Transportation Research Part A 78 (2015) 266–282

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

The same mode again? An exploration of mode choice variability in Great Britain using the National Travel Survey

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ARTICLE INFO

Article history:
Received 22 September 2014
Received in revised form 15 May 2015
Accepted 21 May 2015

Keywords:
Intrapersonal variability
Mode choice
Multimodality
Modal variability
Mobility constraints

ABSTRACT

The main focus of travel behaviour research has been explaining differences in behaviour between individuals (interpersonal variability) with less emphasis given to the variability of behaviour within individuals (intrapersonal variability). The subject of this paper is the variability of transport modes used by individuals in their weekly travel. Our review shows that previous studies have not allowed the full use of different modes in weekly travel to be taken into account, have used categorical variables as simple indicators of modal variability and have only considered a limited set of explanatory indicators in seeking to explain modal variability. In our analysis we use National Travel Survey data for Great Britain. We analyse modal variability with continuous measures of modal variability (Herfindahl–Hirschman Index, the difference in mode share between the primary and secondary mode, the total number of modes used). Taking inspiration from Hägerstrand (1970), we conceive that modal variability is determined by different types of spatial mobility constraints and find that reduced modal variability is predicted for having mobility difficulties, being aged over 60, being non-white, working full-time, living in smaller settlement, lower household income, having regular access to a car, having no public transport pass/season ticket and not owning a bicycle. The findings can support a change in perspective in transport policy from encouraging people to replace the use of one mode with another to encouraging people to make a change to their relative use of different transport modes.

1. Introduction

The main focus of travel behaviour research has been explaining differences in behaviour between individuals (interpersonal variability) with less emphasis given to the variability of behaviour within individuals (intrapersonal variability). Sixty-four per cent of trips in Great Britain are undertaken by car (DfT, 2014), but this does not tell us whether there is a large group of people who are solely car users and a smaller group who are solely users of other modes, or whether most people use a mix of modes with car the most frequently used. The subject of this paper is the variability of transport modes used by individuals in their weekly travel (referred to as modal variability).

Previous studies have assessed the prevalence of modal variability in nationally representative survey samples for Germany (Nobis, 2007) and United States (Buehler and Hamre, 2014). These have identified the existence of distinct groups

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http://dx.doi.org/10.1016/j.tra.2015.05.015
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based on combination of modes used. Whilst these studies have provided some useful insights, there remain some important gaps in knowledge. The objectives of this paper are to clearly set out what is known from the literature about modal variability, to identify appropriate data and indicators to measure modal variability, to use these indicators to identify the distribution of modal variability in the population of Great Britain and to identify predictors of modal variability.

The transport modes used by individuals have implications for the performance of the transport system (e.g. congestion), for the environment (e.g. carbon emissions) and for public health (e.g. physical activity). The potential for population-wide modal shift depends on people's capability and willingness to use alternative transport modes. A better understanding of the extent to which people use a mixture of different transport modes in their everyday travel and the predictors of this is a starting point for assessing this potential. This can support a change in perspective in transport policy from encouraging people to replace the use of one mode with another to encouraging people to make a change to their relative use of different transport modes.

The remainder of the paper is organized as follows. First a literature review is provided to clarify existing knowledge, concluding with research gaps and the contribution of this paper. Section 3 introduces the data used in our study. Section 4 presents results of the analyses, followed by discussions and a conclusion.

2. Literature review

2.1. Intrapersonal variability in travel behaviour

Nearly thirty years ago, Jones and Clarke (1988) reported on a growing interest in the day-to-day variability of individual travel behaviour. This (day-to-day) intrapersonal variability can be considered with respect to various dimensions of travel behaviour such as the types of activities pursued, start times of activities and their duration, destinations visited, transport modes used and routes used. Variability in activities and time patterns has received a relatively large amount of scientific attention (e.g. Jones and Clarke, 1988; Kitamura et al., 2006; Chikaraishi et al., 2010, 2009; Keuleers et al., 2001; Timmermans et al., 2001; Horni et al., 2011), whereas destination variability (Buliung et al., 2008), and modal variability have received less attention. While the focus of this paper is transport mode choice variability, we summarise some broader research into travel behaviour variability which provides relevant insights for mode choice variability.

Huff and Hanson (1986) analysed five-week travel diaries obtained for 149 individuals in Uppsala (Sweden) in 1971. Transport mode was included as one dimension of interest in their analysis with five mode categories considered (walk, bicycle, bus, auto, other). They looked at pairs of travel behaviour dimensions (e.g. mode-purpose) and assessed the extent of repetition exhibited over the full survey period (using an entropy style of measure) for the paired combinations. They found a high level of repetition for all pairs of dimensions considered with a subset of combinations accounting for most of the observed travel of individuals.

