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Intrapersonal mode choice variation: Evidence from a four-week smartphone-based travel survey in the Netherlands

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ABSTRACT

This paper examines mode choice variation in the Netherlands based on the trip data of 432 respondents from a four-week smartphone-based travel survey. Trip characteristics, including origin and destination location, arrival and departure time, mode and trip purpose, were automatically recorded, but checked and if necessary revised in a web-based prompted recall survey. Statistical analyses and mixed logit mode choice models were used to explore intrapersonal variation and its effect on mode choice. We found relatively much intrapersonal variation for short trips (< 2 km) as respondents who usually travel by car also regularly walk and/or cycle. By contrast, intrapersonal variation was significantly smaller in trips longer than 10 km, suggesting that people choose the same mode when they repeat long journeys. The intrapersonal variation is also relatively small for commute trips, implying a high level of habituation. In addition, the results from the mixed logit mode choice models clearly show that including a classification of travellers determined by the degree of intrapersonal variation significantly explains mode choice.

1. Introduction

In most countries, including the Netherlands, our understanding of travel behaviour is based on cross-sectional surveys, in which only one day per respondent is surveyed in representative periods with maximal traffic flows (de Ortúzar Dios et al., 2010). This is not enough to gain a good understanding of the dynamics in travel behaviour. Information on the dynamics of travel behaviour can be obtained by asking respondents to record their trips during more than one day, but this asks too much from most respondents and is therefore not a realistic option for large national travel surveys. Automatic trip detection may be the solution. GPS devices have already been used in travel surveys since the 1990s (e.g., see Wolf, 2000; Stopher, 2009) and there have also been several successful applications of GPS-enabled smartphones in recent mobility studies (e.g., Reddy et al., 2010; Nitsche et al., 2012; Geurs et al., 2015; Cottrill et al., 2013; Prelipcean et al., 2014, 2015).

A large amount of literature is still dedicated to explaining and modelling interpersonal variation in travel behaviour, whereas much less attention is paid to intrapersonal variation. The main cause of the latter is the aforementioned difficulty to obtain travel behaviour data from respondents for longer periods, which is required for this type of analysis (Schlich and Axhausen, 2003). Most of the existing studies on intrapersonal variability deal with temporal and spatial variation in trip generation and destination choice. Studies based on multiple-week travel diary data show that intrapersonal variability is significant, with individual behaviour being neither completely habitual nor completely random (e.g., Schlich and Axhausen, 2003; Raux et al., 2016). However, only a few studies have specifically examined intrapersonal mode choice variation. This is surprising, as many countries in Europe and beyond implement and invest in policies and projects to stimulate the switch from car use to more sustainable travel modes; more in-depth knowledge on habitual travel choice, and mode choice in particular, can help accomplish this. See Gärling and Axhausen (2003) for an introduction on habitual travel choice.

This paper describes our attempt to extend the knowledge on intrapersonal mode choice variation through an analysis of 4-week smartphone-based travel activity data from 432 respondents in the Netherlands. To the authors' knowledge, this is the first published study that examines intrapersonal variation in travel behaviour on the basis of smartphone data, and also the first to examine intrapersonal mode choice variation combining descriptive, statistical and econometric analysis (choice modelling). So far, the work of Cherchi and Cirillo (2014) is one of the very few other studies that have estimated advanced (mixed logit) mode choice models using multiple-week panel data.

In this paper, we firstly address different types of intrapersonal variation in mode choice, i.e., trip frequencies, trip lengths, trip purposes and geographical characteristics of the visited locations.

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Secondly, we use estimated mixed logit models to examine the importance of intrapersonal mode choice variation in explaining mode choice decisions.

The structure of the paper is as follows. Section 2 briefly reviews the literature on intrapersonal travel behaviour. Section 3 describes the data we used and the panel they came from. Section 4 contains the methods we applied for the descriptive analysis and for mode choice modelling. Section 5 provides the models' results and Section 6 presents our conclusions.

2. Literature review

Panel studies can be described and classified in several ways, such as by duration, data collection method (pen and paper, web, GPS, smartphone, etc.), and sample size (see e.g., Schönfelder and Axhausen, 2010; de Ortúzar Dios et al., 2010; Cherchi et al., 2017). Analysing intrapersonal variation in travel behaviour requires the availability of panel data describing travel behaviour of respondents over a longer period. In this section, we give a brief overview of panel studies examining intrapersonal travel variation, divided into unrepeated versus repeated panel surveys, and short-duration versus long-duration panels. Unrepeated panels collect multiple-day travel data, but are not repeated. Repeated panel surveys are carried out several times with the same respondents, for example, for a number of years. Short-duration panels typically use travel diaries of three to seven days. Long-duration surveys measure travel activity for several weeks or months, often using GPS devices to collect data. Table 1 shows a categorisation of panel studies from the literature, with a (non-exhaustive) list of examples. The categorisation is explained in the sections below.

2.1. Unrepeated short-duration panels

Most panels described in the literature are unrepeated short-duration surveys because of their modest respondent burden and low financial costs relative to repeated and long-duration panels. This mostly concerns pen-and-paper and web-based surveys. For example, Pas (1987) examined the effect of intrapersonal variability on trip generation on the basis of seven-day activity diaries recorded in Reading, UK, in 1973 and showed that half of the variation could be explained by intrapersonal variation. In a later study, Pas and Sundar (1995) extended the analysis to trip chaining and travel times based on data from a three-day survey collected in Seattle, US and again found that intrapersonal variation explained significant portions of the overall variability. Recently, Raux et al. (2016) investigated intrapersonal variation in trip and time allocation based on data from a seven-day survey collected in Ghent, Belgium.

In the past decades, the use of GPS devices has also become common in unrepeated short-duration panel surveys. Examples of recent studies analysing the quality of mode choice detection using GPS data are the work of Bohte and Maat (2009) and Feng and Timmermans (2013), both using seven-day GPS data. Dill and Broach (2014) used five-day GPS data to explore how common travel destinations can be defined. Several studies have involved the successful application of GPS-enabled smartphones (e.g., Reddy et al., 2010; Nitsche et al., 2012; Cottrill et al., 2013; Prelipcean et al., 2014, 2015). However, short-duration panels using smartphone or other GPS data have rarely been used to study intrapersonal variation in travel behaviour so far.

2.2. Unrepeated long-duration panels

Well-studied long-duration panels are the 1971 household survey conducted in Uppsala (Sweden) covering a five-week period (e.g., Hanson and Huff, 1988; Huff and Hanson, 1986), the six-week Mobi*drive* survey for the German cities of Karlsruhe and Halle, and a survey related to the latter that was carried out in Thurgau (Switzerland). The Mobi*drive* panels have been used for example for the analysis of the rhythms of daily life (Axhausen et al., 2002), and for a comparison between indices that measure similarities in travel behaviour (Schlich and Axhausen, 2003). Moreover, Schönfelder and Axhausen (2010) produced an extensive overview of unrepeated long-duration panels and examined intrapersonal variation in travel-activity spaces using several multiple-week data sets, including the Mobi*drive* and Uppsala panels, two Swiss studies and three long-duration studies based on in-car GPS devices used in Borlänge (Sweden), Copenhagen (Denmark) and Atlanta (US). These data revealed that the structure of daily destination choices is dominated by a few locations, but that there also is a permanent discovery of new locations. Also, Järv et al. (2014) used mobile phone records to monitor activity locations and spaces for a period of twelve consecutive months. They found a modest monthly variation in the number of activities and a high monthly variation in activity spaces.

There a number of smartphone travel survey applications currently under development around the world. The Singapore Future Mobility Survey (FMS) was one of the first large scale pilots as part of the 2012 Singaporean Household Interview Survey (HITS), where approximately 800 participants completed a 14-day data travel survey using a smartphone app (Cottrill et al., 2013; Zhao et al., 2015). Recently, in Melbourne the FMS platform was also used in a trail in Melbourne involving 90 participants who validated a full two weeks of travel (Roddis et al., 2016).

Few papers have studied mode choice with continuous panel data. Recently, Cherchi and Cirillo (2014) used the Mobi*drive* panel data to model the influence of habitual behaviour on daily mode choices. They concluded that there is a strong inertia effect in mode choice that increases with (or is reinforced by) the number of times the same tour is repeated. The sequence of chosen modes is influenced by the duration of the activity and the weekly structure of the activities. In addition, Cherchi et al. (2017) used mixed logit models to study intrapersonal mode choice variation, accounting for systematic and random heterogeneity in individual preferences and responses. They found that there

Table 1
Categorisation of panel studies, with examples.

