions indicate that some features of the bicycle infrastructure can also affect bicycle accessibility. Based on the performed analyses, it seemed that the prevailing infrastructure in the Copenhagen Metropolitan Area facilitates high travel speeds by bicycle, resulting in a larger reach for commuters. At the same time, this research also provided some signals that this achievement might be at the expense of more vulnerable or less performing cyclists such as children. From a societal perspective, however, a focus on the latter group could be more beneficial on the long run, considering the effects on *travel socialisation* (Baslingtion, 2008) and health (Fox, 2003). A way to deal with contradicting requirements towards bicycle facilities could be to develop hierarchic cycling networks (similar to road networks) which consist of different categories, each of them accommodating the needs of a particular user group or activity type.

5.7 Conclusions and future research

In this paper, we have empirically studied bicycle accessibility in the Netherlands, the Copenhagen Metropolitan Area and the Freiburg Region. Using the scope of outbound trips in home-based tours that involved a single destination only, we related a rich set of factors referring to land-use system, transport system, the features of the traveller and some further control variables to observed cycling distances.

The results showed that cycling distances were similarly distributed in all three regions with a high concentration of short trips around one kilometre and increasingly fewer observations once distances were getting longer. The total sample accounted for a median of two kilometres and a mean of around three kilometres. The quantile regression revealed that *male commuters aged 40 to 64* cycling to *work* and *e*-bike users cycled longer distances, while *escort* and *shop* trips, being a *female* cyclist and having an *age younger than 20* were particularly short. In addition, the OLS models indicated the positive relationship between *activity duration* and observed cycling distances and revealed a few remarkable differences between the three regions, most outstandingly the effects of the *youngest age group* and the *e-bike*.

The contribution of this paper is to describe bicycle accessibility in regions which are best-practice examples in the field of bicycle transportation. The many observed short distances suggest that best-practice bicycle planning entails providing destinations at distances that are probably much shorter than what most people would have accepted to cycle. In this way, a diversity of different types of cyclists can reach their daily-life destinations by bicycle. The high concentration of short trips despite performant cycling facilities also allows to conclude that bicycle-friendly land-use planning should be prioritised to bicycle-friendly transport system planning. Nonetheless, the results from this study suppose that even in best-practice environments, the features of the cycling network and facilities can increase bicycle accessibility for dedicated user groups. The provided estimates can be used by urban planners as benchmark values to assess existing urban structures or planned urban development elsewhere.

Based on the findings of this study, some recommendations can be derived regarding how to develop highly bicycle-accessible urban environments. First, bicycle use has to be facilitated in the neighbourhood. Various daily-life destinations such as supermarkets, day-care facilities or primary schools should be placed within this perimeter. Such a small-scale land-use structure could be accompanied by extensive traffic calming measures, accommodating the needs of various different cyclist types. Second, high urban densities and mixed-use zoning should be favoured at the level of the whole (poly-centric) metropolitan area, increasing the probability to find other frequent destinations such as work or higher education within bicycle reach. Since the planner has less influence on these origin-destination relations, a safe and comfortable cycling network along all important transport corridors should be built to increase bicycle accessibility via the transport system. Thirdly, the promotion of e-bikes seems to be a further tool to improve bicycle accessibility, in particular for longer distances.

Several directions for further research arise from this study. First, the different effects of the e-bike on observed cycling distances in the Netherlands and the Copenhagen Metropolitan Area raise the question under which circumstances the e-bike becomes an effective tool to increase bicycle accessibility. Next, better data availabilities regarding bicycle network and facility characteristics could allow to further disentangle the effects of land-use and transport system on measured bicycle accessibility. And last, a study design that identifies boundary values of *acceptable cycling distances* might be of great help to assess the potential of cycling in environments of lower urban density.

6. Conclusions and recommendations

This thesis studied revealed activity-travel behaviour which involves bicycle use. More precisely, the research objective was to gain empirical insights into spatial activity-travel behaviour of cyclists and to empirically underpin factors that affect related spatial activity-travel patterns.

This last chapter is structured as follows. We first present the answers to the research questions (section 6.1) based on which we draw conclusions with regard to the overall research objective (section 6.2). Subsequently, we discuss the outcomes against the backdrop of the employed data (section 6.3) and highlight their implications for practice (section 6.4). Finally, we provide some directions for future research (section 6.5).

6.1 Answers to the research questions

This section presents the results with regard to the research questions (RQ) addressed in chapter 1 (see section 1.2).

To what extent are cyclists multi-modal travellers in daily-life activity-travelling? (RQ 1)

The outcomes from the latent class cluster analysis (LCCA) presented in Chapter 2 pointed to five different classes of weekday mobility patterns in the Netherlands. With the exception of one unimodal class of 'Exclusive car users', the bicycle was present in all classes to varying extents. Considering the different class sizes, our findings suggest that nearly three out of four travellers include the bicycle to some extent in their weekday activity-travel patterns. Hence, these travellers can be named cyclists in the context of this research. Three of the four classes involving bicycle use were multi-modal, accounting for more than 85 per cent of the cyclists (and approximately two-thirds of all travellers in the sample). These results show that cyclists are prevailingly multi-modal travellers. A slightly different picture of multi-modality arises when we look at bicycle-related activity participation. Since bicycle trips accounted for only 20 to 30 per cent of the trips in the three bicycle-related multi-modal classes, more than 35 per cent of all activity-travelling by bicycle is related to uni-modal cyclists. However, the LCCA revealed significant differences between the classes with regard to personal characteristics and features of the municipality. The class of uni-modal cyclists appeared to particularly include younger travellers which do not (yet) assume full responsibility for a household.

To what extent does activity-travelling by bicycle involve complex trip chains? (RQ 2)

The bicycle seems to be the travel mode that accounts for the second-highest share of complex trip chains. In the trip chain data set that we derived in Chapter 2 from Dutch travel diary data, 15 per cent of all tours travelled by bicycle visited at least two different activity locations before returning back home. Only the car was with 20 per cent related to a slightly higher percentage of complex trip chains. In contrast, both walking and public transport tours were mostly simple (accounting for only six and one per cent respectively). It is noteworthy that our data set did not contain many complex trip chains compared to former findings.

Which hierarchies between activity types in tours can be derived based on spatial travel patterns? (RQ 3)

Using distributions of relative distance positions in home-based tours as a measure, we identified primary and secondary activities. The primary activity is the activity that purposed the travel while the secondary activity is added opportunistically. Based on pairwise comparisons of the distributions of relative distance positions, we ranked all ten considered activity types in a hierarchy scheme consisting of six blocks: *Education* > *Work* > *Sport* > *Visit* / *Service* / *Shop* / *Leisure* > *Escort* / *Dropping off or picking up goods* > *Grocery*. *Education* was the primary activity in all pairs while *grocery* was consistently secondary. Since this hierarchy scheme did not include a quantification of how much one activity type was prominent over another one in a pair, we additionally computed a measure of hierarchy strength. The related results suggest that *work* was the most consistent primary activity throughout all tours in our data set. The revealed hierarchies were in large parts confirmed by a comparative analysis of activity hierarchies derived from relative activity durations in tours. In addition, the results were relatively robust towards contrasting urban densities and different travel modes. In conclusion, the proposed method seems to provide trustworthy insights into activity hierarchies.