Schlich and Axhausen (2003) conducted a similar analysis of the Mobidrive six-week travel diaries (Axhausen et al., 2002) obtained for 317 individuals from 139 households in Karlsruhe and Halle/Salle, Germany, in 1999. They looked at different combinations constructed from mode (9 categories), purpose (10 categories), arrival time (4 categories) and destination (4 categories) and also found a high degree of repetition. For example, they found that on average an individual performed 8.6 of the 36 possible combinations for the mode-destination combination over the 42 days of the survey. The combinations involving mode were found to have greater repetition than other combinations, implying less variation in mode choice than other dimensions.

Susilo and Axhausen (2014) also looked at the repetition over time in combinations of travel attributes (activity type-location, travel mode-location, activity type-travel mode and activity-type-departure time). Six types of travel mode were considered in the analysis using the six-week travel data from Mobidrive and a similar survey conducted in Thurgau (rural Switzerland) with 230 individuals from 99 households. They used the Herfindahl–Hirschman Index (HHI) to measure the degree of repetition of combinations over the survey periods and found higher average index values (lower variability) for the travel mode-location and activity type-travel mode combinations than the other two combinations. Regressing the HHI values against socio-demographic characteristics showed that men, workers, middle aged (35–54) respondents and respondents with a higher number of household cars had lower variability in activity-travel mode choice combinations. Living in larger households and a higher household income increased the level of variability.

It appears from these results that there is a high level of repetition in intrapersonal travel behaviour, but when Huff and Hanson (1986) looked at similarity of behaviour between consecutive days for the Uppsala data set (based on composition of the day's travel in terms of different pairs of travel behaviour dimensions) this was found to be low. They then went on to show, however, that individuals tended to have a set of archetypical days that reappeared over the five week period. We now turn to studies concentrating specifically on modal variability.

2.2. Mode choice variability

2.2.1. Modal variability – measurement and results

Stradling (2007) reported from surveys of 1,220 Scottish car drivers undertaken in 2001 and 2003, which asked about frequency of use of other modes than car, that 56% used bus (20% at least once a week), 56% used train (5% at least once a week), 68% used taxi (9% at least once a week), 27% used bicycle (7% at least once a week) and 91% walked at least 10 min (78% at least once a week). These results based on self-reported mode use show that the number of modes used will depend on time frame considered.

Nobis (2007) used a large data set representative of the German population: the Mobility in Germany (MiD) 2002 survey. The survey collects one day travel diaries and self-reported frequency of transport mode use with the combination enabling weekly mode use to be estimated. She found that 51% of individuals ($\geqslant$14 years) were monomodal in only using one mode of transport from the three categories of car, bicycle or public transport with most of these being solely car users (43% of sample). Of the 49% of sample that were multimodal, 28% were joint car/bicycle users, 11% were joint car/public transport users and 8% used all three mode categories. In contrast, Kuhnimhof (2009) reported that only 12% of a sample drawn from the German Mobility Panel (MOP), which collects one week travel diaries from about 1800 persons per year, was monomodal. The large difference in result appears to stem from the different classification system they used which considered more mode categories (five): car driver, car passenger, public transport, bicycle, walking.

In the results reported above, individuals are classified as multimodal if they use more than one mode, regardless of frequency of use. Nobis (2007) also tested a more stringent definition in her analysis of MiD data where respondents were defined as multimodal if no mode was used for more than 70% of trips. With this definition only 21% of the sample was identified as multimodal (compared to 49% with the more relaxed definition).

Buehler and Hamre (in press-a and b) used National Household Travel Survey (NHTS) data for the United States for 2001 and 2009 to look at the prevalence of multimodal travellers. Multimodality was examined with respect to trip chains, days and weeks. Use of different modes was directly available for trip chains and days from the one-day travel diary obtained for all survey respondents. Weekly mode use was estimated based on the one day diary plus self-reported frequency of walking, bicycling and public transport over past week/month and self-reported mode of transport for the journey to work over past week. The authors acknowledge weaknesses of the data and in particular the lack of weekly car use data and the self-reported frequencies for weekly use of other modes. They recommend collection of weekly trip data.