	Unrepeated panel	Repeated panel
Short duration	Diary based: e.g., Pas (1987); Pas and Sundar (1995); Raux et al. (2016) GPS-based: e.g., Bohte and Maat (2009); Feng and Timmermans (2013); Dill and Broach (2014) Smartphone-based: e.g., Prelipcean et al., 2014, 2015	Diary based: e.g. German Mobility Panel (e.g., Zumkeller and Chlond, 2009; Streit et al., 2015), Mobility Panel for the Netherlands (Hoogendoorn-Lanser et al., 2015), Santiago Panel (Yáñez et al., 2010) GPS-based: e.g., Stopher and Zhang (2011)
Long duration panel	Diary-based: e.g., Uppsala survey (e.g., Hanson and Huff, 1988) Mobidrive panel (e.g. Axhausen et al., 2002); Järv et al. (2014) GPS-based: e.g., Borlänge GPS study, Commute Atlanta study (see Schönfelder and Axhausen, 2010) Smartphone-based: e.g., Singapore Future Mobility Survey (Cottrill et al., 2013); Victorian Future Mobility Sensing (FMS) Trial (Roddis et al., 2016)	Smartphone-based: Dutch Mobile Mobility Panel (Geurs et al., 2015)

Table 2
Descriptive statistics for respondents (sample) and all members of the LISS panel.

Socioeconomic variables (SE)	Sample	Liss panel
Age – average	47	41
Gender		
Male	48.5%	49.2%
Female	51.5%	50.8%
Partner: the household head lives together with a partner		
No	28.8%	25.2%
Yes	71.2%	74.8%
Household size: Number of household members		
One person	20.1%	14.3%
Two persons	36.4%	31.6%
Three persons	14.4%	14.3%
Four persons	19.5%	24.7%
Five persons	7.5%	11.3%
Six persons	0.9%	2.9%
Seven persons	1.0%	0.7%
Eight persons	0.3%	0.2%
Number of living-at-home children in the household		
None	54.0%	45.4%
One child	15.3%	13.6%
Two children	20.9%	25.8%
Three children	7.7%	11.8%
Four children	1.0%	2.5%
Five children	0.8%	0.7%
Six children	0.3%	0.1%
Personal net monthly income in categories		
No income	6.8%	26.6%
EUR 500 or less	6.4%	5.1%
EUR 501 to EUR 1000	14.9%	13.4%
EUR 1001 to EUR 1500	17.3%	14.3%
EUR 1501 to EUR 2000	22.5%	15.3%
EUR 2001 to EUR 2500	16.2%	9.7%
EUR 2501 to EUR 3000	6.8%	4.8%
EUR 3001 to EUR 3500	3.1%	2.0%
EUR 3501 to EUR 4000	2.0%	1.1%
EUR 4001 to EUR 4500	0.4%	0.4%
EUR 4501 to EUR 5000	0.5%	0.3%
EUR 5001 to EUR 7500	0.1%	0.4%
More than EUR 7500	0.4%	0.2%
Urbanity level of place of residence		
Extremely urban	14.6%	14.9%
Very urban	25.5%	25.1%
Moderately urban	22.8%	22.6%
Slightly urban	19.9%	21.0%
Not urban	17.3%	15.1%

is much less variability in mode choice across weeks than across the days of each week, and suggested that a period of one week may be of an appropriate duration to reveal the day-to-day variability in mode choice.

2.3. Repeated short-duration panels

Most repeated short-duration panels reported on in the literature were designed for specific purposes or projects. The Santiago panel, for example, was a five-wave short duration panel to evaluate the effects of the introduction of the Transantiago public transport system (Yáñez et al., 2010). General-purpose mobility panels are used in Germany and the Netherlands. The German Mobility Panel (MOP) has been conducted annually since 1994, using a seven-day trip diary (Zumkeller and Chlond, 2009). The Mobility Panel for the Netherlands (MPN) is a three-day trip diary that has been repeated annually since 2013 (Hoogendoorn-Lanser et al., 2015). Repeated short-duration panels are specifically suited for measuring travel variability between years, e.g., to examine the influence of life events such as childbirth on mode choice. Olde Kalter and Geurs (2016), for example, examined mode choice and household interaction using two waves of the MPN and showed that variability between households and individuals accounts for more than one third of the total variation in the mode choice of home-related tours. Streit et al. (2015) recently analysed changes in intrapersonal mode choice variation over 15 years of the German Mobility Panel. In this study, an indicator was used to estimate multimodality, dividing the number of modes by the use share (in percent) of the most frequently used mode. The results show that travel behaviour patterns of young men and woman in Germany have become more similar.

An example of a GPS-based repeated short-duration panel is the work by Stopher and Zhang (2011), who used seven-day GPS data from 200 households from three consecutive years to study day-to-day variability in trip chains (tours). They found relatively little repetition of tours within the week, and concluded that the underlying assumption that travel is repetitive from day to day is highly suspect.

2.4. Repeated long-duration panels

Although this literature review is not exhaustive by any means, it clearly shows that the use of unrepeated short and long duration panel data has increased over the years, utilizing GPS devices as efficient a data collection tools. More recently, a variety of smartphone applications have been developed and applied in short and long duration panel studies. Repeated panel surveys are, however, still quite rare, with, to the authors' knowledge, the Dutch Mobile Mobility Panel (Geurs et al., 2015) as the only repeated long-duration smartphone-based panel study conducted so far.

3. The Dutch mobile mobility panel

For our analysis, we used data from the last wave of the three-year Dutch Mobile Mobility Panel (see Geurs et al., 2015), collected in the period March–July 2015. This panel was drawn from the LISS (Longitudinal Internet Studies for the Social Sciences) panel (see Scherpenzeel and Das, 2010). The LISS panel consists of > 5000 Dutch households with over 8000 respondents, and if needed, provides households with cost-free equipment and internet access. The respondents also receive a monetary reward for participating in a research experiment. From a random subsample of LISS panel respondents, about 800 expressed an interest in the Dutch Mobile Mobility Panel and consented to having their data temporarily stored at a third party for the trip detection analysis.

To avoid overrepresentation of young people, respondents without a smartphone or with a smartphone not supported by iOS or Android were provided with a loan smartphone. About 59% used a loan smartphone, 24% owned a smartphone supported by Android, and 17% owned a smartphone supported by iOS. These smartphones were used to detect trips automatically during several weeks in 2013, 2014 and 2015. In 2013, panel members participated during two weeks, whereas the 2014 and 2015 waves lasted four weeks. In 2015, 578 persons participated in the Dutch Mobile Mobility Panel (of whom 332 also participated in 2014, while 209 persons participated in all three waves). Table 2 shows demographic characteristics of this sample compared to the whole LISS panel. Table 2 includes the demographic variables that were used in the models. Compared to the LISS panel, our sample appears to be largely representative. The sample is balanced in terms of gender, household composition, urbanity levels and income, with the exception of the no-income category. This difference could be linked to the average respondent's age in the sample (47), which is older than the population average (41). Employment and income status are substantially influenced by age.

3.1. Trip and mode choice detection

Trip registration was automatic with the smartphone application MoveSmarter for iPhone and Android. Geurs et al. (2015) describe the trip and mode choice detection in detail. Each trip record contained the attributes departure and arrival time, origin and destination location, mode, and trip purpose. The respondents were asked to check the trips recorded in MoveSmarter on a website every three days and make any necessary corrections (recall survey); they also completed questionnaires online. They were able to select mode and trip purpose drop-down menus with values (names) matching those used in the Netherlands national travel surveys and could also delete, add, combine or split trips. Note that the term 'trip' in this paper refers to each trip leg for which one mode of transport was used, unless mentioned otherwise. In about 95% of the cases, the respondent used only one travel mode between origin and final destination. Short walks, for example between parking place and final destination, were not included.

The number of trips reported in the 2015 wave is about four per person per day. This is about 30% more than previously reported in national travel surveys in the Netherlands (Statistics Netherlands, 2014), which suffer from under-reporting of non-regular trips. MoveSmarter registered slightly fewer trips than were entered in the recall survey; the respondents deleted > 10% of these automatically trips but added 18%. We did not use added trips in our study as we were unable to determine accurate origin and destination locations for these added trips. We did check for biases in the added trips, but found no systematic differences in the distributions of automatically detected and manually added trips.

This left us with about 39,000 trips in the sample, with still a higher daily number of trips than recorded in the Netherlands national travel survey. About one third of these trips were made from home, another third were not home-related, and the final third were home-bound. Home-bound trips were left out of the mode choice variation analysis as they contain a mix of very different types of trips and can be considered return trips from the visited locations. Finally, about 15% of the trips were only made once to a particular destination and could therefore not be used to determine intrapersonal variation in mode choice. The fact that, in principle, we were able to use 85% of the recorded trips shows that four-week surveys are of an appropriate duration for this type of analysis. As we didn't include the home-bound trips, we ended up using a total of 22,355 trips.

3.2. Explanatory variables and data enrichment

Detailed data are available on the socioeconomic characteristics of participants in the LISS panel. For the model, we used the variables listed in Table 2. These are age, gender, family status (with partner, number of household members, number of children), income level (categories), and urbanity level of the residence. The values of these variables, and their rates of occurrence are listed in Table 2. Note that the "no income" category is a dummy variable, as individuals with "no income" probably are supported by household members for which the income level is unknown. Moreover, as the type of relation between income level and utility is unknown, but probably is non-linear, we tested the categories as dummies and merged them into new dummy variables. These dummies distinguishes between low, medium and high income classes. Models were optimal when the limits of the dummies were EUR 1500 and 2500 respectively. With these limits, aggregated income classes also have similar fractions of respondents.

