Trip chaining of bicycle and car commuters
An empirical analysis of detours to secondary activities

Schneider, Florian; Daamen, Winnie; Hoogendoorn, Serge

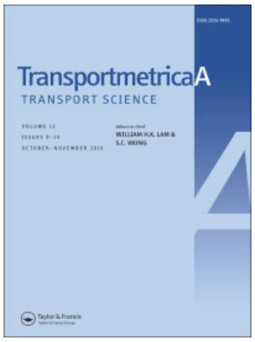
DOI
10.1080/23249935.2021.1901793

Publication date
2021

Document Version
Final published version

Published in
Transportmetrica A: Transport Science

Citation (APA)
Schneider, F., Daamen, W., & Hoogendoorn, S. (2021). Trip chaining of bicycle and car commuters: An empirical analysis of detours to secondary activities. *Transportmetrica A: Transport Science*, *18*(3), 855-878. https://doi.org/10.1080/23249935.2021.1901793



Taylor & Francis
Taylor & Francis Group

Transportmetrica A: Transport Science

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ttra21

Trip chaining of bicycle and car commuters: an empirical analysis of detours to secondary activities

Florian Schneider, Winnie Daamen & Serge Hoogendoorn

To cite this article: Florian Schneider, Winnie Daamen & Serge Hoogendoorn (2021): Trip chaining of bicycle and car commuters: an empirical analysis of detours to secondary activities, Transportmetrica A: Transport Science, DOI: 10.1080/23249935.2021.1901793

To link to this article: https://doi.org/10.1080/23249935.2021.1901793

Published online: 29 Mar 2021.

TRANSPORTMETRICA A: TRANSPORT SCIENCE
https://doi.org/10.1080/23249935.2021.1901793

Taylor & Francis
Taylor & Francis Group

OPEN ACCESS Check for updates

Trip chaining of bicycle and car commuters: an empirical analysis of detours to secondary activities

Florian Schneider , Winnie Daamen and Serge Hoogendoorn

Department of Transport and Planning, Delft University of Technology, Delft, The Netherlands

ABSTRACT

A largely overlooked mode choice factor of cycling is the mode-dependent capability of visiting several activity locations within a trip chain. Due to the bicycle's limited reach in comparison to the car, this capability can be increased by urban environments that facilitate trip chaining by bicycle. In the present paper, we empirically study travel distances between activity locations that facilitate trip chaining by the example of Dutch commute tours. More precisely, we address the question of how much cyclists extend commute tour distances compared to car travellers to include a secondary activity. For this purpose, a Bayesian regression model is proposed to analyse the effects of travel mode, secondary activity type and a series of control variables such as age and time of the day on commute tour extensions. The model results propose that people make on average detours of 7.4 km by car and 1.3 km by bicycle. These values strongly differ depending on the type of secondary activity, gender, the distance of the home-work tour and the duration of the secondary activity. In addition, the comparison between car and bicycle travel revealed some behavioural peculiarities of the active modes, which have implications for bicycle-friendly urban planning and several transport-related concepts.

ARTICLE HISTORY
Received 11 December 2019
Accepted 6 March 2021

KEYWORDS
Trip chaining; commuting; accessibility; travel behaviour; bicycle; car

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.

CONTACT Florian Schneider f.schneider@tudelft.nl Department of Transport & Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, PO Box 5048, Delft, 2600 GA, The Netherlands

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. 2007). 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 is an important mode choice factor (Ho and Mulley 2013).

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 and Godson 1975; Lee and 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 and 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 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 3. Subsequently, the employed statistical model is described in Section 4. Finally, the results are shown and discussed in Section 5, before drawing conclusions in Section 6.

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 conceptualisation, 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 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 activity attraction and travel resistance is largest).

Another necessary assumption within the theoretical framework concerns the spatial knowledge of the commuter regarding locations of secondary activities and related detours. Based on the anchor-point theory of Golledge, it can be argued that each observation stands for an accepted trade-off between the attraction of a secondary activity and the resistance of the related detour. The anchor-point theory explains how humans gain and store spatial knowledge (Couclelis et al. 1987). Within a hierarchical structure (which could be compared to different zoom levels of a map), people arrange their mental maps around so-called anchor points. According to the theory, geographical knowledge is built up and stored around these anchor points. At the level of an urban environment, anchor points can be often visited places of a person, widely known landmarks or frequently used paths. Applied to the context of our study, locations of work and home would be typical anchor points. Consequently, the geographical knowledge in the area around both places as well as along the corridor which connects them can be assumed to be high. This means that people have good knowledge of available activity locations and can make realistic estimations of detours related to the inclusion of a secondary activity in the commute tour.

