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**DOI**

[10.1007/s11116-020-10084-1](https://doi.org/10.1007/s11116-020-10084-1)

**Publication date**

2020

**Document Version**

Final published version

**Published in**

Transportation

**Citation (APA)**

Schneider, F., Ton, D., Zomer, L. B., Daamen, W., Duives, D., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2020). Trip chain complexity: a comparison among latent classes of daily mobility patterns. *Transportation*, 48 (2021)(2), 953-975. <https://doi.org/10.1007/s11116-020-10084-1>

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# Trip chain complexity: a comparison among latent classes of daily mobility patterns

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Published online: 6 February 2020  
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## Abstract

This paper studies the relationship between trip chain complexity and daily travel behaviour of travellers. While trip chain complexity is conventionally investigated between travel modes, our scope is the more aggregated level of a person's activity-travel pattern. Using data from the Netherlands Mobility Panel, a latent class cluster analysis was performed to group people with similar mode choice behaviour in distinct mobility pattern classes. All trip chains were assigned to both a travel mode and the mobility pattern class of the traveller. Subsequently, differences in trip chain complexity distributions were analysed between travel modes and between mobility pattern classes. Results indicate considerable differences between travel modes, particularly between multimodal and unimodal trip chains, but also between the unimodal travel modes car, bicycle, walking and public transport trip chains. No substantial differences in trip chain complexity were found between mobility pattern classes. Independently of the included travel modes, the distributions of trip chain complexity degrees were similar across mobility pattern classes. This means that personal circumstances such as the number of working hours or household members are not systematically translated into specific mobility patterns.

**Keywords** Trip chaining behaviour · Trip chain complexity · Mode choice · Mobility pattern · Latent class cluster analysis

## 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

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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 and 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 and 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 and 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 and Akar 2017; Currie and Delbosc 2011; Frank et al. 2008; Frignani et al. 2011; Hensher and Reyes 2000; Islam and 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 program. As the activity program (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 program 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 programs 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 and 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 program 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 Sect. "[Data: the Netherlands mobility panel](#)". In Sect. "[Research methodology](#)", 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 Sect. "[Results and discussion](#)". Finally, we provide concluding comments and recommendations for future research in Sect. "[Conclusions and future research](#)".

## Data: the Netherlands mobility panel

The latent class cluster analysis and the trip chain identification imply specific requirements on the data. 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 and 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’.

Altogether, the data contains 17,189 trips stemming from 2425 persons. Figure 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 prevalingly in multi-person households and in urban environments.

Table 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

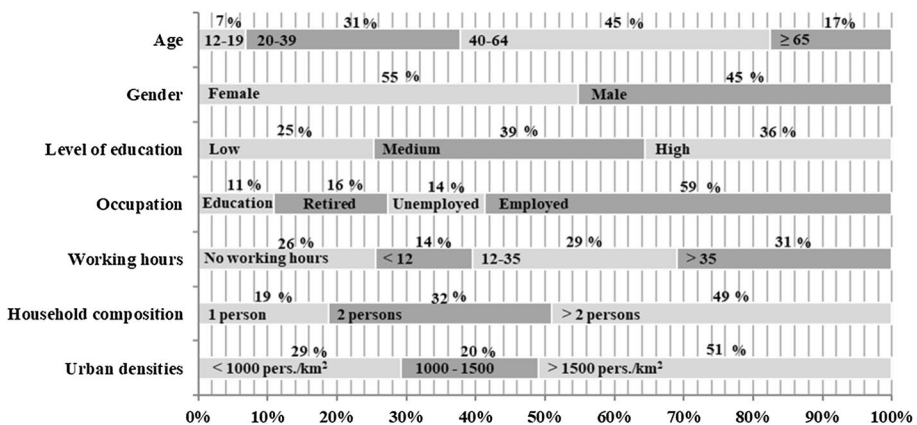


Fig. 1 Socio-demographic characteristics of the sample

**Table 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 <sup>a</sup> | 1.2           | 0.2          | 0.8               | 0.5               | 0.1 <sup>b</sup> | –                    | 1             |

<sup>a</sup>Average mobility rates per travel mode are shown for trips made on Wednesdays in 2016

<sup>b</sup>Includes only trips made with other travel modes than car, PT, bicycle or by foot

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.