We enriched the trip data collected by MoveSmarter with a number of other variables. Firstly, we automatically queried the travel times for non-chosen modes with the aid of a Google Map API, immediately after each trip. Constraints are that bicycle travel times were only estimated for trip distances shorter than 25 km and car/public transport modes only for trips longer than 1 km. We used the trip travel time of chosen and non-chosen modes as input for the mode choice model. Note that all types of trips are present in our sample; from short local trips to long distance trips beyond 100 km (as is shown in Section 5.1). Secondly, we queried the weather conditions for the trips on World Weather Online (2015) and added them for each trip. The categories were: sunny, cloudy, rainy and clear sky. Thirdly, we added the urbanity level (five classes from very urbanised to not urbanised; see also Table 2) for both origin and destination to the location data (Statistics Netherlands, 2014).

4. Methods

We first took an explorative approach to distinguish between intrapersonal and interpersonal mode choice variation and to study how these variations related to each other. This approach is in line with that of for example Järv et al. (2014). We then applied mixed logit models to model the influence of intrapersonal mode choice variation on mode choice.

4.1. Intrapersonal mode choice variation

Several researchers have developed indicators to measure intrapersonal variation in travel patterns in general (e.g., see Schlich and Axhausen, 2003) or mode choice variation in particular. Buehler and Hamre (2013), for example, expressed intrapersonal variability as the share of individuals whose travel behaviour was found dominated by more than one mode after several observation intervals, but this has the disadvantage that all modes appear to be equally important. In the Netherlands, most people use the car as well as active modes of travel (walking, cycling), but they use public transport much less frequently. However, there are still large differences within the group of people who never use public transport. These differences can be captured by expressing intrapersonal variability with a mode variation index (MIX), which measures the relative deviation from a state of maximum variability (Kuhnimhof, 2009). MIX is a relatively indirect way of measuring intrapersonal variation, however, and does not distinguish between the different types of variation. Basically, three types of mode choice variation can be distinguished:

1. Intrapersonal variation for repeated trips: The same respondent can use different modes for repeated trips to the same location, such as for example commutes.
2. Intrapersonal variation for different trips: The same respondent can use different modes for different trips.
3. Interpersonal variation: Different respondents choose different modes.

We estimated the intrapersonal variation for repeated trips directly. When respondents visited a destination at least twice, we kept track of the frequency of the most often used mode and in the case of a tie, we used the tie frequency. We call this the frequency of the dominant mode. The percentage of the dominant mode is the ratio between this frequency and the overall trip frequency (including all modes). We can also estimate this percentage for a group of destinations and/or respondents by taking the ratio of the aggregates, i.e., the sum of the frequencies of the dominant modes, and the sum of the overall trip frequencies. It is important to stress that the dominant mode can vary between destinations, but that we always take the frequency of the most frequently used (i.e., dominant) mode for a given destination. Therefore, the aggregate indicates how often respondents on average choose the same mode for a repeated trip. The (aggregated) intrapersonal variation for repeated trips is defined as 100% minus the percentage of the dominant modes. For example, if the percentage of dominant modes is 100%, the intrapersonal variation for repeated trips is 0 as the respondents always use the same mode for the same repeated trip.

We estimated the intrapersonal variation for different trips indirectly from the variation for each repeated trip and the total intrapersonal variation, as follows. Per respondent, we determined the mode percentages for all trips. The total intrapersonal variation is simply 100% minus the percentage of the most frequently used mode. For example, if someone used the car for 70% of the trips, his or her total intrapersonal variation is 30% (i.e., other modes were used for

30% of the person's trips). Again, we can take the aggregate for a group of respondents who prefer the same mode. This can be viewed as the aggregated estimate of total intrapersonal variation. However, because we aggregated different types of trips, this might also include some interpersonal variation. For example, two respondents may generally prefer the car, but one of them may prefer to use active modes for very short trips, while the other one may stick to the car even for very short trips. In this example, one could also argue that there is interpersonal variation for very short trips. Consequently, we should always be careful when interpreting these aggregate measures of mode choice variation.

Finally, the remaining interpersonal variation can be estimated indirectly from the intrapersonal variation and the total mode choice variation. The latter is simply defined as 100% minus the percentage of the most commonly used mode over all trips made by all respondents.

We distinguished between three main mode types, namely active modes (walking and cycling), car (drivers and passengers) and public transport (PT: train, bus, tram and metro). We assumed a certain hierarchy in mode choice, which suggests that it makes little sense to compare between main and sub-modes simultaneously. For example, the difference between car and bus is not the same as between bus and metro. In this study, we were mainly interested in the main mode classes, although we acknowledge that comparisons within subclasses (for example between PT modes) would be also interesting. Note that in the model, we distinguished between BTM (bus, tram and metro) and train, because these alternatives are not always both available (in contrast to walking and cycling, which both are more or less always available in the Netherlands). As a result, it was not possible to estimate one aggregated PT utility in the logit model.

We classified respondents on the basis of intrapersonal variation. We distinguished a respondent as a 'cyclist' if he or she used active modes (most often cycling) most frequently. A respondent was classified as a car user if he or she used the car most frequently (as driver or passenger). Unfortunately, there were (almost) no respondents who mostly used PT. We therefore decided to define PT users as respondents who used PT in > 10% of their trips. By aggregating respondents in the cyclist and car user groups, we can directly estimate the total intrapersonal variation as 100% minus the percentage of active modes, and 100% minus the percentage of car respectively. For the PT group and the group containing all respondents, the value of 100% minus the percentage of the most commonly used mode corresponds with the overall mode choice variation, as it also includes interpersonal variation.

In our analysis, we also considered distance from home and trip length as we expected those to be important mode choice discriminators. We used Euclidean distances (d_f), because trip length may be mode-dependent for a given origin and destination location. Moreover, Euclidean and network distance are strongly correlated, so we did not expect this choice to have a significant effect on the results. Euclidean distances were grouped in the following bins: $0 < d_f \leq 1$, $1 < d_f \leq 2$, $2 < d_f \leq 5$, $5 < d_f \leq 10$, $10 < d_f \leq 20$, $20 < d_f \leq 40$, $40 < d_f \leq 70$ km, and $d_f > 70$ km. These bin sizes provide a proper aggregation level at they are small enough to limit biases in the aggregated values and large enough to contain enough cases to yield estimates with sufficient statistical weight.

4.2. Identifying destination locations

Origin and destination locations are represented by the complete six-digit postal codes, which we linked to GPS coordinates. Such a postal code provides an accurate description of a location (PC6 area), usually only including a few addresses. We selected 432 respondents whose home locations were well defined.

It is hard to pinpoint the exact destination with smartphone apps, for example due to the fact that people park their cars at a slightly different location. We therefore used a buffer radius, with trip end locations within this buffer being considered the same destination location. A 200-metre buffer radius has been found to be the most appropriate size for GPS data in the United States (Dill and Broach, 2014). Note that using this buffer radius did not yield more (than 432) well defined home locations.

Using a 200-metre buffer may lead to a slight underestimation of the number of visited locations as different destinations may be located within a distance of 200 m from each other. However, for this study, this is less relevant as we are interested in mode choice variability rather than destination choice and a 200-metre buffer is small enough for that purpose. A 500-m buffer is probably even more appropriate, because we do not expect accessibility per mode to vary a lot within this buffer range, especially since locations within this distance can generally easily be accessed on foot. Here too, we used Euclidean distances, because we did not have a map of all footpaths in the Netherlands. In the case of barriers, like rivers, this may have introduced some inaccuracies, but in general, the footpath network in the Netherlands is very dense, and walking distance is strongly correlated with Euclidean distance. The same is actually also true for cycling and car distances.

In the Netherlands, the bicycle is almost always available for access and egress trips and a distance of 2000 m can be considered an acceptable cycling distance for most Dutch people (Statistics Netherlands, 2014). Hence, for long-distance trips that are not often repeated, 2000 m appears to be an appropriate buffer size. An additional advantage is that for train trips, most Euclidean access and/or egress distances are also within 2000 m. Therefore, we could use trip stages to establish mode choice variability for the main mode (car versus train: typical trip length > 2 km) and feeder mode (most often active mode versus BTM: typical trip length ≤ 2 km) simultaneously.

In this study, we therefore use both 500 and 2000 m buffers. To define destinations, we used the buffers as follows. For each respondent in the sample, we estimated Euclidean distances between home and each visited PC6 location. All locations within the buffer radius from home were defined as the first destination location. The other destinations (with larger distances) were ordered by distance. We defined the nearest destination outside the buffer radius as the second destination and all trip end locations within the buffer of this destination were assigned to this second destination. Then the nearest (relative to home) trip end destination without an assigned destination was defined as the third destination. All trip end locations within the buffer of this destination that had not yet been assigned to a destination were then assigned to the third destination. We repeated this procedure until all trip end locations were assigned to a destination.

For the 432 respondents, there were in total 11,843 PC6 locations, 10,249 destinations with 200-metre buffers, 7,881 destinations with 500-metre buffers and 4,368 destinations with 2000 metre buffers. As expected, using a 200-metre radius led to only a small reduction in the total number of destinations, whereas a 2,000-metre radius significantly reduced the number of destinations.