What are the factors that explain commute tour distance extensions by bicycle to accommodate a secondary activity compared to those of the car? (RQ 4)

We investigated in Chapter 4 the distance extensions of commute tours to include a secondary activity in both bicycle and car tours. The model design allowed for identifying factors that significantly explain the observed detours and to disentangle these effects for bicycle and car travel. The model results suggest that people make on average detours of 2.6 kilometres by bicycle and 7.5 kilometres by car. While this difference was not surprising, a remarkable outcome was the low sensitivity (also in relative terms) of bicycle commute tour extensions to most considered factors compared to those of the car. In fact, only grocery shopping was related to considerably shorter and service activities (e.g. doctor’s visit) and age younger than 20 to longer detour distances. In contrast, estimated commute tours extensions by car varied considerably based on activity type, gender and the duration of the secondary activity. Interestingly, some effects (escort and pick up / drop off goods) were reversed between car and bicycle travel.

How far do people cycle from home to typical daily-life destinations in best-practice environments and which factors explain related travel distances? (RQ 5)

The analysis of outbound cycling trip distances from Chapter 5 revealed that distance-distributions are similar in the Netherlands, the Copenhagen Metropolitan Area and the Freiburg Region. Most cycling distances were rather short, with a median of only two and a mean of three kilometres. These values varied depending on the type of activity at the destination, gender and age of the traveller and the type of bicycle that has been used. All regions considered, male commuters aged 40 to 64 and e-bike users cycled longer distances, while escort and shop trips, being a female cyclist and having an age younger than 20 were related to shorter distances. In addition, the duration of the activity was found the be positively related to cycling distances. Furthermore, a few remarkable differences have been identified between the three regions, such as different effects of trip purposes (work, escort, education, shop and leisure), age and e-bike use on reported cycling distances. For instance, Copenhagen cyclists travelled longer to work but shorter to pick up or drop off somebody. With regard to age, cyclists of the youngest age group travelled considerably further in the Netherlands than in the two other regions. And concerning the type of bicycle, the positive effect of the e-bike on cycling distances was significantly less pronounced in the Copenhagen Metropolitan Area than in the Netherlands and in the Freiburg Region.

6.2 Overall conclusions

The main research objective of the thesis was the disclosure of spatial activity-travel patterns of cyclists and the identification of factors that shape them. Based on the presented findings, we can draw the following conclusions.

Activity participation of cyclists often seems to involve more travel modes than only the bicycle. Apparently, the bicycle with its typical properties (limited distance range, restricted transport and storage capacity, etc.) is in many cases inconvenient or unsuitable for visiting all activity locations of an activity programme only by bicycle. The resulting multi-modal day-to-day travel behaviour of cyclists should be born in mind when analysing and interpreting bicycle-related activity-travel patterns.

The spatial and temporal flexibility of the bicycle seems to facilitate complex trip chaining while the limited reach impedes it. The former can be concluded since all three private means of transport had higher percentages of complex trip chains than public transport. Among the travel modes car, bicycle and walking, the distance range appears to be an important parameter, determining why bicycle trip chains are less often complex than car trip chains but more often than trip chains travelled on foot. Considering both facilitating and inhibiting features of the bicycle, the extent of bicycle trip chaining seems to depend on the urban structure and might vary between different contexts.

Trip chaining by bicycle appears to be constrained by relatively inflexible *travel distance budgets*. Such a cycling distance threshold could explain why so little systematic variations in bicycle commute tour extensions were observed between activity types. While car commute tour extensions seem to be subject to pull and push factors (e.g. *activity type*, *duration of the secondary activity* or *time of the day*), complex bicycle commute tours might only occur when the individual distance threshold is not exceeded, regardless of the features of the secondary activity. What is surprising in this context is that not more pronounced effects were found for factors, which describe the traveller (and which could potentially capture systematic variations in travel distance budgets between people). Such effects, however, might in parts be concealed by related variations in simple tour distances.

Unlike complex trip chains, cycling distances to activity locations in simple trip chains vary considerably based on a set of factors. The findings suggest that activity locations in the three considered bicycle-friendly regions were often shorter than what many of the cyclists would have been willing or capable to cycle. Considering the high bicycle shares in all three regions, the availability of activity locations within close proximity, therefore, seems to be favourable for engaging large parts of the potential cycling population. Last but not least, observed deviations between the three regions might be (partly) explained by different infrastructure designs, favouring one user group over another.

6.3 Discussion

Travel diary data was generally deemed suitable for reaching the postulated main research objective of this thesis (see 1.3). Nonetheless, some of the findings and conclusions are worth discussing against the backdrop of the data properties.

In this thesis, we mostly used data from the MPN travel survey. The following characteristics of the survey might have an influence on the results. The MPN travel diary is a self-reporting and self-completion survey (Hoogendoorn-Lanser et al., 2015). The former means that people usually report their trips in the evening based on their memories of the day (and potentially some notes that they made). The latter entails that nobody guides them through the questions, such as an interviewer in a telephone survey. Finally, it is a three-day travel survey, which was a design compromise between capturing the day-to-day variations in travel behaviour, survey fatigue and financial constraints.

The identified mobility pattern classes are based on up to three days of data. This is already a relatively rich data basis in comparison to many other travel diaries, which query a single travel day only (e.g. the travel diaries used in this thesis from Germany and Denmark or the OVIN travel diary from Netherlands Statistics). As a consequence, the MPN travel diary captures some day-to-day travel behaviour variation. For example, much less multi-modal travel behaviour of cyclists would have been revealed when looking at a single day only. Nonetheless, a week-long travel survey would have been a desirable data basis since many activity programmes show a certain repetitiveness on a weekly basis (e.g. football training always Tuesdays and Thursdays, teleworking Wednesdays, etc.). It would be expected that such a longer survey refines the identified mobility pattern classes due to more variation in the trip rates of people. As a result, the respective role of the bicycle in each of the mobility pattern would become more clear (that is how much activity participation is linked to bicycle transportation).

The relatively low share of complex trip chains in our data in comparison to former evidence and the extremely low proportion of complex trip chains related to public transport might be linked to the presented features of the data collection. The usual reporting in the evening (rather than continuous trip entries) might entail that people often forget smaller activities. In this context, smaller “spur-of-the-moment activities” are more likely to be forgotten, when they are not related to larger organizational efforts. In the Netherlands, this is probably more often the case for the active modes and public transport than for car travel. The ease of quickly eating icecream on the way by bicycle or the convenience of buying a snack at a train station might be less remembered than doing the same by car. In the Netherlands, the latter would often require the search for a parking space, the payment of some parking costs and still some meters of walking to the destination. For this reason, we expect an underreporting of small activities (and hence, of trip chain complexity), in particular for the active modes and public transport.

6.4 Implications for practice

The research of this thesis was conducted with the aim to generate knowledge on bicycle-related activity-travel behaviour, which can be also used by practitioners. More specifically, the focus on the spatial dimension of the travel behaviour was chosen to put theoretical concepts of bicycle-friendly planning in more tangible, concrete terms. In this section, we discuss the implications of our findings for urban planners and policy-makers.