Travel distance is only one measurement of travel resistance. In the literature, more factors 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

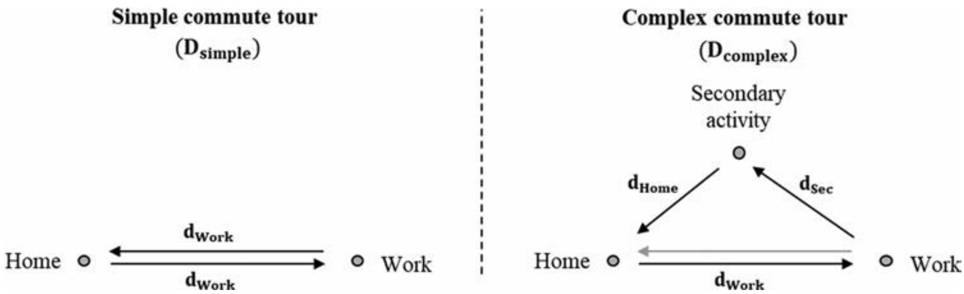


Figure 1. Tour distances in simple (D_{simple}) and complex (D_{complex}) commute tours.

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 is 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 1). In mathematical terms, the extension e for each tour observation $n \in N$ is:

$$e = D_{\text{complex}} - D_{\text{simple}} = (d_{\text{Work}} + d_{\text{Sec}} + d_{\text{Home}}) - (2 \times d_{\text{Work}}) = d_{\text{Sec}} + d_{\text{Home}} - d_{\text{Work}}, \tag{1}$$

where d_{Work} is the travel distance from home (or the secondary activity) to the work location; d_{Sec} is the travel distance from work (or home) to the activity location of the secondary activity; and d_{Home} is the travel distance from the secondary activity (or work) to the home location.

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 2, we put forward a conceptual model that illustrates the assumed relationships. Below, we elaborate the different elements in Figure 2.

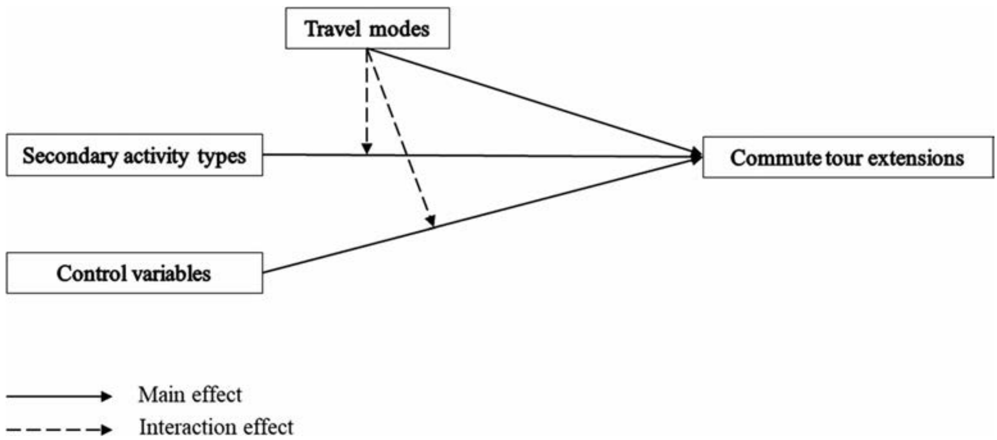


Figure 2. Conceptual model of commute tour extensions.