4.3. Mixed logit mode choice model

Next, we applied mixed logit models to model the influence of intrapersonal mode choice variation on mode choice. As noted in Section 2, mixed logit mode choice have recently been used in a couple of studies to estimate model the influence of habitual behaviour in daily mode choices (Cherchi and Cirillo, 2014; Cherchi et al., 2017). Cherchi et al. (2017) focused on estimating mode for correlation across individuals between the days of the week in a 6-week period. Additionally, Hess and Giergiczny (2015) have discussed the accuracy of scale parameters and found that a multinomial logit with scale parameters does not clearly account for intrapersonal heterogeneity. This model structure combines scaled heterogeneity and mixed logit models; however, the source of variance is not taken into account as separate equations to explain class membership. Other representations of intrapersonal and interpersonal variations accounted for (random) individual taste coefficients and choice-related (error) components with mixed logit models, respectively, see for example Yánez et al. (2011).

Our approach differs in that we estimated a scale-class parameter over the mixed logit structure. This addition means that continuous variables are not required to estimate taste heterogeneity. Furthermore, we estimated mixed logit models to represent intrapersonal variation in two dimensions (a temporal and a spatial dimension) via an error term (time) that varies by respondent and alternatives, and a class parameter (space) that varies by respondent. We analysed the dominant mode, distance and purpose as source of intrapersonal variation. The error components represent heterogeneity in individual preferences over time, but do not explain the source of individual taste heterogeneity. To the latter end, we estimated the class parameter, which represents the space dimension as mode (places reachable), distance and place repetitions (purpose). Those classes (mode, distance, purpose and mode-distance) classify the respondents as either an 'habitual' or 'adventurous' traveller. An habitual traveller often repeats mode and/or place (distance and purpose), whereas an adventurous traveller tends to vary one or both (mode and/or place). Using this typology, we estimated the following six models:

- Two models (with and without repetition) by purpose (home and work);
- Two models (with and without repetition) by repeated mode (active and car);
- Two models (with and without repetition) by repeated distance and mode.[1,2]

Stated more explicitly, a person faces a repeated choice among J alternatives, which can be modified by two error components, of which one is stochastic and the other non-stochastic. The choice set consists of the five alternatives 'car' (driver or passenger), 'train', 'BTM' (bus, tram, metro), 'bicycle' and 'walking'.

In our models, β is a vector of fixed parameters related to socio-economic characteristics, Z is related to urbanisation, W represents the weather factors during the trip, LOS is related to trip variables (travel time, departure time, etc.), while the stochastic part (ε_{in}) is assumed to be independently and identically distributed over alternatives and people. The non-stochastic part (ω_{in}) depends on the individuals' tastes. The utility can be expressed as follows:

$$U_{nit} = \beta_{SE} SE_n + \beta_Z Z_n + \beta_w W_n + \beta_{LOS} LOS_n + \omega_{nit} + \varepsilon_{nit} \mathrm{U_{i,n}} = \beta \mathrm{x_{in}} + \omega_{\mathrm{in}} + \varepsilon_{\mathrm{in}} \tag{1}$$

here, the person n faces a set of characteristics x_{ni} in the alternative i over T choice settings, ω_{in}expresses the random term with zero mean and $\sigma_{\omega,\ i}$ standard deviation, which is estimated over the distribution of the observed data, and ω_{in} is alternative specific, which converts the model in a heteroskedastic logit. In general, the distribution over people and alternatives depends on underlying parameters and observed data relating to alternative i and person n. ε_{in} is independent and identically distributed over the alternatives. For standard logit, ω_{in} $\omega_{\mathrm{in}}$is zero.

The utility of each alternative is then multiplied (scaled) by a class parameter, λ_n, specific to respondent n, and this scale parameter is maximized with the corresponding log-likelihood function.

With the corresponding normalizations of ϕ_{g1} and ϕ_{g2}, the structure consists of fixing the scale for one group of respondents and estimating the scale for the other group of respondents. So the answers from one group of respondents are scaled to those of the other group in order to verify differences between groups. Therefore,

$$\lambda_n = \phi_{g1} G_1 + \phi_{g2} G_2$$

and

$$\lambda_n U_{nit} = \lambda_n (\beta_{SE} SE_n + \beta_Z Z_n + \beta_w W_n + \beta_{LOS} LOS_n + \omega_{nit} + \varepsilon_{nit} \mathrm{U_{i,n}} = \beta \mathrm{x_{in}} + \omega_{\mathrm{in}} + \varepsilon_{\mathrm{in}}) \tag{2}$$

here, ϕ_{g1} is a group-class parameter to be estimated. $\phi_{g2}$is normalized to 1, for identification purposes. Since λ_n directly affects the utility, we are interested in the ration between ϕ_{g2} and ϕ_{g1}. When $\phi_{g2}$is normalized to 1, the more ϕ_{g1}differs from 1, the larger the variation between the two groups.

We impose that $\lambda_n \geq 0 \, \forall \, n$. Then, $\lambda_{n_1}{}^2 var \ (\varepsilon_{nit1}) = \lambda_{n_2}{}^2 var$ $(\varepsilon_{nit2}), \forall \, n_1, \, n_2$ are expressed as follows:

$$\frac{\lambda_{ni_1}^2}{\lambda_{ni_2}^2} = \frac{var\ (\varepsilon_{nit_2})}{var\ (\varepsilon_{nit1})} \tag{3}$$

I.e., if $\lambda_{ni_1}{}^2 > \lambda_{ni_2}{}^2$, then $var\ (\varepsilon_{nit1}) < var(\varepsilon_{nit_2})$, based on the multinomial logit model. We then estimate the ratio $\frac{\lambda_{ni_1}^2}{\lambda_{ni_2}^2} = \frac{\mu_{n1}}{\mu_{n2}} =$. As normalisation is required, we set $\lambda_{n_1} = 1$. Thus, we now have:

$$\mathrm{var.}\ (\varepsilon_{nit}) = \frac{1}{\lambda_n^2} var(\varepsilon_{1it}) \tag{4}$$

There are four cases for the G groups:

(1) Mode choice is repeated:
  a. $G_1 = 1$ if the dominant mode of the user is 'active', otherwise zero (car and PT); G_2 is equal to 1 if the dominant mode is PT or car, otherwise zero.
  b. $G_1 = 1$ if the dominant mode of the user is 'car', otherwise zero (active and PT); G_2 is equal to 1 if the dominant mode is PT or active, otherwise zero.
(2) Purpose is repeated:
  a. $G_1 = 1$ if the trip purpose is work, otherwise zero; G_2 is equal to 1 if the trip purpose is non-work, otherwise zero.
  b. $G_1 = 1$ if the trip is home-related, otherwise zero; G_2 is equal to 1 if the trip is not home-related, otherwise zero.
(3) Distance range is repeated:
  a. $G_1 = 1$ if the trip distance from home is shorter than 2 km, otherwise zero; G_2 is equal to 1 if the distance from home is larger than 2 km, otherwise zero.
(4) Both distance and mode are repeated

With the corresponding normalizations, one value of ϕ_g is obtained from each model, so yielding four values in total. To implement the mixed logit, an integral is performed. For any given value of θ, where θ refers to the parameters of the distribution, such as the mean and covariance, the function can be expressed in the form:

$$P_{nit} = \int L_{nit}(\omega_{ni}, \lambda_n) f(\omega_{ni} \mid \theta_i) d\omega \mathrm{P_{nj}} = \int \mathrm{L_{ni}}(\omega_{\mathrm{in}}) \mathrm{f}(\omega_{\mathrm{in}} \mid \theta) \mathrm{d}\omega \tag{5}$$

We can then proceed to the model estimations, as follows. In Eq. (5), $L_{ni}(\omega)$ is the logit probability evaluated at parameters of ω_{in}, and $f(\omega_{in})$ is the density function written as:

$$L_{nit}(\omega) = \frac{e^{\lambda U_{nit}}}{\sum_{j=1} e^{\lambda U_{njt}}} \mathrm{L_{ni}}(\omega) = \frac{\mathrm{e}^{\beta \mathrm{x_{in}} + \omega_{\mathrm{in}} + \varepsilon_{\mathrm{in}}}}{\sum_{\mathrm{j}=1} \mathrm{e}^{\mathrm{U}_{\beta \mathrm{x_{jn}} + \omega_{\mathrm{jn}} + \varepsilon_{\mathrm{jn}}}}} \tag{6}$$

The probabilities do not exhibit independence of irrelevant alternatives (IIA). Simulation is usually applied to estimate the mixed logit. Given the values that describe the population parameter of the individual parameters, R values of $\omega_{in}\omega$ are drawn from its distribution and the probability in Eq. (5) is calculated conditional on each realization. The simulated probability is the average of the conditional probabilities over R draws:

[1] Sample size was reduced to 21,000 observations to consider the clusters.
[2] The model with both repetitive distance and mode proved to be unidentifiable.

$$SP_n = \frac{1}{R} \sum_{r=1,\ldots,R} L_{ni}\left(\omega^r\ SP_{nit} = \frac{1}{R} \sum_{r=1,\ldots,R} L_{ni}(\omega^r)\right. \tag{7}$$

Then, the simulated log-likelihood (SLL) function is constructed as $SLL(\omega_{in}) = \sum_{n,j} ln(SP_{in})$ and the estimated parameters are those that maximize SLL. The model accuracy increases with the number of draws. However, there is a trade-off between computational time and accuracy (Hensher and Greene, 2003). In this study, we used 150 draws for all models, which appears to be an acceptable number (Train, 2000). For some models, we also checked that results did not change significantly when using 250 draws.