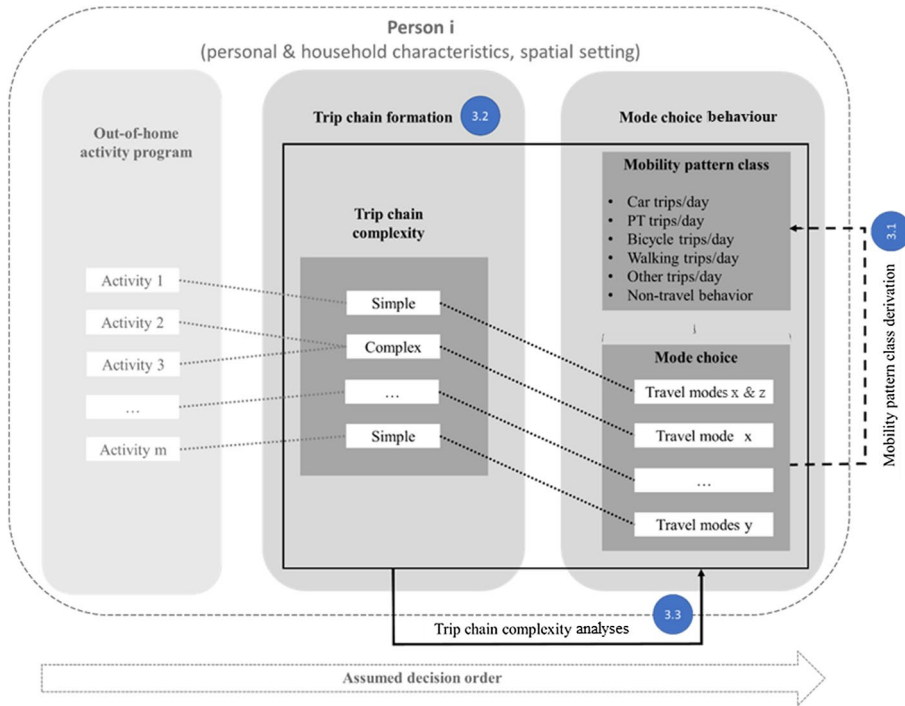
Given the data requirements defined above, the used data provides rich and sufficiently representative information on Dutch mobility behaviour. The sample includes enough people and trips to identify prevailing mobility patterns. However, the number of around seven trip observations per person does not 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).

## 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 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 Fig. 2 as out-of-home activity program) 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 Fig. 2 by a black frame), should preferably be studied at the level of an individual.

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 Sect. “[Trip chain identification and association](#)”). 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



**Fig. 2** Scope of the study in the context of activity-travel behaviour. The different trip chain complexity analyses are visualised in Fig. 3

of mobility pattern classes, the trip chain identification and association and the trip chain complexity analyses are described in detail.

**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 and 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 and 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 the Sect. “[Mobility pattern classes](#)”.

## 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 Fig. 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 and Delbosc 2011; Frank et al. 2008; Ho and 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 multi-modal 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 trip chain sample is outlined in the Sect. “[Properties of the identified trip chains](#)”.

### Trip chain complexity analysis

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

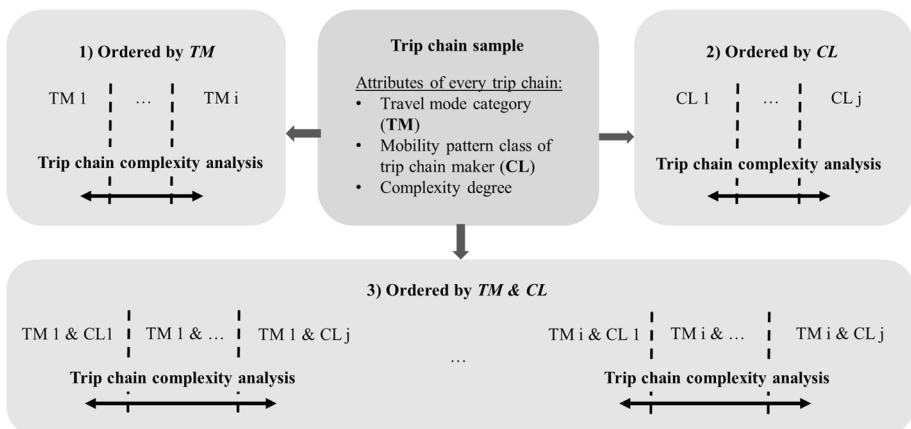


Fig. 3 Different analyses of trip chain complexity

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 0.1 on, a medium from 0.3 on and a large effect for values greater than 0.5 (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 0.05 level of significance.