Buehler and Hamre (in press-a) differentiated between monomodal car users and multimodal car users based on the number of trips made by walking, bicycling and public transport (WBT). Multimodal car users at the day level were defined as making two or more trips by WBT a day and multimodal car users at the week level were defined as making seven or more trips by WBT a week. It was found from the 2009 data that 14% of Americans were multimodal car users at the day level and 25% at the week level. Walking was the only non-car mode used by the majority of multimodal car users.

In another analysis using the same data, Buehler and Hamre (in press-b) differentiated between three groups: (1) monomodal car users (2) multimodal car users, (3) WBT only users. They investigated variability at three levels: trip chain, day and week level. Monomodal car users were defined as only using car, WBT only users were defined as only using WBT (and not car) and multimodal car users were defined at trip chain level as having at least one stage by car and at least one stage by WBT, at day level as having at least one trip by car and at least one trip by WBT and at week level as having at least one daily trip by car and at least one weekly trip by WBT. Buehler and Hamre (in press-b) found from the 2009 data that 28% of Americans were monomodal car users, 65% were multimodal car users and 7% were WBT only users. The greater prevalence of multimodal car users in this analysis stems from the less stringent definition. More stringent definitions for multimodal car users were tested with thresholds of at least 3, 5 and 7 trips by WBT modes. This led to figures of 48%, 33% and 23% for multimodal car users. This shows that choice of thresholds has a strong effect on results obtained for multimodality and that sensitivity to this should be acknowledged.

Kuhnimhof (2009) took a different approach from defining multimodality in terms of discrete groups. He constructed a mode variation index, MIX, on a continuous scale between 0 and 1 for an individual's level of modal variability. The index is based on HHI used by Susilo and Axhausen (2014) but adjusted to account for the problem he identified of a small number of observations per individual (small number of tours over survey period) compared to choice options (modes). Tours were used as unit of analysis with these defined as being trip chains that start and end at same location. Mode categories considered were car driver, car passenger, public transport, bicycle and walking. MIX calculates choice variance taking into account the number of tours made. It considers the difference between the actual use of each mode and the expected use of each mode if the individual maximizes his/her variation for the tours made. A value of 0 represents monomodality and 1 represents a balanced use of modes. The mean score for MIX based on MOP data was 0.34, which was interpreted as meaning that 'about two thirds of all mode choice decisions are not made in line with variation maximization but cluster on particular modes'. A plot of the distribution of values showed it was spread across the range with 12% of individuals monomodal (MIX value of 0) and 90% of individuals having a MIX value lower than 0.6.

2.2.2. Modal variability for specific types of travel

The above findings suggest a significant proportion of the populations (in Germany, Scotland and United States) use more than one transport mode across their overall travel activities, but less modal variability would be expected when considering specific activities. Kuhnimhof et al. (2006) found from MOP data that 90% of workers were monomodal for commuting over a one-week period. Subsequently, Kuhnimhof (2009) found from the same data when analysing commuting and non-commuting routines (defined as tours occurring at least twice in survey week and with similar characteristics in terms of location and other attributes) that 72% of people used only one mode of transport for commuting routines over a week and 78% of people used only one mode of transport for non-commuting routines. Block-Schachter (2009) examined survey data for 2008 for about 10,000 staff and students at MIT (Cambridge, United States) and found 19% varied their commuting mode during the survey week. These results show that there is reduced modal variability for specific travel purposes and destinations but still about one in five people vary mode over a week for routine travel.

Carrel et al. (2011) used the Mobidrive data (covering the longer period of six weeks) to examine multimodality for commuting and non-commuting travel and found 57% of the sample monomodal for work travel and only 30% monomodal for non-work travel. They used a relaxed definition of monomodality where the car monomodal group was defined as having at least 90% of trips by car and the biking/walking and public transport monomodal groups were defined as having at least 80% of trips by these modes.

Heinen et al. (2011) were able to look at modal variability over an even longer period by obtaining commuting mode used on a particular day from 633 bicyclists every two weeks over a 12 month period and found that only 51% of bicyclists used the bicycle on more than two thirds of occasions. The finding that there is modal variability even with a specific type of travel such as commuting emphasises the importance of gaining further knowledge of the extent of modal variability and its determinants.

2.2.3. Predictors of modal variability

Nobis (2007) showed using German MOP data that there is a U-shaped relationship between multimodality and life stage. Multimodals (defined as users of car, bicycle and public transport) are much more prevalent among students (who will mostly not be car drivers) with a 26% share. Their share decreases to 8% among young persons without children and is even lower for those in households with children, but is 9% for retirees.