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 the spatial availability. Observed extensions thus do not only 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 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 3 for the data description and Section 4.1 for the variable selection). The list included commonly used socio-demographic variables (age and gender) as well as variables that represent the built environment and related availability constraints (urban density and land-use (Susilo and Maat 2007; van Acker and Witlox 2011)). Furthermore, a set of variables that capture space–time constraints (time of the day, simple tour distance, work duration (Brunow and Gründer 2013; Kondo and Kitamura 1987; Krygsman, Arentze, and Timmermans 2007; van Acker and Witlox 2011)) and the importance of the secondary activity (activity duration (Doherty and Mohammadian 2011; Schneider, et al., n.d.)) were added to the list. Similarly to the 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 2).

3. Trip chain data set

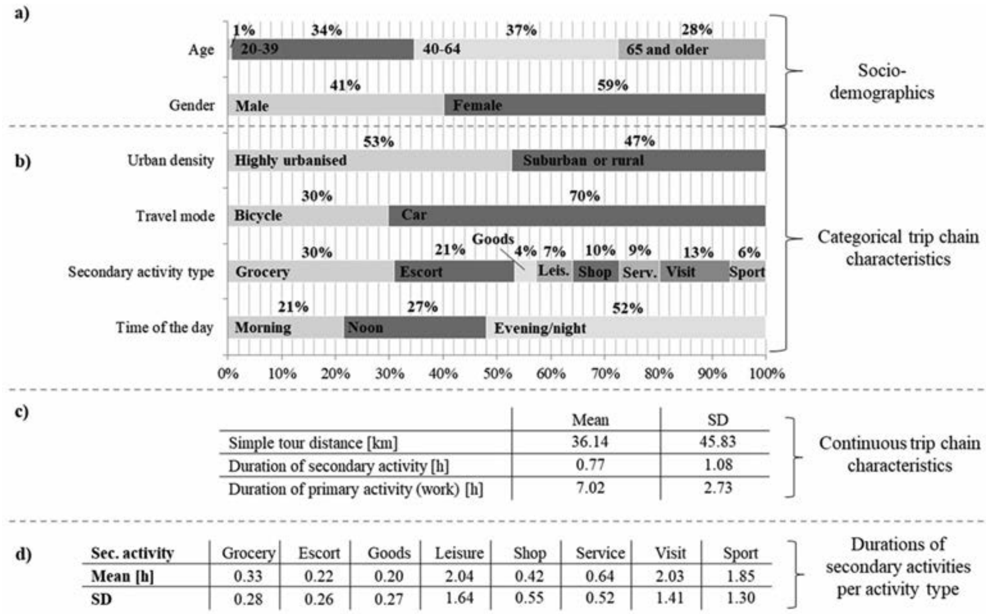
The study was based on data from the Netherlands Mobility Panel (MPN), a longitudinal panel that covers the whole Netherlands. The MPN consists (among other things) of a 3-day travel diary, a personal survey and a household survey. All three surveys are conducted yearly with around 4000 participants. The MPN has been described in more detail in (Hoogendoorn-Lanser, Schaap, and Oldekalter 2015). The current analyses employed data from the years 2013–2016 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 five aggregated travel modes *car* (driver and passengers), *public transport* (train, metro, tram and bus), *bicycle*, *walk* 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 at the (same) home location.
- The origin of each trip had to be the destination of the previous trip.
- One of the two included activities 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 included 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 duration and time category (morning, noon and 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 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 destinations). Lastly, tours were excluded in which work appeared to be clearly the secondary activity. We assumed this case



	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

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

Figure 3. Sample description regarding all considered explanatory variables, grouped in socio-demographics (a), categorical (b) and continuous (c) trip chain characteristics and durations of the secondary activities per type (d).

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 et al. n.d.). The trip chain data set included 1488 trip chains that were travelled by 1424 different persons.

Figure 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 and Habib 2012).

Concerning the categorical trip chain characteristics presented in Figure 3(b), 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 urban density at the municipality level, a similar proportion of trip chains was related to people living in highly urbanised areas and people residing in suburban or rural environments. The cut-off point between both urban density categories was chosen 1500 inhabitants per square kilometre. Figure 3(b) also shows the sample composition regarding 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* (6 h00–10 h59) and during *noon* (11 h00–15 h59), 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, Arentze, and Timmermans 2007).