The chosen methodology is the outcome of an 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 multinomial 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.

## 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 Sect. "[Mobility pattern classes](#)". In Sect. "[Properties of the identified trip chains](#)", the identified trip chains are outlined regarding important characteristics 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 the Sects. "[Trip chain complexity between travel modes](#)", "[Aggregated trip chain complexity between mobility patterns](#)" and "[Disaggregated trip chain complexity between mobility patterns](#)".

### 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 and bicycle' (CB), 'Exclusive car users' (C), 'Car and walk and 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 and 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.

Table 2 shows that the 2425 participants were unequally distributed over the mobility pattern classes. The classes 'Car and bicycle', 'Exclusive car users' and 'Car and walk and 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. The trip rates deviated considerably from the total average of 3.3 trips per person and day (see Table 1). While people of the class 'Car and walk and 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).

### Properties of the identified trip chains

In total, 5121 trip chains could be extracted from the data, stemming from 2004 persons. Figure 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 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). 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 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

**Table 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 |
| <i>Indicators</i>                                    |                |      |      |      |      |     |
| 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 |
| <i>Active covariates</i>                             |                |      |      |      |      |     |
| Gender (Wald=15.43, $\rho < 0.01$ )                  | Female         | 55%  | 49%  | 60%  | 54%  | 58% |
|  | Male           | 45%  | 51%  | 40%  | 46%  | 42% |
| Education (Wald=21.04, $\rho < 0.01$ )               | Low            | 26%  | 22%  | 24%  | 23%  | 35% |
|  | Medium         | 39%  | 42%  | 40%  | 36%  | 33% |
|  | High           | 34%  | 36%  | 36%  | 41%  | 32% |
| Occupation (Wald=268.15, $\rho < 0.001$ )            | 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, $\rho < 0.01$ )       | 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, $\rho < 0.001$ )          | High           | 49%  | 47%  | 50%  | 62%  | 57% |
|  | Medium         | 23%  | 16%  | 21%  | 17%  | 22% |
|  | Low            | 28%  | 37%  | 29%  | 22%  | 22% |
| <i>Inactive covariates</i>                           |                |      |      |      |      |     |
| 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 and bicycle, C exclusive car users, CWB car and walk and bicycle, PT+ public transport+, B exclusive bicycle users