5. Results

In our analysis, we looked at both mode choice variation for all destinations and mode choice variation for repeatedly visited locations.

5.1. Mode choice variation – all destinations

As described in Section 4, we distinguished between car users (who used the car most frequently), cyclists (who used active modes most frequently) and PT users (who made at least 10% of their trips by PT). However, many PT users actually use active modes most frequently. Table 3 shows the modal split for the different respondent types; the modal share of PT users is comparable to that of cyclists, when only considering active modes and car. Therefore, we decided to lump cyclists and PT users together in a non-car user group in the modal split comparison. The shares of car and non-car users are also approximately the same, with only slightly more car users.

For the cyclists and car users, the intrapersonal variation for all visited locations follows directly from Table 3, as they all used active modes and the car, respectively, most frequently. On average, the most frequently used mode was chosen for about 70% of the trips. In other words, the intrapersonal variation over all trips lies around 30%. This is a substantial percentage considering the fact that these respondents basically choose between two major modes. Part of this substantial intrapersonal variation is due to the fact that we made no distinction between destinations. Travellers, however, may use different modes for different destinations. This can be seen in Fig. 1, which shows the modal split (mode shares) as a function of distance from home (upper panel) and trip length (lower panel). It is clear that trip length is the most discriminating factor in mode choice, and that dominant modes are not necessarily the same as the most frequently used mode overall. For example, even the car users preferred active modes when trips are very short. By contrast, the car is mostly used for medium distances, even among non-car users (cyclists and PT users) for distances between 10 and 40 km. These results are all statistically significant as the random errors (one standard deviation in the multinomial distributions of the sample percentages) are quite small because of the relatively large sample sizes. The results indicate that a substantial part of the overall intrapersonal mode choice variation is actually caused by intrapersonal mode choice variation between different trips.

However, it should be noted that in all cases, i.e., for all trip lengths, car users use the car about twice as often as non-car users. Non-car users use active modes (especially for short distances) and public transport (especially for long distances) much more frequently. This suggests that there mainly is a competition between car use and active modes for short trips (i.e., below 10 km), and between car and PT for long trips (i.e., beyond 10 km).

A remarkable feature of the upper panel of Fig. 1 is that active modes are used most frequently for short trips, i.e., Euclidean trip length smaller than 2 km, even when the visited location is far from home. This may partly be explained by the fact that we actually considered trip legs rather than trips. However, the percentage of trip legs to a transfer location (rather than the final destination) is only substantial for PT users (about 20% versus 2% for both cyclists and car users). Although short trips and/or trip legs that take place far from home may include egress trips, their share is negligibly small for non-PT users. Note that half of these short trips are indeed very short, with trip lengths shorter than 500 m. These trips are therefore mainly made to locations close to the main destination. These are likely typically cases of travellers stopping by at a shop, café or restaurant near their main destination. This explanation is also supported by the fact that most of these trips have a recreational or shopping purpose.

5.2. Mode choice variation for repeatedly visited locations

In addition to mode choice variation between destination locations, we can expect intrapersonal mode choice variation for repeated trips to the same location, for example, due to variation in weather circumstances. As mentioned in Section 4, we explored this intrapersonal mode choice variation by determining the percentages of dominant modes per destination. Fig. 2 displays the results, using 2000-metre buffers. We checked that the results did not differ significantly from the results for the 500-metre buffer. We aggregated respondents in groups (i.e., cyclists, car users and PT users), and aggregated destinations based on distance from home (i.e., eight distance bins; see Section 4.1) and trip length (i.e., trips shorter than 2 km and trips longer than 2 km, which we also did to separate between main and feeder modes in multimodal trips).

In Fig. 2, we have plotted the percentage of the dominant modes (per bin) versus the percentage of the most frequently used mode over all trips (per bin). This yielded interesting results. First, the percentages of the dominant modes and the most frequently used mode are almost equal for trips shorter than 2 km for non-car users, and for trips beyond 2 km for car users, irrespective of distance from home. This indicates that the same dominant mode is used for repeated trips. Note that the overall variation is also limited, as the most frequently used mode was used in > 85% of the trips. In other words, the fact that intrapersonal variation for repeated trips is more or less similar to the total intrapersonal variation is not very surprising as there is little intrapersonal variation to start with.

By contrast, we found much more mode choice variation for trips longer than 2 km for non-car users and shorter than 2 km for car users. Dominant modes are less dominant in these cases, with a share typically below 85%, but the difference with the percentage of the most frequently used mode also becomes larger. This implies that there is other intrapersonal or interpersonal variation as well. For distances below 2 km, some car users vary more frequently, some stick to their car, and some are switching to active modes. Similarly, some cyclists and PT users also use the car beyond 2 km, some keep preferring active modes and PT, and some are switching to the car. As the remaining intrapersonal (and interpersonal) variation increases (with in some cases the percentage of the most frequently used mode dropping below 50%),

Table 3
Modal split aggregated over all destinations visited at least twice. The random errors are provided as one standard deviation of the sample percentages.

	Active modes	Car	PT	Other	N trips
Cyclists (N = 142)	73.8 ± 0.5%	23.6 ± 0.5%	0.7 ± 0.1%	1.9 ± 0.2%	7767
Car users (N = 246)	28.2 ± 0.4%	69.2 ± 0.4%	0.4 ± 0.1%	2.3 ± 0.1%	11,609
PT users (N = 44)	54.3 ± 0.9%	17.6 ± 0.7%	26.1 ± 0.8%	2.0 ± 0.3%	2979

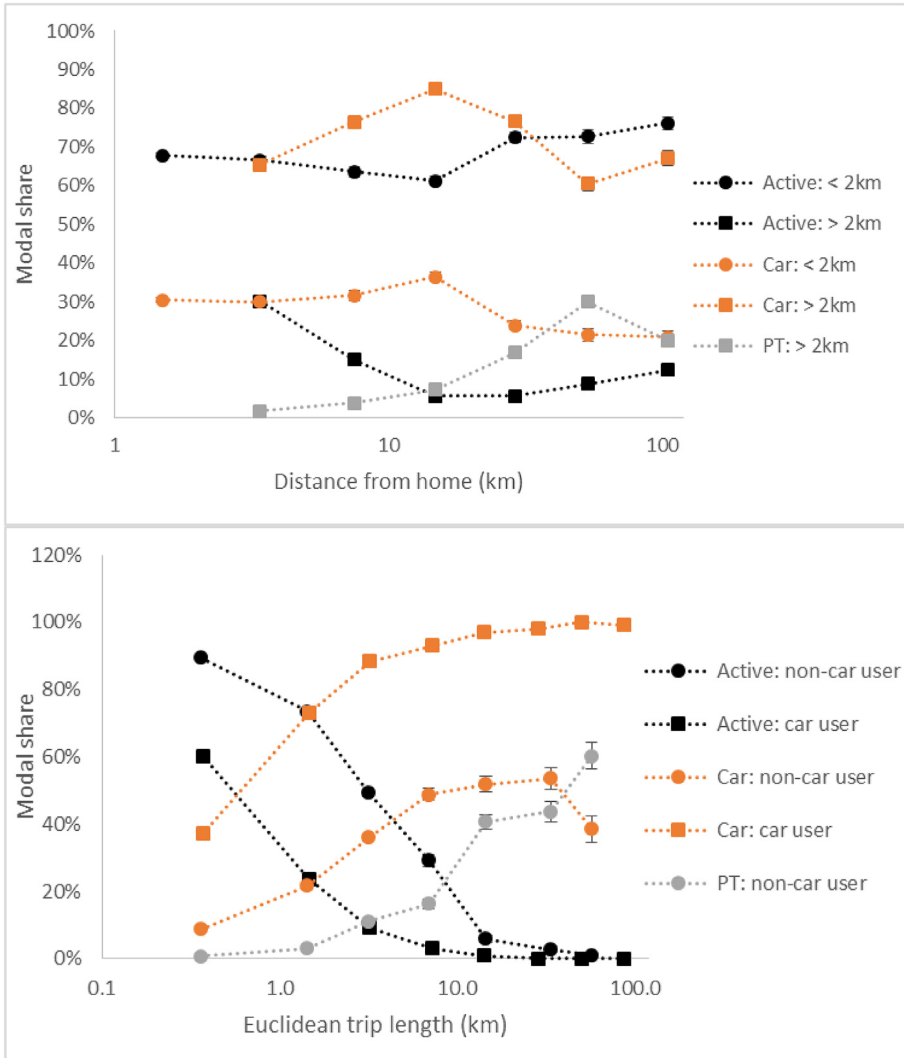


Fig. 1. Modal share as function of Euclidian distance from home (upper panel) and trip length (lower panel). For small samples, bins were combined or omitted. The error bars indicate the random error; for most percentages, the error is smaller than the symbol size and therefore not visible in the figure.