Next, mean values and standard deviations are provided for *simple tour distances* and the *durations of work* and the *secondary activity* in Figure 3(c). 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 3(d) indicates mean durations per type of secondary activity and related standard deviations. Activity duration is a proxy for activity attraction (Doherty and 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. Model development

The objective of this paper is to analyse the effects of different types of activities on detours, which are caused by the inclusion of a secondary activity into a commute tour. To answer the related research questions, inference about the relationships between the type of secondary activity and commute tour extensions is necessary. Unlike with machine learning techniques (where prediction is often the principal interest), inference is conceptually at the core of statistical modelling (Bzdok, Altman, and Krzywinski 2018). For this reason, this section describes how the postulated conceptual model (see Figure 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 4.1. Then, we explain how these variables are coded in Section 4.2. And finally, we describe the chosen statistical procedure to estimate the effect of each explanatory variable.

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

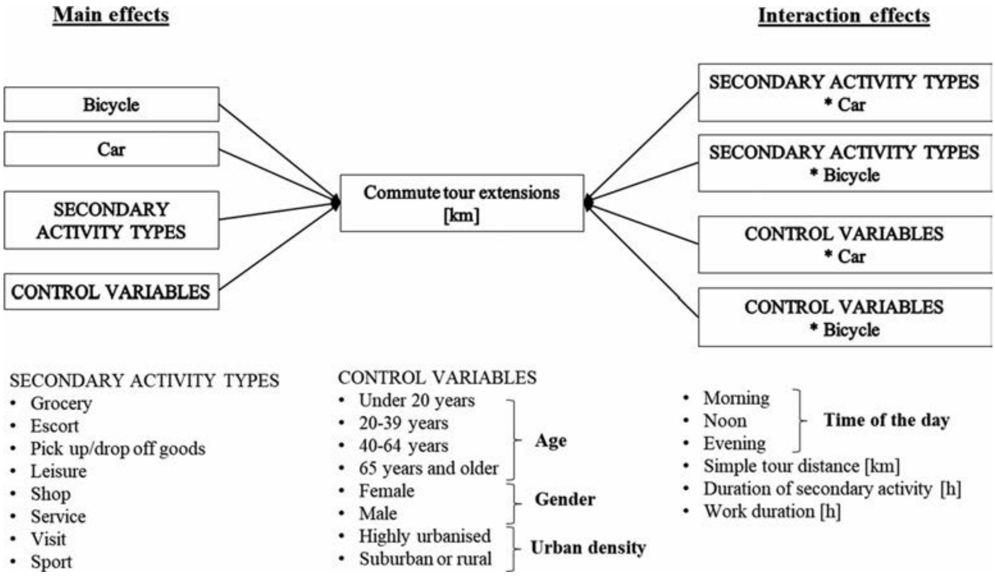


Figure 4. Composition of statistical model of commute tour extensions.

situations in which *work* is the secondary activity (Schneider et al. n.d.). Concerning the selection of control variables, the factors derived from the literature (see Section 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 was suitable for inclusion. The resulting variable selection of the statistical model is presented in Figure 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, and Pelzer 2017). In addition, explanatory variables with a continuous measurement level were mean-centred.

4.3. Parameter estimation

The statistical model estimating the effects of the variables from FIGURE 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 and van de Schoot 2014). This has to do with the way how each method treats the uncertainty arising from 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 and van de Schoot 2014).

Having said that, we did estimate an accordant OLS model to enrich Bayesian estimates with information on statistical significance. Both models are based on the following equation:

$$Y = X\beta + \varepsilon \tag{2}$$

where Y is the vector of observed commute tour extensions [in km]; X_{isthe} design matrix that includes the values of selected variables; β is the vector of parameters and ε is the vector of errors

We estimated the Bayesian regression models using the *stan_glm* function from the R *rstanarm* 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 and that interference is only made based on the assumed model and the available data. We applied 10,000 iterations to estimate the posterior distributions. 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).

The model performance was assessed using R squared as a simple measure of goodness of fit. Indicating how well a postulated model fits the data, the R squared is a standard statistic of OLS models. Very recently, Gelman et al. (2019) defined a similar measure for Bayesian regression models. Similarly to the conventional R squared, this Bayesian R squared can be considered as the part of the variance that is explained by the postulated model. We calculated the Bayesian R squared using the *bayes_R2* function from the R *rstanarm* package. Both R squared values will be provided in the results section. 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 1). This entails the use of 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 the missing interaction effects.