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

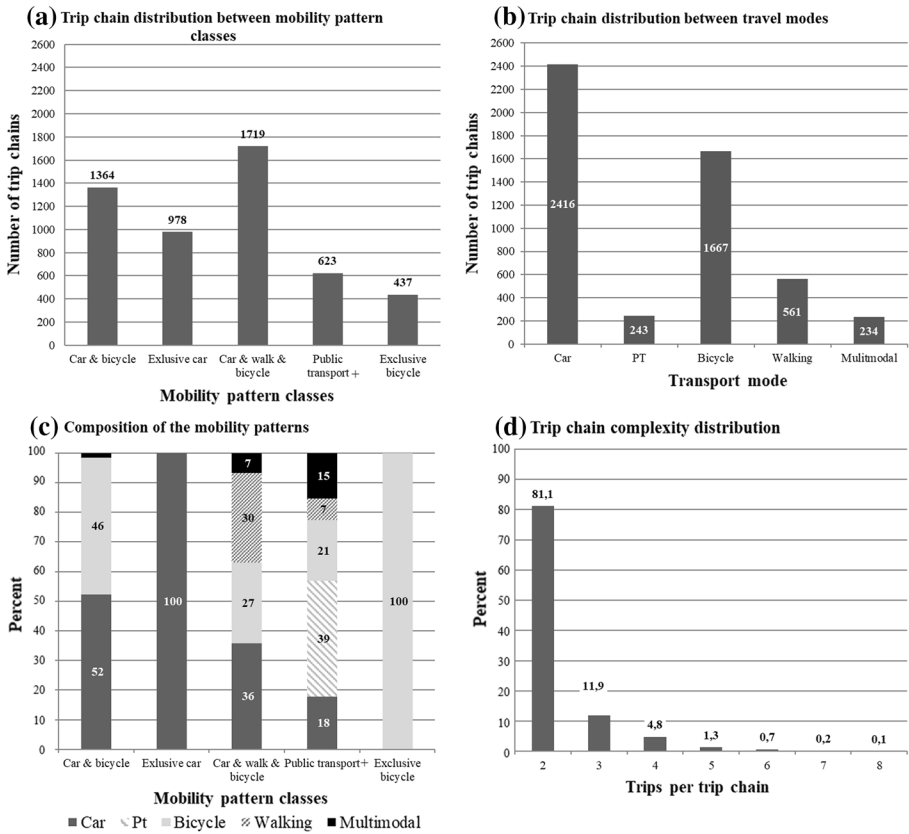


Fig. 4 Trip chain related distributions

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 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 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 and Reyes 2000; Ye et al. 2007; Ho and 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.

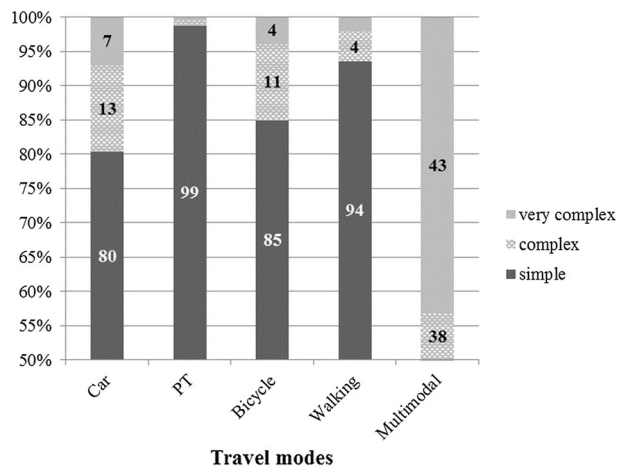
### Trip chain complexity between travel modes

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.

Figure 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. 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 and 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 from a spatially restricted network and from timetables (characteristics which are particularly attributed to the car in comparison to public transport; Hensher and 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

**Fig. 5** Trip chain complexity distribution between travel mode categories. Note that the y-axis starts at 50% for readability reasons



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.

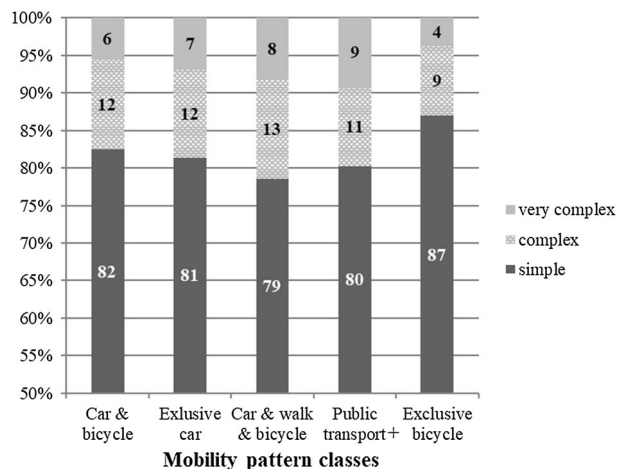
To summarise, this section provided a more complete picture of the relationship between trip chain complexity and mode choice for independent trip chains. The analysis revealed substantial differences in trip chain complexity between the different travel mode categories.

### 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 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 and bicycle’, ‘Exclusive car users’, ‘Car and walk and bicycle’ and ‘Public transport+’, these differences shrunk 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.

**Fig. 6** Trip chain complexity distribution between mobility pattern classes. Note that the y-axis starts at 50% for readability reasons



The question 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 ( $\chi^2(8)=28.042$ ,  $p<0.001$ ,  $n=5121$ ). However, Cramér's V showed that the strength of this association is negligible (Cramér's V = 0.052,  $p<0.001$ ). 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 program. 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 suggest, in this study (see Sect. "[Trip chain complexity between travel modes](#)") and in former research (e.g. Hensher and 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 and walk and 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).