The current cycling population and the prospects of a further increase of bicycle mode share in the Netherlands

Based on the findings of the latent class cluster analysis from Chapter 2, almost 75 per cent of all people in the sample pertained to the cycling population. Recent research suggests that attitudes of people are more positive towards travel modes that they use for daily-life travelling than towards those that they do not use (Ton et al., 2019). Since attitudes are considered an important mode choice factor, the large extent of the cycling population is promising. Besides attitudes, the perceived feasibility (of travelling to a particular destination by bicycle) seems to be an important factor for explaining (mode choice) behaviour (Ajzen, 1991). Consequently, many people of the cyclist population might be willing to cycle more often if they deemed it feasible from different perspectives such as distance or safety. Policies that contribute to enable more activity participation by bicycle have hence good prospects to increase cycling levels in the Netherlands. The next paragraphs will give concrete examples for such policies based on the findings of this thesis.

Making destinations accessible by bicycle

It is obvious that a high mode share of cycling is only possible when many daily-life destinations can be reached by bicycle (by many people). To make destinations accessible, both bicycle-friendly land-use and transport systems are necessary.

This thesis provided empirical underpinning of spatial activity-travel behaviour by bicycle which can be used for land-use planning. Since the findings stem from study areas with high bicycle mode shares, they represent benchmark values to assess planned or existing land-use structures. Our research showed that reported bicycle distances from home to destinations vary depending on both the profile of the activity and the features of the travellers. For these reasons, accessibility evaluations should be target group-specific. Moreover, the large proportion of short distances in all three regions suggests that bicycle-friendly land-use structures should be guided by the physical capabilities of the weakest cyclists. A positive side effect of such an approach is that it also ensures destination choices within cycling distances for a large part of the cycling population.

Besides the land-use system, the transport system is indispensable for accessibility. While this thesis was not explicitly investigating how different bicycle infrastructures affect bicycle accessibility, indications were identified that network properties can increase cycling travel distances. The network in Copenhagen appeared to be more optimised on bicycle travel times due to green waves (at a speed of 20 kilometres per hour) and direct connection along the main arteries of the city. In this way, a range of 10 kilometres can theoretically be reached in 30 minutes travel time. While this is favourable for long-distance travellers, such as many commuters, weaker users might be discouraged by the high speeds and the exposure to motorised traffic (in particular at intersections). For this reason, we recommend the development of consistent hierarchical bicycle networks. Similarly to the classification of urban car roads, bicycle networks could also have several layers, each of them pertaining to different functions and user groups.

An accessibility-relevant feature of the transport system, which is worth a separate mention, is the e-bike. Our findings show that the e-bike considerably increases travel distances. However, depending on the user group, the lower disutility of travel that comes along with the e-bike can have two different effects. Based on our results, it can be hypothesised that particularly former users of conventional bicycles extend their reach when switching to an e-bike. In contrast, former non-cyclists or physically weaker cyclists such as pensioners might not travel further than people with conventional bicycles. Thanks to the e-bike, this group has gained the necessary accessibility to use the bicycle in the first place. Consequently, policies that increase the acquisition (e.g. subsidies) and use of e-bikes (e.g. the offer of protected bicycle parking with charging points) can be recommended from the viewpoint of accessibility. The higher speeds in general and the decoupling of physical fitness and speed in particular might, however, also have downsides from a safety perspective.

Enable bicycle trip chaining

People make mode choices in light of their activity programme. In this context, the capacity of trip chaining can be an important mode choice factor that might not sufficiently be considered by policymakers and urban planners. Based on our findings, the bicycle seems to be on the one hand a travel mode that is rather suitable for complex trip chaining due to its spatial and temporal flexibility. However, a limited travel distance budget seems to pose a barrier as well as a limited capacity of transporting people and goods.

Policies to facilitate complex trip chaining by bicycle could comprise several measures. First, the concentration of activity locations at centres would provide a wide range of different destinations within a small range. As a consequence, trip chaining without extensive detours would be enabled. Second, activity locations of frequently visited secondary activities should be placed close to residential areas. In this way, the inconvenient transport of goods or people by bicycle would only be conducted over short distances. And third, policies that support the acquisition, use and safe intermediate parking of cargo-bikes or bicycle trailers would improve the suitability of the bicycle for trip chaining. For instance, dedicated parking at daycare centres would enable parents to drop off and pick up their child and trailer jointly.

The bicycle-oriented city

Based on our findings, we return to the notion of a bicycle-oriented city from the introduction and outline, how such a city could be planned. Bicycle-oriented urban planning would start at the neighbourhood level. A basic supply of frequently used services should be located at this level. Among these activity locations are child-care centres, kindergartens or supermarkets. By placing these destinations in the immediate vicinity of home locations, car use would already be reduced for a substantial share of all activity-travelling. In addition, the activity types grocery shopping and picking up or dropping off children are often included as secondary activities in complex trip chains. By placing these activities close to home locations, trip chaining by bicycle is facilitated.

Destinations requiring larger catchment areas, such as health or financial services, schools and a range of more specialised shops, should be concentrated at the district level. Such a concentration would again enable trip chaining by bicycle since additional activities can be included in a tour with little extra travel distance. By implication, bicycle-oriented urban planning would hence result in poly-centric urban structures.

These more concrete design principles would be accompanied by high urban densities and mixed land-uses. High densities decrease the distances between all possible origin-destination pairs and mixed land-use increases the number of different destinations that can be found around each location in the city. These are important supplements since many origin-destination pairs are beyond the control of the planner due to free choices of people (place of residence, work location, locations where friends live, personal shopping preferences, etc).

Besides these principles of bicycle-friendly land-use planning, a safe and comfortable bicycle network is indispensable to link origins to destinations. To achieve high bicycle mode shares, this network should accommodate the needs of different user groups. A good way to do so would be a hierarchical network that interlinks with the two land-use levels. At the neighbourhood level, travel speed is not important since travel distances to destinations (or a higher-level cycle path) are short. The design should, therefore, be guided by the needs of the most vulnerable cyclists such as children or elderly people. In contrast, an inter-neighbourhood or even inter-district network could ensure attractive travel times for trips with longer distances by providing direct connections with little travel time losses at intersections.

6.5 Directions for future research

Based on our findings and the related discussion presented in the sections 6.1 and 6.3, we formulate the following directions for future research.

Estimating activity-travel patterns instead of mobility patterns

In this thesis, we identified *mobility pattern classes* based on average weekday trip rates of different travel modes. While the variability found in the data allowed to identify five distinctive patterns of day-to-day mode choice behaviour, the link to the underlying activity programme could be improved. Findings from this thesis suggest that the features of a person’s activity programme (and the role in a household, which it reflects) have an influence on the mobility pattern. For instance, the mobility pattern class ‘Exclusive Bicycle user’ was mostly related to people whose profile suggests a limited responsibility for the household. By including features of the activity programme in the clustering process, a more refined picture could be gained of who are “the cyclists” and what is the role of the bicycle in their daily activity-travelling. In practical terms, this could be done by using average trip purpose rates (i.e. the average numbers of activities per day and activity type) as additional indicators in the latent class cluster analysis. In this context, we would recommend to only use the most characterising or aggregated activity types to limit the fragmentation of resulting *activity-travel pattern* classes.

Further research on bicycle trip chaining

Since the possibility to travel to several trips in a tour is a mode choice factor, the circumstances that are related to complex trip chaining by bicycle deserve further attention. First, a review of trip chain complexity degrees of different travel modes would be recommended once high-resolution data is available. We hypothesised that “spur-of-the-moment” activities are more often conducted by bicycle than by car. In the future, smartphone-based travel diary data might become the new standard, capturing more reliably such short activities. Second, a disaggregated view on bicycle trip chain complexity per activity type would provide a deeper understanding of the bicycle characteristics that shape related activity-travel behaviour. And last, more disaggregated information about the urban environment such as detailed information on land-use characteristics at origin and destination would allow linking bicycle trip chaining to the urban form. The last two mentioned recommendations could be realised by modelling bicycle trip chain complexity (simple versus complex) using activity types and features of the land-use at origin and destination of a tour as predictor variables in a logistic regression model.