The applied effect coding scheme allowed to merge the results of all four models into a single results table since the 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.

5. Results and discussion

This section discusses the results and is divided into three sections. Section 5.1 provides descriptive statistics of commute tour extensions for travel modes and secondary activity types. Subsequently, Section 5.2 presents the results of the regression model explained in Section 4 before discussing the outcomes in Section 5.3.

5.1. Descriptive statistics of commute tour extensions

Table 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 km whereas extensions by bicycle were considerably shorter with a mean value of approximately 1.3 km. The coefficient of variation (which is a standardised measure of spread)

Table 1. Omitted categories in the different models where applicable (omission for continuous variables is not applicable, indicated by n.a.).

	Model 1		Model 2		Model 3		Model 4	
Variable	Main effect	Interaction effect	Main effect	Interaction effect	Main effect	Interaction effect	Main effect	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

Table 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

revealed that the distance extension of *car* tours was quite heterogeneous compared to the bicycle. This means that even though 7.4 km 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, and 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 2 also shows the total available data per secondary activity type (i.e. car and bicycle observations together) and the number of observations pertaining to the bicycle. The table reveals that the bicycle is more used for some particular types of secondary activities than for others. This can be seen by calculating the proportion of bicycle to total observations, which is not stable across activity types. The bicycle seems to be particularly used for work-grocery tours while *visit*, *pick up or drop off goods* and *escort* are proportionally less often added to the commute tour. Considering the mean extensions per secondary activity type, the small proportion of *visit* might be explained by on average long related detours. Conversely, both *escort* and *pick up or drop off goods* could be (at least partly) related to the higher inconvenience of transporting people and goods by bicycle. Nonetheless, most secondary activity types still have enough observations pertaining to the bicycle to perform the intended statistical analyses (with the exception for *pick up or drop off goods*).

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.

5.2. Results of regression model

This section shows and discusses the results of the postulated Bayesian and OLS regression models (see Section 4).

The convergence statistics of the *stan_glm* function indicated that chain convergence was reached for all parameters of the estimated 4 Bayesian models. The goodness of fit of the proposed models reached an R squared of 0.20 for the Bayesian and 0.16 for the OLS models. Both values are acceptable proportions of explained variance considering the complex context in which trip chaining behaviour takes place. Nonetheless, we can note that a significant proportion variance remains unexplained, suggesting that some important explanatory variables are still missing (e.g. variables pertaining to the built environment).

Table 3 presents the estimated coefficients of the posterior distributions of all main and interaction effects. The posterior distribution represents the uncertainty regarding the

Table 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

(*continued*).

Table 3. Continued.

Main effect	Interaction effect	Mean	Standard deviation	Lower bound∗∗	Upper bound∗∗
	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
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.
∗∗ 95% Credible Interval.

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 and 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 4.3). Moreover, insignificant results from the OLS model coincide with high credible intervals in the Bayesian model. The estimated main effects in Table 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., 2017; 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 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 $5.59–1.19 = 4.40$ km and the mean distance extension of *men* $5.59 + 1.76 = 7.35$ km. 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 km shorter than those of *men* ($-1.19–1.76 = -2.95$ km). 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 $\times$ bicycle interaction effect) = 2.88 km. 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: $(1.76 + (-1.71) – (-1.19 + 0.74)) = 0.50$ km. The difference between estimated average *male* and *female* car commute tour extensions was 3.82 km. 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 km and those by bicycle 3.33 km. 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 2.

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 km detour, whereas *service* entailed the longest mean extensions with 9.12 km. Interestingly, the estimated effects of the model did not always correspond to the means presented in Table 2. This signifies that the presented means of Table 2 confound several features of tours that also affect commute tour extensions. For instance, the mean of *escort* extensions shown in Table 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 km below cycling average extension (i.e. 3.33 km) for *grocery* shopping to 1.75 km above cycling average for *service*. This was a considerably lower spread than for those of car tours, for which *leisure* was 3.58 km below and *service* 20.4 km above the average of 6.53 km. 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 km 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 km for *leisure* and 0.97 km 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 km and shortest for the age group of *20–39 years* with 4.90 km. The age group of people aged *40–64* accounted for a small positive effect for the whole sample (extensions of around 6.21 km), 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% 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 proposed that commute tour extensions relating to *highly urbanised* municipalities are 0.53 km longer than those of *suburban or rural* municipalities. This result is counterintuitive at first sight. 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 km longer in highly urbanised municipalities than in suburban or rural municipalities. In contrast, bicycle commute tour extensions were, as intuitively expected, slightly longer in the suburban or rural context (by estimated 0.10 km). An explanation of the 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 km 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 and Kitamura 1987; Krygsman, Arentze, and Timmermans 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 am to 4 pm). 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 km, 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 km 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 km by car would relate to a 1.50 km detour and a simple commute tour distance of 10 km by bicycle an extension of only 0.20 km.