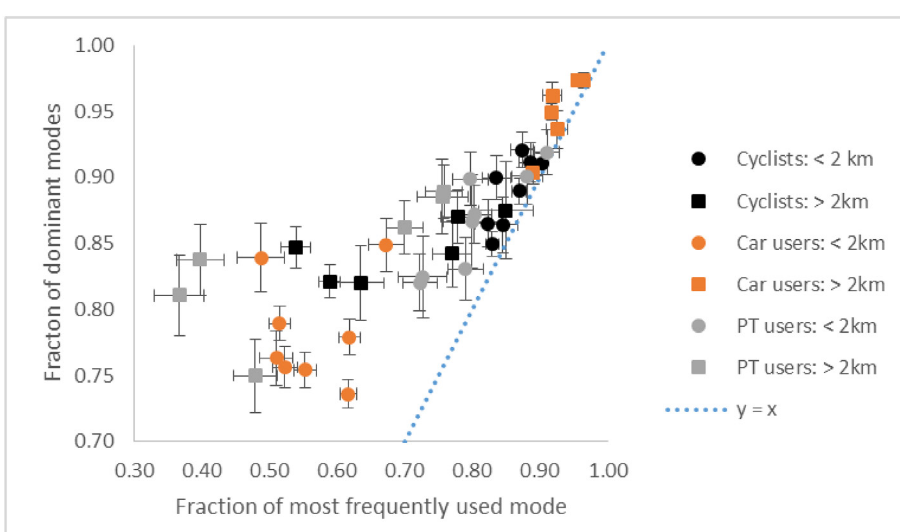
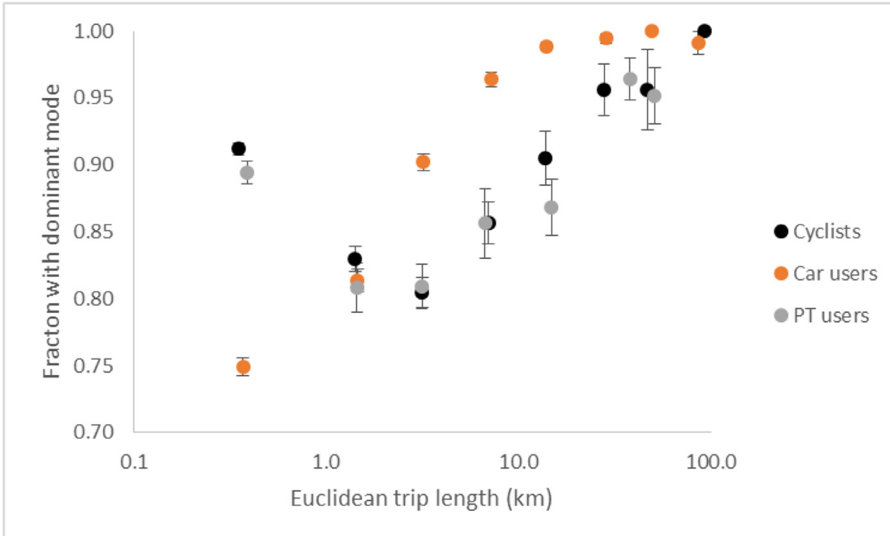


Fig. 2. Percentage of dominant mode versus percentage of the most frequently used mode. The error bars show the random error (1-sigma).



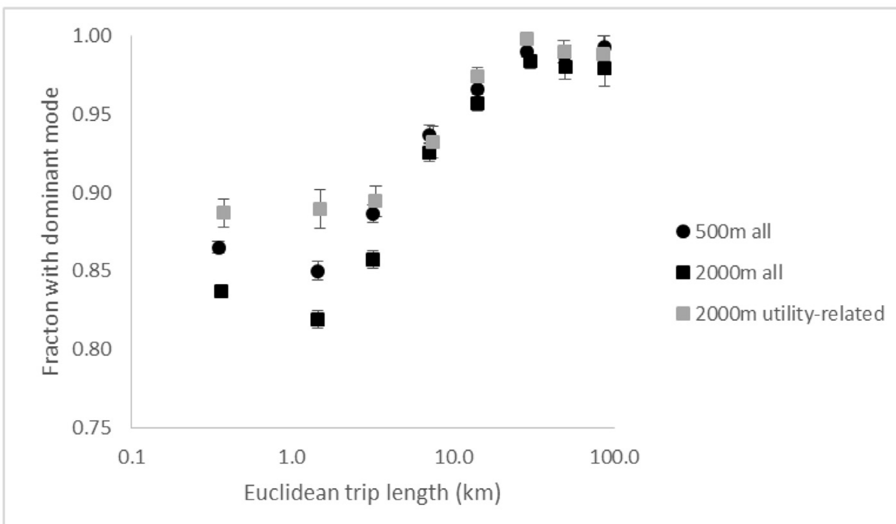


Fig. 3. Average percentage of the dominant mode (per destination) by trip length for different users (upper panel) and buffer sizes (lower panel). The error bars indicate the random error (1-sigma). In some cases, the error is smaller than the symbol size and therefore not visible in the figure.

the intrapersonal variation for repeated trips increases as well. This is not entirely unexpected, but it is not a linear relationship.

The data in Fig. 2 suggest that the contribution of intrapersonal variation to the total variation is generally larger for car users travelling short distances than for non-car users travelling larger distances. This result may be explained as follows. In the Netherlands, active modes are almost always a viable alternative for short trips, even for car users, but active modes or PT are not always available for longer trips, resulting in less intrapersonal variation per visited location. This interpretation is further supported by the upper panel of Fig. 3, which shows the percentage of dominant modes as a function of trip length for cyclists, car users and PT users.

From Fig. 3, we can derive the following statistically significant trends. Car users show most intrapersonal variation for the shortest trips. In 25% of these cases, they chose an alternative mode to visit the same location. The intrapersonal variation gradually decreases with longer trip lengths, and is almost 0% for trips longer than 10 km. In other words, car users almost always use the car for longer trips. Assuming that it is easier to change a behaviour towards a behaviour people are already familiar with, policymakers should start with focusing on short trips (no > 10 km) to encourage car users to shift to sustainable modes. For cyclists and PT users, there is little intrapersonal variation for the shortest trips as active modes are most frequently chosen for those trips. However, although active modes remain dominant for trips up to 5 km, intrapersonal variation increases rapidly with trip length and the car becomes a serious alternative. Beyond 5 km, the shares of car and other (non-car) modes are basically equal all the way up to very long trips (as Fig. 1 also shows for the non-car users). Still, intrapersonal variation continues to decline with distance. Beyond 20 km, the share of active modes is very small and there is little intrapersonal variation left. Only in about 5% of the cases, alternative modes are chosen when visiting the same location. This is hardly more than for car users, and the difference is not actually statistically significant. This indicates that people from the non-car groups either choose PT or the car for long trips and stick to that choice when they repeat the trip.

The lower panel of Fig. 3 shows results for 500-metre and 2000-metre buffers. Similar results are found for both buffer sizes, although the intrapersonal variation for the 500-metre buffer is slightly lower than that for the 2000-metre buffer. This is no surprise. For such short trips, mode choice is very sensitive to an increase in distance and may therefore change between locations in close proximity of each other. The lower panel also includes trips for utility-related purposes (mostly to work or to school). For all trip lengths, intrapersonal mode choice variation is smaller for work trips. This result is quite significant. A possible explanation is that those trips often have a habitual character.

Table 4
Mode choice variation based on trip frequency and trip distance.

Mode choice variation based on trip frequency

	100% minus % of dominant mode	100% minus % of most frequently used mode	Contribution intrapersonal variation to same location	Most frequently used mode
Cyclists	12.6 ± 0.4%	26.2 ± 0.5%	0.48	Active
Car users	14.8 ± 0.3%	30.8 ± 0.4%	0.48	Car
PT users	13.4 ± 0.6%	45.7 ± 0.9%	0.29	Active
All	13.8 ± 0.2%	52.5 ± 0.3%	0.26	Active

Mode choice variation based on cumulative trip length

	100% minus % of dominant modes weighted by trip length	100% minus % of most frequently used mode weighted by trip length	Contribution intrapersonal variation to same location	Most frequently used mode weighted by trip length
Cyclists	10.9 ± 0.4%	38.0 ± 0.6%	0.29	Car
Car users	3.3 ± 0.2%	5.7 ± 0.2%	0.57	Car
PT users	9.4 ± 0.5%	30.0 ± 0.8%	0.31	PT
All	5.8 ± 0.2%	24.2 ± 0.3%	0.24	Car

For example, commuters repeat their commute each workday, often starting work at approximately the same time.