Accounting for bicycle-related particularities in utility-based choice models

Utility theory is a concept that is broadly applied in transport analyses to explain and predict all kinds of travel choices such as mode or route choice. In this context, travel is usually attributed to a disutility, which has to be minimised. The disutility of an alternative is often formulated as a linear equation summing up all considered components (e.g. travel time and travel costs) weighted by a parameter that reflects the relative importance of disutility. However, based on our findings, this practice might not realistically capture bicycle-related choices for two reasons.

First, fatigue-related components of disutility might not be linear but rather exponential. Assuming a daily cycle distance budget which reflects physical abilities, a marginal increase in travel distance would have different effects on disutility depending on how close one is to his or her personal limit. While such a mode-specific feature could explain some of our results in Chapter 4 related to bicycle trip chaining, dedicated empirical research on this matter is needed. In case that future studies verify our hypothesis, transport modellers would need to think about ways how to accommodate for (mode-specific) non-linearity in the utility function.

A second proposed direction for future research pertains to a potentially positive utility gained during (utilitarian) cycling. While travelling is usually considered a pure means of reaching activity locations, cycling has some positive side effects for the traveller. A rich body of literature demonstrated various positive health effects, such as cardiovascular and physical fitness or stress relief (provided that functional cycling infrastructure is available). Consequently, it can be assumed that in activity-travelling by bicycle utility is not only gained by activity participation but also during travelling. Further empirical underpinning is necessary to understand the extent and circumstances that induce positive travel utility.

Investigating e-bike user groups and the effects on bicycle accessibility

While the bicycle-oriented city (which we sketched in section 6.4) relies in large parts on bicycle-friendly land-use planning, reality looks different in many places. Decades of car-oriented land-use policies have often lead to environments that do not have high levels of bicycle accessibility. Against this backdrop, improvements of bicycle accessibility in evolved structures might be achieved faster at the level of the transport system by implementing, for example, so-called bicycle highways. For this reason, it is recommended to address the effect of such infrastructures on accessibility in future research. In addition, findings from this thesis pointed out that e-bikes have the potential to increase the range of accessible destinations by bicycle. However, the contradicting effects of the e-bike between regions found in this thesis indicate that more research is necessary to fully understand the implications of e-bike use on bicycle accessibility. In this context, future research should particularly examine the link between different e-bike user groups and accessibility and the interactions that the features of the infrastructure have on this accessibility.

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Summary

Many cities aim for increasing the use of the bicycle at the expense of the car to reduce many transport-related urban problems such as air pollution, noise or congestion. A common notion of transport is that it is driven by the demand for activity participation. For instance, people travel to get to work or school. Consequently, facilitating a mode shift towards the bicycle requires that a large part of peoples' activity participation can be ensured by bicycle. Therefore, urban environments have to accommodate typical activity-travel behaviour of cyclists.

Travelling by bicycle has peculiar functional properties, suggesting that activity-travel patterns of cyclists differ from those of other travellers.

- Locomotion by bicycle is based on a physical effort, making cyclists more distance sensitive.
- The transport of people and goods (and the intermediate storage of purchases) is restricted for the bicycle.
- Cycling is not only a means of transport but it can be an activity (a purpose) in itself.

To plan and assess bicycle-friendly urban environments, knowledge on the spatial features of bicycle activity-travelling is needed as well as insights into how these features depend on contextual factors. Since this knowledge is largely lacking, we formulate the following research goal:

To gain empirical insights into spatial activity-travel behaviour of cyclists and to empirically underpin factors that affect their spatial activity-travel patterns.

To achieve this objective, we performed empirical analyses on activity-travel patterns at three different zoom levels, namely multi-day travel patterns, trip chain patterns and single trips. At the level of the multi-day travel pattern, we derived mobility pattern classes to identify the extent to which the bicycle is used (by cyclists) for daily activity-travelling (Chapter 2). At the level of trip chain patterns, we looked at two different characteristics of home-based trip chains. The first focus was put on the number of activities (referred to as trip chain complexity)

included in such a pattern (Chapter 2). Complex trip chains have the potential to reduce the travel distance required for activity participation. The comparison of trip chain complexity distributions between travel modes allowed to discern this first feature of typical bicycle-related activity-travel behaviour. The second studied characteristic was the spatial dimension of trip chaining behaviour (Chapter 4). Since the potential of complex trip chaining can be a mode choice factor, we studied detours that people make in home-based trip chains to include a secondary activity and their determinants for both car and bicycle travel. In order to correctly determine primary and secondary activity in a complex trip chain, we additionally developed a new distance-based method to derive activity hierarchies (Chapter 3). At the trip level, we investigated bicycle trip distances to different types of destinations and studied their determinants (Chapter 5). This last analysis of the thesis provides empirical insights into distances between origins and destinations that are accessible for different types of cyclists.

In short, we first developed an understanding of how activity participation by bicycle is organised in terms of activities and trips before drawing our attention to the spatial features of the corresponding activity-travel patterns. In the following we specify for each of the analyses the employed data and methods and present shortly the main findings and their interpretations. Finally, we highlight the most important implications for future research and practice of our findings.

Cyclists as multimodal activity-travellers (Chapter 2)

Due to the peculiar functional properties of the bicycle, many cyclists might not only use the bicycle to conduct their daily activities but also other travel modes. A part of understanding activity-travelling by bicycle is, therefore, the disclosure of travel mode combinations that are typically used by people to conduct daily activity programmes. In a latent class cluster analysis (LCCA), we derived weekday mobility pattern classes in the Netherlands using the three-days travel diary from the Netherlands Mobility Panel (MPN). The clustering was based on average daily trip rates per travel mode and person and included only trips that were related to activity-travelling.

Four of the five identified weekday mobility pattern classes included the bicycle, among them a class of ‘Exclusive cyclists’. Considering the class sizes, the outcomes suggest that almost 75 per cent of the people in the panel used the bicycle to some extent in their weekday activity-travel patterns. Among these travellers, who can be called *cyclists* in the context of this thesis, 85 per cent (or two-thirds of all travellers in the sample) were attributed to classes with multi-modal day-to-day travel behaviour. These results show that cyclists are prevailingly multi-modal travellers. The contribution of the bicycle to the average activity-travelling in the three multimodal mobility pattern classes varied between 20 and 30 per cent. The class of ‘Exclusive cyclists’ was characterised by younger travellers which still might have different tasks in the household than the older members.

In conclusion, activity participation of cyclists often seems to involve more travel modes than only the bicycle. Apparently, the bicycle with its typical properties is in many cases inconvenient or unsuitable for visiting all activity locations of an activity programme only by bicycle. This context should be kept in mind when analysing and interpreting the features of bicycle-related activity-travel patterns.

The extent of complex trip chaining by bicycle (Chapter 2)

Home-based trip chains are a suitable activity-travel pattern to study mode-specific activity-travel behaviour as personal means of transport (mostly) rotate in spatial loops. From the MPN travel survey, we derived trip chains by merging all trips and activities of home-based travel loops. Each of the trip chains was assigned to one of the five travel mode classes ‘Car’, ‘Public transport', 'Bicycle', 'Walking' and 'Multimodal'. In addition, trip chains were attributed to a complexity degree depending on the number of trips they included.