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 km 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 to activity time) remains stable (Dijst and Vidakovic 2000; Schwanen and 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 km 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 km 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 km per working hour, bicycle commute tour extensions decrease by 0.06 km. Applied to an eight-hour working day, the effects add up to 2.08 km by car and 0.48 km 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.

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 indications of the way in which trip chaining behaviour of both travel modes differs. 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 (Stopher, Ahmed, and Liu 2017)) as a regulative principle of bicycle travel behaviour. The high distance-sensitivity of cyclists could also explain why cyclists seem to have higher values of time (Börjesson and Eliasson 2012). 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. In general, the high distance-sensitivity of cyclists suggests that a concentration of jobs and activity locations in central areas of the city in combination with high urban densities can foster complex trip chaining by bicycle. By facilitating the formation of complex trip chains, 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.

A limitation of the study is the limited consideration of built environment variables. Due to data constraints, only urban density at an aggregated level was included in the analysis. Further information on the characteristics of the respective urban environment could improve the estimated models and refine our understanding of complex commute tours by car and bicycle. In this context, we would expect the highest increase of explanatory power by the inclusion of small-scale land-use variables, capturing the density of different types of activity locations in an area. A challenge, however, is to not only consider this information around the home location but also along the corridor between home and work. Features of the transport system, such as street network characteristics (e.g. speed limits, connectivity, intersection design, …), would probably add less to the postulated model due to similar planning principles across the country. Those principles include, for instance, that bicycle networks are generally denser than those of cars. An interesting feature with regard to trip chaining behaviour by car, however, could be the availability of on-street parking facilities.

6. 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 km, car tours accounted on average by 6.53 km. 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 km 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 km 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 (and thereby increase the mode share of the bicycle). 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. This holds for the urban context at the home location, but also at the work location and the location of the secondary activity. Especially when distances between these locations are large, the built environment may change considerably. The missing link to the built environment is a limitation of this study. 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* for active mode travel.

Acknowledgement

The data was made available by the Netherlands Mobility Panel administered by KiM Netherlands Institute for Transport Policy Analysis. The authors would like to acknowledge the fruitful discussion on statistical methods with Alexandra Gavriilidou (Department of Transport & Planning, Delft University of Technology) and Rense Nieuwenhuis (Swedish Institute for Social Research, Stockholm University).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research was supported by the Allegro project (no. 669792), which is financed by the European Research Council and the Amsterdam Institute for Advanced Metropolitan Solutions.

ORCID

Florian Schneider http://orcid.org/0000-0002-6596-0833
Serge Hoogendoorn http://orcid.org/0000-0002-1579-1939

References

Alkharusi, H. 2012. "Categorical Variables in Regression Analysis: A Comparison of Dummy and Effect Coding." *International Journal of Education* 4 (2): 202–210. https://doi.org/10.5296/ije.v4i2.1962.

Annema, J. A. 2013. "Transport Resistance Factors: Time, Money and Effort." In *The Transport System and Transport Policy*, edited by D. Van Wee, B. Annema, and J. A. Banister, 0–424. Cheltenham: Edwardd Elgar Publishing Limited. https://doi.org/10.1002/jgrd.50202.

Börjesson, M., and J. Eliasson. 2012. *The Value of Time and External Benefits in Bicycle Appraisal* 46: 673–683. https://doi.org/10.1016/j.tra.2012.01.006.

Brunow, S., and M. Gründer. 2013. "The Impact of Activity Chaining on the Duration of Daily Activities." *Transportation* 40: 981–1001.. https://doi.org/10.1007/s11116-012-9441-6.