Nobis (2007) found monomodal car use is more likely for men, 36–50 year olds, full-time employees and those with young children. She estimated logistic regression models using MiD data for the probability of belonging to four multimodal groups (car-bicycle, car-public transport, bicycle-public transport, three modes). She found lower probability of belonging to all four groups for being in employment, greater car availability and presence of young children. Larger size of residential population, higher income and younger age increased probability of belonging to a multimodal group involving public transport. After accounting for other factors, females were less likely to be in the three groups involving bicycle use.

Buehler and Hamre (in press-b) used multinomial logistic regression with NHTS data for the US to identify predictors of belonging to the three multimodality groups: (1) monomodal car users (2) multimodal car users, (3) WBT only users. The groups were defined based on week level data. They estimated a variant model for four groups, distinguishing between multimodal car users making 1–6 trips by WBT modes and multimodal car users making 7 or more trips by WBT modes. Results showed that the probability of being a multimodal car user was increased for those that are younger, male, do not have children, more highly educated, have higher income, not in employment, have fewer cars, live in high population density area and have rail access. Considering the full set of results, they suggest that multimodal car users are between monomodal car users and WBT only users in characteristics and that there is a continuum of mobility types between monomodal car users at one extreme and WBT only users at the other end (via multimodal car users making 1–6 WBT trips and multimodal car users making 7 or more WBT trips). This indicates the merit of exploring modal variability further using continuous indicators such as that used by Kuhnimhof (2009).

Buehler and Hamre (in press-b) compared the extent of multimodality in US between 2001 and 2009 and found a significant shift away from monomodal car use towards multimodal car use and WBT only use. This indicates a potentially important transition towards reduced reliance on the car in the US. A similar trend of reduced reliability on the car of younger drivers has been noted over this period in Germany by Kuhnimhof et al. (2012).

Whilst, the above findings provide some informative insights on socio-demographic and spatial determinants of modal variability in Germany and US it would be useful to examine this in other contexts and to explore a wider range of determinants.

2.3. Modality styles

Modal variability can also be studied by considering predispositions towards using different modes, rather than actual usage. Lavery et al. (2013) referred to predispositions towards using different modes as 'modality styles' in an investigation of perceptions of transport modes among respondents to a survey at McMaster University, Canada. They found an increase in the number of perceived mode options for those that were male, staff rather than student and had shared car with other household members. Higher density and perceptions of a safe environment for cycling increased the number of perceived mode options. Perceptions of travel experience were found to be important with preferring to travel alone and viewing travel time as wasted time decreasing the number of perceived mode options, while viewing travel time as transition time and viewing travel time as tiresome increased number of perceived mode options. Also a willingness to limit auto travel increased number of perceived mode options, suggesting a pro-environmental orientation influences likelihood of being multimodal.

Vij et al. (2013) operationalized the concept of modality style using latent class modelling for work tours and non-work tours of 117 individuals from the Mobidrive data. Where multiple modes were used, the mode was defined as the mode that covered the most motorised distance. The model simultaneously inferred modality style class and class-specific coefficients for a mode choice model (which considered auto, transit, bicycle, walk). The best fitting model included three classes with these identified as habitual drivers, time sensitive multimodals (probability of belonging to this class was higher for females, those not working, transit pass owners) and time insensitive multimodals (probability of belonging to this class was higher for those not living alone, transit pass owners).

Diana and Mokhtarian (2009a) also segmented a sample of travellers into modality styles. They used a data set for San Francisco Bay Area collected in 1998 ($n = 1904$) which collected not only objective and subjective measurements but also desired amounts of mobility by different modes and overall. Multimodality indices were produced for actual, perceived and desired use of different modes which took the value 0 where only one mode was used/considered and 1 where all modes are used/considered equally. The indices were calculated based on information theory and using an entropy formula. A cluster analysis was performed and the preferred solutions involved four clusters: (1) light travellers/monomodal car users; (2) moderate travellers/multimodal but auto dominated; (3) light travellers/multimodal but auto dominated; and (4) heavy travellers/multimodal but auto dominated. The authors emphasised the value for policy of identifying segments that differ according to modal mix and have different preferences for changing their use of modes.