The bicycle seems to be the travel mode that accounts for the second-highest share of complex trip chains (i.e. trip chains involving more than two trips). Overall, 15 per cent of all tours travelled by bicycle visited at least two different activity locations before returning back home. Only the car was with 20 per cent related to a slightly higher percentage of complex trip chains. In contrast, both walking and public transport tours were mostly simple (accounting for only six and one per cent respectively).

The spatial and temporal flexibility of the bicycle seems to facilitate complex trip chaining while the limited reach (and a correspondingly smaller number of accessible destinations) impedes it. The former can be concluded since all three private means of transport had higher percentages of complex trip chains than public transport. Among the travel modes car, bicycle and walking, the distance range appears to be an important determinant of trip chain complexity, explaining why bicycle trip chains are less often complex than car trip chains but more often than trip chains travelled on foot.

With regard to the overall research objective, it is interesting to note that, despite its potential of reducing travel distances for activity participation, complex trip chaining by bicycle appears to be inhibited by a lack of bicycle accessibility to destinations. By implication, bicycle-centred urban planning, which provides more destinations in bicycle reach, has the potential to increase trip chaining by bicycle (and hence the mode share of the bicycle).

Distance-based activity hierarchies in trip chains (Chapter 3)

In order to study the spatial features of trip chaining behaviour, an understanding of the inner structure of complex trip chains is necessary. To this end, we proposed a new method to derive and assess hierarchies between activity types using travel diary data. To identify the activity in a trip chain that purposed the travel (primary activity) and the activity that has been added opportunistically (secondary activity), we looked at distance positions of each activity relative to the total trip chain distance. Therefore, we extracted home-based trip chains that included two different activity types from the MPN travel diary.

Based on pairwise comparisons of the distributions of relative distance positions, we ranked all ten considered activity types in a hierarchy scheme consisting of six blocks (listed below from highest to lowest hierarchy): 1) *Education*, 2) *Work*, 3) *Sport*, 4) *Visit* / *Service* / *Shop* / *Leisure*, 5) *Escort* / *Dropping off or picking up goods*, 6) *Grocery*. *Education* was the primary activity in all pairs in which it was included while *grocery* was consistently secondary. Since this hierarchy scheme did not include a quantification of how much one activity type was prominent over another one in a pair, we additionally computed a measure of hierarchy strength. The related results suggest that *work* was the most prominent primary activity throughout all trip chains in our data set. For this reason, commuting trip chains form the best starting point when studying trip chaining behaviour.

Features of spatial trip chaining behaviour by bicycle (Chapter 4)

We analysed detours that bicycle and car travellers make during their commute tour to include a secondary activity. For this purpose, we derived commute trip chains, which include a second activity from the MPN travel diary data. Detours were calculated by subtracting from the distances of these complex commute trip chains the distances of their hypothetical simple counterparts (i.e. the same trip chain without the second activity). Furthermore, a regression model was employed to identify important determinants of these detours for both travel modes.

The model results suggest that people make on average detours of 2.6 kilometres by bicycle and 7.5 kilometres by car. While this difference was not surprising, a remarkable outcome was the low sensitivity (also in relative terms) of bicycle commute tour extensions to most considered factors compared to those of the car. While bicycle detours were only considerably deviating for the activity types *grocery* and *service* and the age class *younger than 20*, estimated commute tours extensions by car varied considerably based on activity type, age class, gender, time of the day and the duration of the secondary activity.

In conclusion, trip chaining by bicycle appears to be constrained by relatively inflexible *travel distance budgets*. Such a cycling distance threshold could explain why so little systematic variations in bicycle commute tour extensions were observed between activity types. While car commute tour extensions seem to be subject to pull and push factors (e.g. *activity type*, *duration of the secondary activity* or *time of the day*), complex bicycle commute tours might only occur when the individual distance threshold is not exceeded, regardless of the features of the secondary activity. Such a cycling distance budget could therefore become a guiding principle of bicycle-friendly urban planning.

Cycling distances to destinations and their determinants (Chapter 5)

The last analysis of this thesis revealed the spatial features of simple activity-travel patterns in an accessibility framework. Using travel diary data from the Netherlands (MPN), the Copenhagen Metropolitan Area in Denmark (Danish National Travel Survey) and the Freiburg Region in Southwest Germany (Travel survey ZRF), we isolated outbound trips of trip chains travelled by bicycle which included a single destination only. Travel distances were related to a set of activity features and other factors by means of regression models.

The results of the analysis indicated that distance-distributions are similar in the Netherlands, the Copenhagen Metropolitan Area and the Freiburg Region. Most cycling distances were rather short, with a median of only two and a mean of three kilometres. These values varied depending on the type of activity at the destination, gender and age of the traveller and the type of bicycle that has been used. In addition, a few remarkable differences have been found between the three regions, such as different effects of trip purposes (work, escort, education, shop and leisure), age and e-bike use on reported cycling distances.

Considering these outcomes and the high bicycle shares in all three regions, the availability of activity locations within close proximity seems to be favourable for engaging large parts of the potential cycling population.

Conclusions and implications

Based on the findings of the different analyses, several conclusions can be drawn with regard to the nature of activity-travel behaviour by bicycle. In addition, the gained knowledge has implications for both science and practice.

Most activity-travelling by bicycle is done by multimodal travellers. As a consequence, interactions between modes and activity-travelling are likely. This context should be considered when analysing activity-travel patterns related to the bicycle (e.g. the trip chaining behaviour). Furthermore, the revealed multimodality is also of interest for policy makers. The large proportion of people from the sample that use the bicycle to some extent for activity-travelling seems to be a promising basis for a further increase of the bicycle mode share in the Netherlands. Policies that seek to make more destinations accessible by bicycle have good prospects among these people.

Unlike car or public transport travel, bicycle travel behaviour is subject to constraints caused by physical efforts. This additional factor needs to be addressed when comparing travel behaviour across travel modes (e.g. mode choices, accessibility evaluations). Furthermore, since the physical effort increases with longer travel distances, proximity to destinations seems to an important factor of activity-travelling by bicycle. This finding has practical implications. First, urban planning schemes should aim for providing a variety of different types of destinations within bicycle distance. And second, policies that reduce the physical effort of cycling, such as prioritised bicycle traffic axes or the promotion of e-bikes, can potentially increase the reach of the bicycle.

The extent of bicycle travel in terms of distance depends on a lot of different factors. Bicycle accessibility evaluations should therefore be activity type and target group-specific. In this context, the findings from this thesis can serve as empirical benchmarks. Furthermore, the concentration of short trips in all three best-practice regions proposes that accessibility planning should be oriented towards the weakest potential cyclists. Since trip chaining capability can be a mode choice factor, the notion of bicycle accessibility should also include the accessibility to secondary activities on the way to or from a primary activity by bicycle. In this context, spatial planning might decrease space-related barriers to complex trip chaining by bicycle (e.g. by placing typical secondary activities close to residential areas).