Bzdok, D., N. Altman, and M. Krzywinski. 2018. "Statistics Versus Machine Learning." *Nature Methods* 15 (4): 233–234. https://doi.org/10.1038/nmeth.4642.

Couclelis, H. M., R. G. Golledge, N. D. Gale, and W. R. Tobler. 1987. "Exploring the Anchor-Point Hypothesis of Spatial Cognition." *Journal of Environmental Psychology* 7: 99–122.

Cullen, I., and V. Godson. 1975. *Urban Networks: The Structure of Activity Patterns* 4: 1–96.

Depaoli, S., and R. van de Schoot. 2014. "Bayesian Analyses: Where to Start and What to Report." *The European Health Psychologist* 16 (2): 75–84.

Dijst, M., and V. Vidakovic. 2000. "Travel Time Ratio: The Key Factor of Spatial Reach." *Transportation* 27 (2): 179–199. https://doi.org/10.1023/A:1005293330869.

Doherty, S. 2006. "Should we Abandon Activity Type Analysis? Redefining Activities by Their Salient Attributes." *Transportation* 33 (6): 517–536. https://doi.org/10.1007/s11116-006-0001-9.

Doherty, S. T., and A. Mohammadian. 2011. "The Validity of Using Activity Type to Structure Tour-based Scheduling Models." *Transportation* 38 (1): 45–63. https://doi.org/10.1007/s11116-010-9285-x.

Duncan, M. 2016. "How Much Can Trip Chaining Reduce VMT? A Simplified Method." *Transportation* 43 (4): 643–659. https://doi.org/10.1007/s11116-015-9610-5.

Field, A. 2009. *Discovering Statistics Using SPSS (and Sex and Drugs and Rock "n" Roll)*. 3rd ed. Los Angeles, CA: Sage.

Gelman, A., B. Goodrich, J. Gabry, and A. Vehtari. 2019. "R-squared for Bayesian Regression Models." *The American Statistician* 73 (3): 307–309.

Hägerstrand, T. 1970. "What About People in Regional Science?" *Papers of the Regional Science Association* 24: 6–21.

Ho, C., and C. Mulley. 2013. "Multiple Purposes at Single Destination: A Key to a Better Understanding of the Relationship Between Tour Complexity and Mode Choice." *Transportation Research Part A: Policy and Practice* 49: 206–219. https://doi.org/10.1016/j.tra.2013.01.040.

Hoogendoorn-Lanser, S., N. T. W. Schaap, and M. J. Oldekalter. 2015. "The Netherlands Mobility Panel: An Innovative Design Approach for Web-based Longitudinal Travel Data Collection." *Transportation Research Procedia* 11: 311–329. https://doi.org/10.1016/j.trpro.2015.12.027.

Islam, M. T., and K. M. N. Habib. 2012. "Unraveling the Relationship Between Trip Chaining and Mode Choice: Evidence from a Multi-Week Travel Diary." *Transportation Planning and Technology* 35 (4): 409–426. https://doi.org/10.1080/03081060.2012.680812.

Kondo, K., and R. Kitamura. 1987. "Time-space Constraints and the Formation of Trip Chains." *Regional Science and Urban Economics* 17 (17): 49–65.

Kroesen, M. 2017. "To What Extent do E-bikes Substitute Travel by Other Modes? Evidence from the Netherlands." *Transportation Research Part D: Transport and Environment* 53: 377–387. https://doi.org/10.1016/j.trd.2017.04.036.

Krygsman, S., T. Arentze, and H. Timmermans. 2007. "Capturing Tour Mode and Activity Choice Interdependencies: A Co-evolutionary Logit Modelling Approach." *Transportation Research Part A: Policy and Practice* 41 (10): 913–933. https://doi.org/10.1016/j.tra.2006.03.006.

Lee, M. S., and M. G. McNally. 2003. "On the Structure of Weekly Activity/Travel Patterns." *Transportation Research Part A: Policy and Practice* 37 (10): 823–839. https://doi.org/10.1016/S0965-8564(03)00047-8.