Table 4 summarizes the relative importance of intrapersonal variation for repeated trips (aggregated over all respondents and destinations) relative to mode choice variation for all trips. The contribution of intrapersonal variation for repeated trips to the same location is expressed as the ratio between both percentages. Table 4 shows that about half of the variation (12.6% vs. 26.2% for cyclists and 14.8% vs. 30.8% for car users) is intrapersonal mode choice variation for repeatedly visited destinations, while the rest can be attributed to intrapersonal mode choice variation for different destinations. In the group with all respondents (and to a lesser extent, the group with PT users), there is a similar amount of intrapersonal variation for repeated trips. However, the overall variation is larger as the group with all respondents is heterogeneous, i.e., consists of respondents with different mode choice preferences. The overall mode choice variation is 50%, suggesting that about half of all mode choice variation is interpersonal. Note that the contribution of intrapersonal mode choice variation for repeatedly visited destinations looks quite high, but it should be stressed that short trips (below 2 km) contribute disproportionally to the total result, which becomes clear when we look at percentages based on cumulative trip length rather than trip frequency.

5.3. Results from the mixed logit mode choice models

Table 5 shows the model results for the classified models and for the general model without classifications representing intrapersonal variation. In this section, we discuss the main results by groups of variables (socioeconomic, level of service, weather, urbanisation), class parameter, alternative specific error components and constants. As we can observe in Table 5, the constants are less significant in the scaled models, indicating that a substantial amount of explanation is transferred from the constants to the new class parameters. The alternative-specific standard deviations of the error components, to cover the 'habitual' respondent, are statistically significant, indicating a strong intrapersonal correlation in mode choice. The scale parameters show the source of such intrapersonal correlation. The class parameter (ϕ_{g1}) is significant in all models, indicating a significant difference in the degree of intrapersonal correlation in the spatial dimension by trip purpose (work-related vs. non-work trips), trip origin (home-related vs. not home-based trips), dominant mode (active vs. PT/car, and car vs. PT/active) and repeated short trips (< 2 km) and mode (active/car). The ϕ_{g1} parameters also indicate that differences in utility perceived between groups (mode or purpose) are statistically significant.

The class parameters also indicate correlation within groups. Table 6 summarizes the class parameters for each estimated mode choice model. We conducted a *t*-test zero for each parameter in the output and found the parameter significantly different from zero in the utility function. Since we were interested in the ratio between the ϕ_g parameters of the two groups, and $\phi_{g2}$was normalized to 1 for one of the groups, we expected the remaining estimated scale (ϕ_{g1}) parameter to be significantly different from 1, and conducted the test for 1 instead of zero. We can observe that the classification parameter is significant for all cases estimated. Among the distance- mode combinations of class models, the highest variance (largest t-test 1) is explained by the mode-distance classification model (t-test = 12.20). Consistent with the intrapersonal variation presented in Section 5.2, car drivers within 2 km, present stronger patterns than active mode users. The results show that the mode choice of car users who travel farther than 2 km and users of active modes (cycling, walking) who travel < 2 km is highly repetitive (little intrapersonal mode choice variation). This conclusion is based on the estimated value for the scale parameter. Also, there is statistically significant intrapersonal correlation for trip purpose, specifically for 'home' trips (t-test 1 = 12.8), and for 'work-related and non-work trips' (*t*-test 1 = 18.1). This means that trip purpose is an important explanatory factor in intrapersonal mode choice variation, with little intrapersonal mode choice variation in commuting trips. This result is consistent with findings by Järv et al. (2014), who found more significant variation in spatial locations (e.g., up to certain distance) than in the frequency of activities (e.g., commutes).

Furthermore, we obtained the best model fit for the classifications given both dominant modes (car and active) and distance. It indicates that travel demand estimation should be based on the respondents' patterns. This is consistent with previous research that highlighted the power of repeated past choices to explain future behaviour (see for example Cherchi and Cirillo, 2014).

The socioeconomic variables show the expected signs. For example, respondents with higher incomes are more willing to car use and the presence of children in the household also strongly determines car use. Female have a stronger tendency to choose the car, consistent with the descriptive statistics. However, individuals with children but without (a high) income are less willing to use the car, and young people and women are more oriented towards public transport. This is in line with findings of Olde Kalter and Geurs (2016) and shows that household composition has a significant influence (one-third) on mode choice.

The class parameters produced changes in the level of significance of certain socioeconomic variables. For example, the number of children at home was significant only for some specifications and alternatives. When both mode and distance repetition were used as class, the number of children at home became irrelevant for car use. In the

Table 5
Model results for classified mode choice models.[a]

Name	General model		Work/non-work		Home-related trips		Active mode dominant		Car dominant		Mode and distance scale: car > 2 km; active < 2 km		
	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Affected alternative[b]
ASC BTM	Reference												BTM[c]
ASC Car	4.94	20.61	5.42	36.35	5.14	35.29	4.88	17.37	3.37	14.56	0.94	4.98	Car
ASC Train	3.36	11.68	3.51	16.83	2.99	14.39	1.61	4.63	2.1	7.73	−0.52	−2.04	Train
ASC Bicycle	5.06	19.58	4.29	23.06	5.33	34.76	6.15	20.91	4.97	22.39	1.38	5.03	Bicycle
ASC Walking	6.11	26.71	4.38	35.01	4.83	34.56	6.55	23.8	5.19	28.98	1.64	21.21	Walking
Class parameters			1.6	48.28	1.19	80.09	1.09	29.84	1.19	34.81	1.57	33.68	
											1.29	27.36	
Socioeconomic variables (SE)													
Age	−0.04	−7.31	−0.06	−13.61	−0.05	−13.59	−0.03	−5.21	−0.04	−6.56	−0.02	−4.35	Train
									0.01	5.16	0.03	14.75	Car
	0.04	7.20			0.00	1.02	0.03	5.59	0.02	5.58	0.03	5.91	BTM
	0.01	3.76	0.01	3.15	0.00	−3.34	0.01	5.29	0.00	0.03	0.02	3.94	Bicycle
Gender (female)			−0.03	−0.55	−0.05	−1.21	0.56	5.94	0.35	4.61	0.50	4.39	PT
	1.62	12.59	0.85	10.34	0.73	9.17	1.60	10.43	1.38	10.88	1.59	11.67	Car
Partner	0.30	2.63											Car
	0.20	1.88											PT, Bicycle
							1.50	7.51			0.93	5.12	BTM
			0.34	5.70	0.29	5.34	0.85	6.96	−0.10	−0.98	0.55	4.41	Car
					0.365	7.260	0.81	4.65	0.482	5.710	0.380	2.240	Train
							−0.53	−4.85			0.51	4.17	Bicycle
Household size	−0.09	−2.51	−0.13	−5.33	−0.25	−11.73	−0.16	−3.65	0.11	3.31	−0.10	−2.07	Walking
Number of kids	−0.11	−2.59	0.16	5.21	0.36	13.26	0.13	3.04			0.15	3.61	Car
	0.17	3.02	−0.21	−3.91	−0.15	−3.61			0.18	2.94	0.36	4.64	Train
Head of household	2.35	15.26	2.24	20.17	1.47	17.39	1.23	8.87	2.43	16.30	1.22	9.12	PT
	1.46	13.02	0.88	10.94	1.08	17.79			0.75	6.95	−0.50	−3.00	Bicycle
	0.90	8.51	0.65	10.58	0.47	9.48	0.58	6.75	0.38	3.91			Walking
	0.26	28.80	0.12	25.17									Car
Category income level	0.10	10.74									0.18	20.09	Car
(1 to 12, see Table 2)	−0.06	−4.77			−0.01	−2.00			−0.05	−6.62	0.06	3.21	Bicycle
Income1500 other			−0.80	−5.79	−0.49	−4.41	0.16	0.80	0.83	4.84	0.31	1.97	Walking
Income1500 PT			0.94	5.21	0.33	2.14	1.63	6.37	1.86	7.56	1.99	7.94	PT
Income1500 BIKE			0.20	1.25	−0.13	−1.14	−0.31	−1.54	0.57	3.10			Bicycle
Income1500 CAR			−0.95	−6.79	0.57	5.43	−0.43	−2.30	−0.03	−0.16			Car
Income high CAR * kids (+1500eur)			0.48	16.71	0.47	22.29	0.62	10.04	0.32	10.59	0.42	9.40	Car
Income CAR passenger-up to 2500			−0.60	−6.69	0.15	2.25	0.18	1.75	−0.12	−1.28	0.41	4.30	Car passenger
No income, with kids							−0.64	−10.54					Car
	0.33	4.83	0.81	17.21	0.58	14.50	−0.21	−2.71	0.32	5.13	0.53	8.74	PT
			−0.16	−2.34	−0.47	−13.67			−0.41	−6.04	−0.21	−3.26	Bicycle
Z: Urbanisation level[d]													
At origin			1.17	20.28	1.30	28.82	1.77	15.55	1.15	14.65	1.15	7.90	Car
	−0.47	−1.97	−1.00	−6.89	−1.73	−13.70			0.37	1.62			Train
At destination	−1.04	−4.99	−0.27	−2.47	0.34	3.68	−1.07	−6.50	−1.08	−6.39	−0.82	−5.02	PT
	0.21	2.91	0.04	0.88	0.30	8.37			−0.06	−0.92	0.18	1.65	Car
Travel-related variables (LOS)													
Morning peak:	0.83	8.07	0.60	11.27	0.46	7.99	0.91	8.75	0.94	10.06	0.91	9.27	Car
departure time	0.62	3.56	1.25	11.53	0.93	7.47	0.73	4.15	0.83	4.96	0.52	3.09	Train
between 5 and 8	0.99	8.47	0.49	7.74	0.31	4.26	0.92	8.07	0.92	8.62	0.91	8.20	Bicycle
Off–peak: departure	0.22	4.39	0.13	4.13			0.29	5.79	0.28	6.40	0.20	4.10	Car
time between 3 and 6	0.31	5.70	0.19	5.37	0.08	2.92	0.34	6.45	0.32	6.34	0.30	5.51	Bicycle
Travel time	−0.02	−6.74	0.00	−1.77	0.00	−2.76	−0.01	−5.50	−0.02	−6.48	−0.02	−6.37	Train
	−0.06	−14.35	−0.01	−4.59	−0.01	−5.94	−0.06	−14.28	−0.05	−12.55	−0.06	−14.56	BTM
	0.006	2.55	0.00	−8.10	0.00	−10.01	0.00	2.74	0.00	2.47	0.00	−1.85	Car
	−0.03	−15.89	0.00	−3.91	0.00	−4.17	−0.02	−14.63	−0.03	−16.02	−0.03	−16.09	Bicycle
	−1.35	−25.08	0.00	48.04	0.00	26.94	−1.35	−25.13	−1.21	−23.42	−1.33	−24.63	Walking
Weather parameters (W)													
Sunny	0.26	5.48	0.11	3.50	0.24	9.13	0.22	4.88	0.21	5.01	0.24	5.33	Bicycle
Clear sky	−0.36	−1.94	−0.06	−0.50			−0.35	−2.03	−0.35	−2.04	−0.36	−2.07	Bicycle