Samenvatting

Veel steden streven naar een toename van het gebruik van de fiets ten koste van de auto. Op deze manier kunnen veel verkeersgerelateerde stedelijke problemen zoals luchtvervuiling, lawaai of congestie worden verminderd. Een gangbare opvatting is dat vervoer wordt gedreven door de vraag naar activiteiten die buitenshuis worden uitgevoerd. Mensen reizen bijvoorbeeld om naar hun werk of naar school te gaan. Om een overstap naar de fiets mogelijk te maken, is het dus noodzakelijk dat een groot deel van de activiteiten van de mensen op fietsafstand kan worden verricht. Daarom moet de stedelijke omgeving rekening houden met de manier waarop de fiets wordt gebruikt om activiteitenlocaties te bereiken.

Reizen met de fiets heeft specifieke functionele kenmerken. Deze kenmerken suggereren dat het reisgedrag van fietsers anders is dan dat van andere reizigers:

- Voortbeweging per fiets is afhankelijk van een fysieke inspanning, waardoor fietsers gevoeliger zijn voor afstand.
- Het vervoer van personen en goederen (en de tussentijdse opslag van aankopen) is moeilijker met de fiets.
- De fiets is niet alleen een vervoermiddel, maar fietsen kan ook een doel op zich zijn.

Voor het plannen en beoordelen van fietsvriendelijke stedelijke omgevingen is kennis nodig over de ruimtelijke kenmerken van activiteitenpatronen van fietsers en inzicht in hoe deze kenmerken afhankelijk zijn van contextuele factoren. Omdat deze kennis grotendeels onbekend is, formuleren we het volgende onderzoeksdoel:

Het verkrijgen van empirisch inzicht in het ruimtelijke reisgedrag van fietsers om activiteitenlocaties te bereiken en het empirisch onderbouwen welke factoren van invloed zijn op hun ruimtelijke activiteitenpatronen.

Om dit doel te bereiken, hebben we empirische analyses uitgevoerd op activiteitenpatronen op drie verschillende detailniveaus, namelijk meerdaagse reispatronen, verplaatsingsketens en individuele reizen. Voor meerdaagse reispatronen hebben we categorieën voor mobiliteitspatronen afgeleid om te bepalen in hoeverre de fiets wordt gebruikt voor dagelijkse activiteitenreizen (hoofdstuk 2). Voor verplaatsingsketens hebben we gekeken naar twee aspecten van verplaatsingsketens die starten of eindigen op de thuislocatie. Het eerste aspect is het aantal activiteiten (de zogenaamde complexiteit van de verplaatsingsketens) in een verplaatsingsketen (hoofdstuk 2). Complexe verplaatsingsketens hebben de potentie om de reisafstand die nodig is voor het uitvoeren van activiteiten te verkleinen. De vergelijking van de complexiteit van de verplaatsingsketen tussen de modaliteiten maakte het mogelijk om te kijken of fietsers een voorkeur hebben voor een bepaalde complexiteit in hun verplaatsingsketens. Ten tweede hebben we gekeken naar de ruimtelijke dimensie van verplaatsingsketens (hoofdstuk 4). We bestudeerden de omweg die mensen maken om een secundaire activiteit op te nemen in hun verplaatsingsketens en verklarende factoren voor de omwegen voor zowel auto- als fietsritten. Om te beginnen hebben we daarvoor een nieuwe methode ontwikkeld om de hiërarchie in activiteitenketens af te leiden op basis van afgelegde afstand (hoofdstuk 3). Met deze methode kunnen we de primaire en secundaire activiteit in een complexe verplaatsingsketen accuraat bepalen. Voor individuele reizen hebben we de afstanden van fietsverplaatsingen naar verschillende bestemmingen onderzocht en de bijbehorende invloedsfactoren bestudeerd (hoofdstuk 5). Deze laatste analyse van het proefschrift geeft empirisch inzicht in herkomsten en bestemmingen die voor verschillende soorten fietsers bereikbaar zijn.

Kortom, we hebben eerst inzichten ontwikkeld in hoe fietsers activiteitenlocaties bereiken, en vervolgens gekeken naar de ruimtelijke kenmerken van de activiteitenpatronen. Hieronder specificeren we voor elke analyse de gebruikte gegevens en methoden en presenteren we kort de belangrijkste bevindingen en hun interpretaties. Tot slot belichten we de belangrijkste implicaties van onze bevindingen voor toekomstig onderzoek en de praktijk.

Fietsers als multimodale activiteitenreizigers (hoofdstuk 2)

Door de bijzondere functionele kenmerken van de fiets is het waarschijnlijk dat veel fietsers niet alleen de fiets voor hun dagelijkse activiteiten gebruiken, maar ook andere modaliteiten. Voor het ontwikkelen van meer begrip van de activiteit ‘reizen met de fiets’ kijken we daarom naar de combinaties van modaliteiten die typisch worden gebruikt om dagelijkse activiteitenprogramma's uit te voeren. In een *latent class cluster analysis* (LCCA) hebben we aan de hand van het driedaagse reisdagboek van het Mobiliteitspanel Nederland (MPN) categoriën afgeleid die op een weekdag de mobiliteitspatronen in Nederland beschrijven. De clustering is gebaseerd op het gemiddelde aantal dagelijkse verplaatsingen per vervoermiddel en per persoon.

In vier van de vijf geïdentificeerde categoriën is de fiets als modaliteit opgenomen, waaronder een klasse 'Exclusieve fietsers'. De grootte van de categoriën suggereert dat bijna 75 procent van de mensen in het panel de fiets in meer of mindere mate heeft gebruikt in hun doordeweekse activiteitenpatroon. Van deze reizigers, die in dit proefschrift ‘fietsers’ worden genoemd, wordt 85 procent (overeenkomend met tweederde van alle reizigers in de steekproef) toegedeeld aan categoriën met dagelijks multimodaal reisgedrag. Deze resultaten laten zien dat fietsers overwegend multimodale reizigers zijn. Het aandeel fietsverplaatsingen in de drie multimodale mobiliteitspatroonklassen varieerde van 20 tot 30 procent. De categorie 'Exclusieve fietsers' bestaat vooral uit jongere reizigers die waarschijnlijk andere taken in het huishouden hebben dan de oudere leden.

Concluderend lijken de activiteitenpatronen van fietsers vaak meer modaliteiten te omvatten dan alleen de fiets. Blijkbaar is de fiets met zijn typische eigenschappen in veel gevallen onhandig of ongeschikt om alle activiteitenlocaties van een activiteitenprogramma te bezoeken. Deze context moet in het achterhoofd worden gehouden bij het analyseren en interpreteren van de kenmerken van fietsgerelateerde activiteitenpatronen.