## 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 Figs. 5, 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 7a shows for car trip chains that complexity levels were very similar between the classes 'Car and bicycle', 'Exclusive car users' and 'Public transport+'. The class 'Car and walk and bicycle', however, had considerably more complex and very complex trip chains.

Likewise, also bicycle trip chains were least often simple in the class 'Car and walk and bicycle' (shown in Fig. 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.

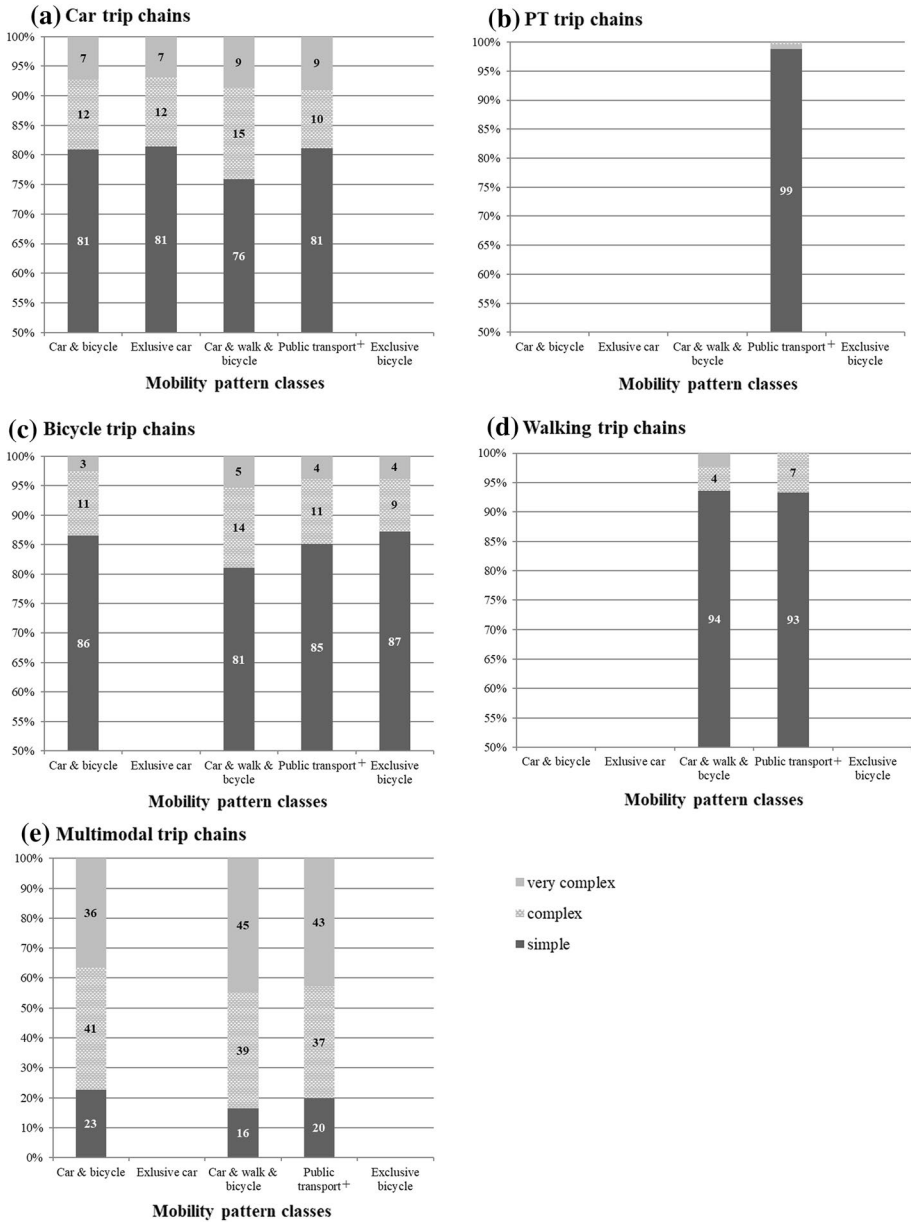
For multimodal trip chains, again, trip chains were least often simple in the class 'Car and walk and bicycle' (see Fig. 7e) and most often simple in the class 'Car and bicycle'. Regarding the differences in complex or very complex trip chains, an interesting observation can be made. The findings suggest 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 and bicycle' (compare Figs. 4a, c and 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 Fig. 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 and walk and 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).