(*continued on next page*)

Table 5 (*continued*)

Name	General model		Work/non-work		Home-related trips		Active mode dominant		Car dominant		Mode and distance scale: car > 2 km; active < 2 km		
	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Value	*t*-test	Affected alternative[b]
ASC BTM	Reference												BTM[c]
Standard deviations error components	−1.79	−51.49	−1.93	−57.98	2.40	39.31	−2.90	−30.83	−2.03	−35.24	−1.79	−51.49	Car driver
	1.72	41.15	−1.51	−42.08	−1.85	−23.51	−1.20	−25.89	1.55	29.41	1.72	41.15	Car passenger
	1.63	49.64	−1.77	−62.03	−1.63	−28.09	1.63	30.86	1.57	33.82	1.63	49.64	Bicycle
	2.41	36.68	−2.73	−36.09	−2.34	−15.27	1.71	15.27	−2.16	−16.72	2.41	36.68	BTM
	3.00	29.35	−2.07	−34.59	2.51	18.77	1.52	15.40	1.89	21.13	3.00	29.35	Train
Goodness of fit													
Rho squared	0.52		0.35		0.53		0.58		0.57		0.48		
Log-likelihood test for the initial model	−36,222		−115,507		−115,507		−36,222		−28,852		−42,144		
Log-likelihood	−15,486		−7379		−53,155		−15,476		−15,843		−21,952		
Likelihood ratio test for the initial model	41,472		216,256		124,704		41,492		26,018		40,384		
Sample size	21,658		59,359		59,359		21,658		21,658		21,658		
Number of draws	150		150		150		150		150		150		

[a] Statistically insignificant variables are not included. Note that not all included variables are significant in all models, probably because of the segmentation in the scale parameter. We have scales for work, home-based trips, car dominant and active dominant. It is very likely that both socioeconomic and travel related characteristics are correlated with those profiles. For example, a car-dominant user, can typically be a male with a certain age (e.g., 40 years old), living in a suburban area. Similarly, the scale for work trips can also be related to age (of the worker) and the time of the trip.

[b] 'PT' means that the variable is included in the utility function of both train and BTM; 'Train' means that the variable is only included in the utility function of the 'Train' alternative.

[c] BTM means Bus-Tram-Metro.

[d] Low to medium level of urbanisation.

Table 6
Class parameters and t-test for mode choice models.

Class parameter (ϕ_{g1})	Value	*t*-Test	Standard error	*t*-Test 1	Model rho squared	N
Work/non-work	1.6	48.28	0.0331	18.1	0.35	59,359
Home	1.19	80.09	0.0149	12.8	0.53	59,359
Mode-distance class: Car, > 2 km	1.57	33.68	0.0466	12.2	0.47	21,658
Mode-distance class: Active, < 2 km	1.29	27.36	0.0471	6.2		21,658
Car dominant	1.19	34.81	0.0342	5.8	0.57	21,658
Active dominant	1.09	29.84	0.0365	2.9	0.58	21,658

general model, the number of children was insignificant for train use, but turned significant and positive when the model was classified (either by mode or distance recurrence). However, the robust *t*-test indicates that this significance is low. It means that classification absorbs part of the explanation coming from certain socioeconomic variables, and the influence can be correlated with those variables.

Level of service variables showed diverse results. Travel time coefficients were negative for (almost) all modes and every model, as expected. These negative travel time coefficients significantly contribute to the utility, even after capturing the intrapersonal correlations. We can observe certain fluctuations between negative and positive sings for the car travel time coefficient, which means a positive perception of the time spent travelling by car. A positive coefficient for travel time means that this value cannot be used for estimations of value of time or demand elasticities. See for example, the models 'active dominant' and 'car dominant'. Considering departure time, there was no clear competition between PT, bike and car use during peak hours; all modes were used indistinctively. This is surprising, as it means that there is no avoidance of car use during rush hours.

Urbanity level is an important factor in the model. The respondents tended to choose the car in less urbanised areas and public transport in more urbanised areas. Similarly, low urbanisation levels at the destination are related to a preference for car use. Urbanisation level becomes less significant when more variability is captured (mode and distance class model). This is associated with an inherent correlation between availability of transport modes and size of urban areas. See for example the study of Heinen and Chatterjee (2015), who found that variability in transport modes is lower in smaller settlements. Surprisingly, rainy and cloudy weather were not significant for car choice. However, sunny weather stimulated people to cycle, as expected. These results are in line with the descriptive statistics.

6. Conclusions and discussion

Our study examined intrapersonal and interpersonal variation in mode choice in the Netherlands based on trip data for 432 participants collected in a four-week smartphone-based travel survey, yielding a unique database in terms of accuracy and density of information, including from non-smartphone owners. We used two approaches (statistical and discrete choice model estimations) to provide more detailed explanations of intrapersonal variation and its effect on mode choice. The results may be useful for policy makers trying to change the behaviour of travellers, assuming that behavioural change is easier to accomplish among travellers that already use different modes. Within this context, one of the main questions is whether car users without (much) intrapersonal variation would be even considering other transport modes, even if those modes are provided as viable alternatives.

We found that slightly more than half of the respondents were real car users, preferring the car above other modes even when those were good alternatives. They only regularly walked or cycled for very short trips (< 2 km). The intrapersonal variation for these very short trips is high for the car users in our study, but for longer trips, car users almost always used the car. For the non-car users, active modes were clearly dominant for short distances, while PT was very important for longer distances (beyond 10 km). For this group, intrapersonal variation is relatively high for distances between 1 and 10 km, for which they used the car alongside active modes. This group of travellers too seemed to alternate between car and active modes (mostly cycling), but for longer distances than car users.

In addition, for the non-car users, we found that for distances beyond 10 km, the modal share was about 50% for PT and 50% for the car, but the intrapersonal variation for repeated trips was very low, indicating that travellers tend to stick with their mode choice. If we assume that all non-car users would like to be able to choose a viable alternative for the car, it implies that for about 50% of the trips, PT was not a viable alternative.

Factors that influence intrapersonal variation were further explored by the mixed logit models. The models confirm the statistical analyses. Trip purpose is an important explanatory factor in intrapersonal mode choice variation. Consistent with findings by Järv et al. (2014), we found relatively little intrapersonal mode choice variation in commuting trips. This may be attributed to the habitual character of these trips. The models also confirm the importance of intrapersonal variation in explaining mode choice and, consistent with the results of Cherchi et al. (2017), show the importance of both spatial (e.g., trip distance and activity purpose) and temporal dimensions (as repeated behaviour over time) in explaining intrapersonal variation. The classified models show that characteristics of mode and locations are important factors in the development of travel habits.

The results of this paper can be helpful in targeting efficient transport policies. This paper indicates that having multiple transport options, in particular for short distance trips, increases intrapersonal mode choice variation. Some intrapersonal variation may be necessary to incentivize further behavioural change. For example, Fioreze et al. (2018) showed that commuters that cycle occasionally to work are more likely to be encouraged to cycle more often than commuters that never cycle. Some local and regional governments in the Netherlands are currently experimenting with smartphone-based behavioural change projects that offer financial and non-financial incentives to encourage bicycle use among commuters. In future research, we may explore whether such programs are useful in cases in which there is no intrapersonal variation to start with.

Finally, the approach in the present paper shows that transport strategies should be designed to cover the flexibility of mode choices and destinations. As mentioned by Heinen and Chatterjee (2015), the introduction of mode choice-related measures will enhance the performance of the transport network (avoid congestion), but such measures must be flexible and accommodate the temporal and spatial variations in the users' trips.

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