Lee, M., and M. G. McNally. 2006. "An Empirical Investigation on the Dynamic Processes of Activity Scheduling and Trip Chaining." *Transportation* 33 (6): 553–565. https://doi.org/10.1007/s11116-006-7728-1.

Melia, S. 2012. Filtered and unfiltered permeability: The European and Anglo-Saxon approaches, 6–9. Retrieved from http://eprints.uwe.ac.uk/16905/1/FilteredPermeability-forproject.pdf.

Nieuwenhuis, R., M. Grotenhuis, and B. Pelzer. 2017. "Weighted Effect Coding for Observational Data with wec." *The R Journal* 9 (1): 477–485. https://doi.org/10.32614/rj-2017-017.

Nijkamp, P., P. Klamer, and C. Gorter. 2003. "The Attraction Force of out-of-Town Shopping Malls: a Case Study on Run-fun Shopping in the Netherlands." *Tijdschrift Voor Economische En Sociale Geografie* 94 (2): 219–229. https://doi.org/10.1111/1467-9663.00250.

Primerano, F., M. A. P. Taylor, L. Pitaksringkarn, and P. Tisato. 2007. "Defining and Understanding Trip Chaining Behaviour." *Transportation* 35 (1): 55–72. https://doi.org/10.1007/s11116-007-9134-8.

Schneider, F., W. Daamen, S. Hoogendoorn-Lanser, and S. P. Hoogendoorn. n.d. "Deriving and Assessing Activity Hierarchies from Relative Distances in Tours." *Travel Behaviour and Society*.

Schneider, F., D. Ton, L. B. Zomer, W. Daamen, D. Duives, S. Hoogendoorn-Lanser, and S. Hoogendoorn. 2020. "Trip Chain Complexity: A Comparison among Latent Classes of Daily Mobility Patterns." *Transportation*, 0123456789. https://doi.org/10.1007/s11116-020-10084-1.

Schwanen, T., and M. Dijst. 2002. "Travel-time Ratios for Visits to the Workplace: The Relationship Between Commuting Time and Work Duration." *Transportation Research Part A: Policy and Practice* 36 (7): 573–592. https://doi.org/10.1016/S0965-8564(01)00023-4.

Stopher, P. R., A. Ahmed, and W. Liu. 2017. "Travel Time Budgets: New Evidence from Multi-Year, Multi-day Data." *Transportation* 44 (5): 1069–1082. https://doi.org/10.1007/s11116-016-9694-6.

Susilo, Y. O., and K. Maat. 2007. "The Influence of Built Environment to the Trends in Commuting Journeys in the Netherlands." *Transportation* 34 (5): 589–609. https://doi.org/10.1007/s11116-007-9129-5.

te Grotenhuis, M., B. Pelzer, R. Eisinga, R. Nieuwenhuis, A. Schmidt-Catran, and R. Konig. 2017a. "A Novel Method for Modelling Interaction Between Categorical Variables." *International Journal of Public Health* 62 (3): 427–431. https://doi.org/10.1007/s00038-016-0902-0.

te Grotenhuis, M., B. Pelzer, R. Eisinga, R. Nieuwenhuis, A. Schmidt-Catran, and R. Konig. 2017b. "When Size Matters: Advantages of Weighted Effect Coding in Observational Studies." *International Journal of Public Health* 62 (1): 163–167. https://doi.org/10.1007/s00038-016-0901-1.

Ton, D., L. B. L.-B. Zomer, F. Schneider, S. Hoogendoorn-Lanser, D. Duives, O. Cats, and S. Hoogendoorn. 2019. "Latent Classes of Daily Mobility Patterns: The Relationship with Attitudes Towards Modes." *Transportation*, 0123456789. https://doi.org/10.1007/s11116-019-09975-9.

van Acker, V., and F. Witlox. 2011. "Commuting Trips Within Tours: How Is Commuting Related to Land Use?" *Transportation* 38 (3): 465–486. https://doi.org/10.1007/s11116-010-9309-6.

Wagenaar, C. 2015. *Town Planning in the Netherlands Since 1800 : Responses to Enlightenment Ideas and Geopolitical Realities*. Second ed. Rotterdam: nai010 publishers.

Wakefield, J. 2013. *Bayesian and Frequentist Regression Methods. The Elements of Statistical Learning*. New York: Springer.