De omvang van complexe fietsverplaatsingsketens (hoofdstuk 2)

Verplaatsingsketens die thuis beginnen en eindigen zijn een geschikt activiteitenpatroon om modaliteitsspecifiek reisgedrag te bestuderen omdat persoonlijke vervoersmiddelen (meestal) in ruimtelijke lussen rouleren. Uit de gegevens van het MPN hebben we verplaatsingsketens afgeleid door het samenvoegen van alle verplaatsingen van het verlaten van het huis tot aan de thuiskomst. Elke verplaatsingsketen is toegewezen aan een van de vijf modaliteiten 'Auto', 'Openbaar vervoer', 'Fiets', 'Lopen' en 'Multimodaal'. Daarnaast is van de verplaatsingsketens de complexiteit bepaald, afhankelijk van het aantal verplaatsingen dat de ketens omvatten.
De fiets lijkt de vervoerswijze te zijn die het op één na grootste aandeel heeft in complexe verplaatsingsketens (die meer dan twee verplaatsingen omvatten). In totaal zijn in 15 procent van alle verplaatsingsketens met de fiets ten minste twee verschillende activiteitenlocaties bezocht voor de terugkeer naar huis. Alleen bij verplaatsingsketens met de auto was dit met 20 procent iets hoger. Daarentegen waren zowel de verplaatsingsketens te voet als met het openbaar vervoer meestal simpel (met respectievelijk slechts zes en één procent complexe verplaatsingsketens).
De ruimtelijke en temporele flexibiliteit van de fiets lijkt complexe verplaatsingsketens te vergemakkelijken, terwijl het beperkte bereik van de fiets (en een navenant kleiner aantal bereikbare bestemmingen) dit bemoeilijkt. Het eerste kan worden geconcludeerd uit het feit dat alle particuliere vervoermiddelen een hoger percentage complexe verplaatsingsketens hadden dan het openbaar vervoer. Bij de modaliteiten auto, fiets en lopen blijkt het afstandsbereik een belangrijke bepalende factor te zijn voor de complexiteit van de verplaatsingsketens, hetgeen verklaart waarom verplaatsingsketens met de fiets minder vaak complex zijn dan verplaatsingsketens met de auto, maar vaker dan verplaatsingsketens die te voet worden afgelegd.
Met betrekking tot de algemene onderzoeksdoelstelling is het interessant om op te merken dat complexe verplaatsingsketens per fiets geremd lijken te worden door een beperkte bereikbaarheid van de bestemmingen met de fiets. Dit betekent dat een op de fiets gerichte stedelijke planning, die meer bestemmingen binnen fietsbereik biedt, de potentie heeft om het aantal complexe verplaatsingsketens met de fiets te vergroten (en daarmee het aandeel van de fiets in de modaliteitskeuze).

Op afstand gebaseerde hiërarchie in activiteiten in verplaatsingsketens (hoofdstuk 3)

Om de ruimtelijke kenmerken van verplaatsingsketens te bestuderen is inzicht nodig in de structuur van complexe tripketens. We hebben een nieuwe methode voorgesteld om de hiërarchie tussen typen activiteiten af te leiden en te beoordelen aan de hand van reisdagboeken. Om de primaire activiteit in een verplaatsingsketen te identificeren (dat wil zeggen de activiteit die de reis nodig maakt) en te onderscheiden van de activiteit die opportunistisch is toegevoegd (secundaire activiteit), hebben we gekeken naar de afstanden voor elke activiteit ten opzichte van de totale afstand van de verplaatsingsketen. Daarom hebben we uit het MPN-reisdagboek verplaatsingsketens geselecteerd, die thuis beginnen en eindigen en die precies twee verschillende typen activiteiten omvatten.
Op basis van een vergelijking van de verdeling van de relatieve afstandsposities per combinatie van het type van de primaire en de secundaire activiteit hebben we tien typen activiteiten geordend in een hiërarchie die bestaat uit zes blokken (hierna genoemd van de hoogste naar de laagste hiërarchie): 1) *Onderwijs*, 2) *Werk*, 3) *Sport*, 4) *Bezoek* / *Diensten* / *Winkel* / *Overige vrijtijdsbesteding*, 5) *Afhalen of brengen van personen of goederen*, 6) *Dagelijkse boodschappen*. *Onderwijs* was de primaire activiteit in alle verplaatsingsketens waarin het werd opgenomen, terwijl de *Dagelijkse boodschappen* consequent secundair was. Bovendien hebben

we een maat voor de sterkte van de hiërarchie berekend. De resultaten hiervan suggereren dat *Werk* de meest prominente primaire activiteit was in alle verplaatsingsketens in onze dataset. Daarom zijn woon-werkverplaatsingsketens het beste uitgangspunt bij het bestuderen van verplaatsingsketensgedrag in het vervolg van de studie.

Ruimtelijke kenmerken van complexe verplaatsingsketens per fiets (hoofdstuk 4)

We analyseerden de omwegen die fietsers en automobilisten maken tijdens hun woon-werkverkeer om een secundaire activiteit uit te voeren. Daartoe hebben we uit de reisdagboekgegevens van het MPN woon-werkverplaatsingsketens afgeleid, die een tweede activiteit omvatten. De omwegen zijn berekend door het vergelijken van de afstanden van deze complexe woon-werkverplaatsingsketens en de hypothetische afstanden van dezelfde reis zonder de secundaire activiteit. Bovendien werd een regressiemodel gebruikt om belangrijke invloedsfactoren op deze omwegen voor zowel fietsers als automobilisten te identificeren.

De resultaten suggereren dat mensen gemiddeld 2,6 kilometer omrijden met de fiets en 7,5 kilometer met de auto. Hoewel dit verschil op zichzelf niet verrassend is, is het opmerkelijk dat omwegen met de fiets voor de meeste invloedsfactoren minder gevoelig zijn in vergelijking met die van de auto (ook in relatieve zin). Omwegen met de fiets verschilden alleen aanzienlijk voor de typen activiteiten *dagelijkse boodschappen* en *diensten* en de leeftijdsklasse *jonger dan 20 jaar*, terwijl de geschatte omwegen met de auto aanzienlijk varieerden op basis van type activiteit, leeftijdsklasse, geslacht, tijdstip van de dag en de duur van de secundaire activiteit.

Concluderend kan worden gesteld dat het opbouwen van complexe verplaatsingsketens met de fiets beperkt lijkt te worden door het relatief inflexibele budget voor de reisafstand. Een dergelijke afstandsdrempel voor de fiets zou kunnen verklaren waarom er zo weinig systematische variaties zijn waargenomen in de verlenging van de fietstochten voor woon-werkverkeer tussen de verschillende typen activiteiten. Terwijl de verlenging van woon-werkverkeer met de auto onderhevig lijkt te zijn aan pull- en push-factoren (bijvoorbeeld het type activiteit, de duur van de secundaire activiteit of het tijdstip van de dag), kunnen complexe woon-werkverplaatingsketens met de fiets alleen voorkomen als de individuele afstandsdrempel niet wordt overschreden, ongeacht de kenmerken van de secundaire activiteit. Een dergelijk afstandsbudget van fietsers zou dus een leidend principe kunnen zijn van fietsvriendelijke stedelijke planning.

Fietsafstanden tot bestemmingen en hun invloedsfactoren (hoofdstuk 5)

De laatste analyse van dit proefschrift onthulde de ruimtelijke kenmerken van simpele verplaatsingsketens. Met behulp van reisdagboeken uit Nederland (MPN), de Deense metropoolregio Kopenhagen (Danish National Travel Survey) en de regio Freiburg in Zuidwest-Duitsland (Travel survey ZRF) hebben we de verplaatsingen die thuis beginnen van fietsverplaatsingsketens met slechts één bestemming geïsoleerd. De reisafstanden werden gerelateerd aan een combinatie van activiteitskenmerken en andere factoren door middel van regressiemodellen.

De resultaten van de analyse geven aan dat de afgelegde fietsafstanden in Nederland, de metropoolregio Kopenhagen en de regio Freiburg vergelijkbaar zijn. De meeste afstanden waren vrij kort, met een mediaan van slechts twee kilometer en een gemiddelde van drie kilometer. Deze afstanden varieerden afhankelijk van het type activiteit op de bestemming, het geslacht en de leeftijd van de reiziger en het type fiets dat is gebruikt. Daarnaast zijn er enkele opmerkelijke verschillen gevonden tussen de drie regio's, zoals verschillende effecten van de reisdoelen (*Werk*, *Halen of brengen van personen*, *Onderwijs*, *Winkel* en *Overige vrijtijdsbesteding*), leeftijd en e-bike gebruik op de gerapporteerde fietsafstanden.