In Table 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 program) 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



**Fig. 7** Distribution of trip chain complexity for different travel mode categories between mobility pattern classes. Note that the y-axis starts at 50% for a–e for readability reasons

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 and walk and bicycle’, bicycle trip chains were less often very complex in the class ‘Car and bicycle’.

**Table 3** Relationships between trip chain complexity (in number of trips) and mobility pattern classes for different travel modes

| Nr. of trips                           | Car trip chains |        |                   | Bicycle trip chains |      |       | Walking trip chains |      |      | Multimodal trip chains |      |      |
|--|-----------------|--------|-------------------|---------------------|------|-------|---------------------|------|------|------------------------|------|------|
|  | 2               | 3      | ≥4                | 2                   | 3    | ≥4    | 2                   | 3    | ≥4   | 2                      | 3    | ≥4   |
| Pearson's $\chi^2$                     | 9.271           | 10.576 | 1.304             | 0.958               |      |       |                     |      |      |                        |      |      |
| Df                                     | 6               | 6      | 2                 | 4                   |      |       |                     |      |      |                        |      |      |
| p                                      | 0.159           | 0.102  | .503 <sup>a</sup> | 0.916               |      |       |                     |      |      |                        |      |      |
| Nr. of valid cases                     | 2416            | 1667   | 561               | 234                 |      |       |                     |      |      |                        |      |      |
| Cramér's V                             | 0.062           | 0.080  | .055 <sup>b</sup> | 0.064               |      |       |                     |      |      |                        |      |      |
| <i>Adjusted standardised residuals</i> |                 |        |                   |                     |      |       |                     |      |      |                        |      |      |
| Car and bicycle                        | 0.9             | -0.8   | -0.4              | 1.4                 | -0.4 | -2.0* | -                   | -    | -    | 0.6                    | 0.2  | -0.7 |
| Exclusive car                          | 1.6             | -1.1   | -1.0              | -                   | -    | -     | -                   | -    | -    | -                      | -    | -    |
| Car and walk and bicycle               | -2.8**          | 2.5*   | 1.2               | -2.8**              | 1.9  | 2.1*  | 0.1                 | -0.8 | 1.0  | -0.8                   | 0.1  | 0.5  |
| Public transport+                      | 0.3             | -0.9   | 0.6               | 0.1                 | -0.1 | 0.1   | -0.1                | 0.8  | -1.0 | 0.5                    | -0.3 | -0.1 |
| Exclusive bicycle                      | -               | -      | -                 | 1.4                 | -1.5 | -0.1  | -                   | -    | -    | -                      | -    | -    |

Significant values are emphasised in bold

\*Significant at 0.05 level of significance (2, 0); \*\*Significant at 0.01 level of significance (2, 6)

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

<sup>b</sup>The p value of Cramér's V (Exact significance:  $p=0.449$ ) differs from the p-value of Fisher's exact test

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 and walk and bicycle' seems to entail not only higher trip chain complexity for the car but also for other travel modes (here the bicycle).

## 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 and bicycle, Exclusive car users, Car and walk and 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 com-

plexity 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

program 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.

**Acknowledgements** 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. The data was made available by the Netherlands Mobility Panel administered by KiM Netherlands Institute for Transport Policy Analysis. An earlier version of this work was presented during the 15th International Conference on Travel Behaviour Research in Santa Barbara, California.

**Author contributions** FS: study conception and design, data collection, analysis and interpretation of results, draft manuscript preparation. DT: data collection, analysis and interpretation of results, manuscript review. L-BZ: data collection, analysis and interpretation of results. WD: study conception and design, analysis and interpretation of results, manuscript review. DD: data collection, analysis and interpretation of results. SH-L: data collection. SH: study conception and design, manuscript review.

## Compliance with ethical standards

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

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