Conclusies en implicaties

Op basis van de bevindingen van de verschillende analyses kunnen conclusies worden getrokken met betrekking tot de aard van hoe de fiets wordt gebruikt om activiteitenlocaties te bereiken. Daarnaast heeft de opgedane kennis implicaties voor zowel de wetenschap als de praktijk.

Het merendeel van de verplaatsingen per fiets wordt gedaan door multimodale reizigers. Als gevolg daarvan zijn interacties tussen modaliteiten, activiteiten en de locaties waar die activiteiten worden uitgevoerd waarschijnlijk. Deze context moet worden meegenomen bij het analyseren van patronen van reizen die verband houden met de fiets. Bovendien is de gevonden multimodaliteit interessant voor beleidsmakers. Het grote aandeel mensen uit de steekproef dat de fiets gebruikt voor een deel van de verplaatsingsketens lijkt een veelbelovende basis te zijn voor een verdere toename van het aandeel van de fietsmodaliteit in Nederland. Beleid dat erop gericht is om meer bestemmingen per fiets bereikbaar te maken, zal deze mensen kunnen verleiden om vaker de fiets te gebruiken.

Anders dan bij het reizen met de auto of het openbaar vervoer kent het gedrag van fietsers beperkingen die worden veroorzaakt door fysieke inspanningen. Deze extra factor moet worden meegenomen bij het vergelijken van het reisgedrag tussen de verschillende vervoersmodaliteiten (bijv. keuze van de vervoersmodaliteiten, bereikbaarheidsevaluaties). Aangezien de fysieke inspanning toeneemt bij langere reisafstanden, lijkt de nabijheid van bestemmingen bovendien een belangrijke factor bij het bereiken van activiteiten met de fiets. Deze bevinding heeft praktische gevolgen. Ten eerste moeten stedenbouwkundige plannen gericht zijn op het bieden van een verscheidenheid aan bestemmingen binnen fietsafstand. Ten tweede kan beleid dat de fysieke inspanning van fietsers vermindert, zoals het ontwerpen van fietsverkeersassen met prioriteit of de promotie van e-bikes, het bereik van fietsers vergroten.

De omvang van het fietsverkeer in termen van afstand is afhankelijk van veel verschillende factoren. Evaluaties van de bereikbaarheid van de fiets moeten daarom specifiek zijn per type activiteit en doelgroep. In deze context kunnen de bevindingen van dit proefschrift dienen als empirische benchmarks. Verder leidt de concentratie van korte verplaatsingen in alle drie *best-practice* regio's ertoe om de plannen van de bereikbaarheid te richten op de fietsers die de minste fysieke inspanning aankunnen. Aangezien de mogelijkheid om meerdere verplaatsingen te verbinden tot een verplaatsingsketen een factor in de modaliteitskeuze kan zijn, moet het begrip fietstoegankelijkheid ook de toegankelijkheid van secundaire activiteiten omvatten. In deze context kan ruimtelijke planning de ruimtegebonden hindernissen voor complexe verplaatsingsketens per fiets verminderen (bijvoorbeeld door het plaatsen van secundaire activiteiten in de buurt van woonwijken).

About the author

Florian Schneider was born in Munich, Germany, on July 24th, 1984. After high school graduation in 2005, he worked for one year with refugee minors in Berlin. Back in Munich, he started to study Environmental Engineering at the Technical University of Munich, a programme which he finished after four years with a BSc. degree.

In 2010, Florian moved to Brussels, Belgium, where he studied Environmental Management and Science at Université Libre de Bruxelles. He wrote his thesis on the environmental effects of the reintroduction of the tram in France ("avec grande distinction").

After his studies, he worked for several months as a skiing instructor in the Alpes before starting in 2013 as a transport planner for the city of Freiburg, Germany. His projects included the development of a local bicycle marketing strategy, the design of (bicycle) infrastructure and the planning of both car and bicycle sharing.

In 2016, Florian moved on to the Netherlands, joining the Transport and Planning department at Delft University of Technology. Within the four years of his PhD, he had the opportunity to conduct a month-long research visit at the Technical University of Denmark in Copenhagen.

Florian is fascinated by well-functioning, liveable cities and the contribution that the bicycle can make to achieving them. Accordingly, his research interests comprise travel behaviour, policy measures and the interaction between city and transport.

List of publications

Journal articles

- Schneider, F., Ton, D., Zomer, L., Daamen, W., Duives, D., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2020). Trip chain complexity: a comparison among latent classes of daily mobility patterns. *Transportation*. https://doi.org/10.1007/s11116-020-10084-1
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Under review

- Schneider, F., Daamen, W., Hoogendoorn-Lanser, S., & Hoogendoorn, S. Deriving and assessing activity hierarchies from relative distances in tours.
- Schneider, F., Daamen, W., & Hoogendoorn, S. Trip chaining of bicycle and car commuters: An empirical analysis of detours to secondary activities.
- Schneider, F., Jensen, A.F., Daamen, W., & Hoogendoorn, S. Bicycle accessibility: What can we learn from best-practice examples?

Peer-reviewed conference contributions

- Schneider, F., Ton, D., Zomer, L.B., Daamen, W., Duives, D., Hoogendoorn-Lanser, S., & Hoogendoorn, S. Trip chains: a comparison among latent mobility pattern classes – *Presented at the International Association of Travel Behaviour Research Conference*, July 2018, Santa Barbara, USA.

- Zomer, L.B., Schneider, F., Ton, D., Hoogendoorn-Lanser, S., Duives, D., Cats, O., & Hoogendoorn, S. Wayfinding styles: The relationship with mobility patterns & navigational preferences – *Presented at the International Association of Travel Behaviour Research Conference*, July 2018, Santa Barbara, USA.
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- Schneider, F., Daamen, W., Hoogendoorn-Lanser, S., & Hoogendoorn, S. How far do people walk and cycle for different activities? Evidence from the Netherlands– *Presented at the hEART conference*, September 2018, Athens, Greece.
- Schneider, F., Daamen, W., Hoogendoorn-Lanser, S., & Hoogendoorn, S. Deriving and assessing activity hierarchies from relative distances in tours – *Presented at the 98th Transportation Research Board*, January 2019, Washington DC, USA.
- Schneider, F., Daamen, W., & Hoogendoorn, S. Bicycle and Car Trip Chaining Behavior: Which Traveler Extends Commute Tour Distances by How Much to Incorporate Which Secondary Activity? – *Presented at the 99th Transportation Research Board*, January 2020, Washington DC, USA.

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Summary

Knowledge about the way how the bicycle is used for activity participation is still scarce. This thesis provides empirical insights into typical activity-travel behaviour of cyclists. A special focus is put on the spatial dimension of activity-travelling by bicycle and its determinants. The findings can be used to design more bicycle-friendly urban environments.

About the Author

Florian Schneider did his PhD at Delft University of Technology. He has a Master degree in Environmental Management and a Bachelor in Environmental Engineering. Florian is fascinated by the transformative power of the bicycle towards more liveable cities.

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