2.4. Research gaps and opportunities

The review has shown that travel behaviour in general exhibits a moderately high repetition over a period of a week and longer but that multiple modes are used by most people in their overall travel activities and even for specific types of travel such as commuting many people vary their mode. The gaps in knowledge addressed by the paper are set out next. Firstly, data used in previous studies have not allowed the full use of different modes in everyday travel to be taken into account. This has been due to broad definitions of modes (such as public transport or active transport), whereas other research has revealed different determinants for different public transport options (e.g. bus and rail) or active transport options (e.g. walking and cycling). By considering more specific mode categories (e.g. bus, rail) this paper offers a comprehensive treatment of the subject. The research reported has mostly used trips or tours, whereas using trip stages as the unit of analysis allows account to be taken of secondary modes in a trip (e.g. use of taxi as access mode for rail trip). Secondly, simplified categories have been used to group people by modal variability behaviour without recognising the range of variation in mode use. This paper has an emphasis on continuous indicators which is intended to enable a complementary picture to be obtained of modal variability to that based on discrete categories. Thirdly, only limited factors have been considered in explaining the modal variability of individuals. In this paper we put forward a wider set of explanatory variables based on theoretical considerations. Finally, modal variability has so far been examined in the relatively polarised contexts of Germany, where car use is less dominant, and the United States, where car use is highly dominant. We extend the empirical evidence base to Great Britain.

3. Method

3.1. Data

We used data from the National Travel Survey (NTS) of Great Britain which has been running since 1965/66 (Rofique et al., 2011). The sample is designed to be a representative sample of private households in Great Britain. The survey is administered through a face-to-face interview with household members followed by the request for each member to complete a seven-day travel diary. We used data from 2010 when diaries were obtained for 19,072 individuals from 8097 households. 60% of households selected to take part in the survey fully co-operated.

The data is organised into separate files for *Households*, *Vehicles*, *Individuals*, *Days*, *Journeys* and *Stages*. The *Journeys* file contains a separate record for each trip or journey (defined as a one-way course of travel from one place to another with a single main purpose) and the *Stages* file contains a separate record for each stage. A trip can have more than one stage when there is a change in the mode of transport used during the trip. We used the *Stages* file for our analysis of modal variability, since it contains a full record of the modes used during the survey week.

Weights are available in NTS to address short walks (at least 50 yards and less than one mile) only being requested to be recorded in the travel diaries for the last of the seven days and drop-off in trip/stage reporting over course of survey week. We carried out the following series of steps to prepare the data for analysis of modal variability:

1. Using the *Stages* file, we calculated for each individual the total number of stages, distance travelled, time spent travelling recorded by eight categories of mode of transport (walk,[2] bicycle, car driver, car passenger, bus,[3] rail,[4] taxi, other[5]) (with weighting applied for short walks and drop-off in reporting).
2. The information derived above from the *Stages* file was appended to the *Individuals* file.
3. Various indicators of modal variability were calculated for each individual:
   - Total number of modes used;
   - Percentage of travel (in term of number of stages) by each mode category;

[2] Walk trips of less than 46 m (50 yards) excluded in NTS.
[3] Bus includes local and non-local (coach) services.
[4] Rail includes London underground and surface rail.
[5] Other includes motorcycle, other private (mostly private hire bus) and other public.

- Primary, secondary, trinary, etc. mode (in cases of ties both modes were assigned the 'lowest number', for example twice 'primary mode');
- Difference in proportion of stages between primary and secondary mode; and
- Herfindahl–Hirschman Index (HHI) (defined in Section 3.3.2).

Our analyses were restricted to adults (aged 16 and over) ($n = 15{,}207$) and excluded those that recorded no trips in the diary week ($n = 600$). For the regression analyses reported in Section 4 we randomly selected one adult per household to avoid including respondents in the analysis with shared unobserved characteristics (resulting in $n = 7897$).

3.2. Mode usage

Before considering modal variability, Table 1 gives an overview of the number of modes used by the survey respondents (left part of table).[6] 63.6% of the respondents drove a car and 52.5% of the respondents had been a car passenger. The other modes were used to a more limited extent. Less than half (43.0%) of the respondents walked and only 4.5% indicated to have cycled at all.

The right hand column shows the percentage of respondents for whom a mode was the primary mode if they used it at all in their modal mix. For 79.5% of individuals who drove a car it was their primary mode. For 47.8% of individuals who walked during the survey week, walking was their main form of transport. Bus users, rail users and cyclists had lower percentages of individuals using the respective modes as their main form of transport.

3.3. Modal variability indicators

3.3.1. Mode combinations

Table 2 shows the prevalence of combinations of modes used based on a three category definition of modes: private transport (car driver, car passenger); public transport (bus, rail, taxi, other); and active transport (walk, bicycle). 44% of the respondents only used one form of transport (private transport, public transport or active transport) and 56% used a combination of these. Car is the largest monomodal group, and dominates in the multimodal groups, but all modal combinations are present in the population.

3.3.2. Continuous indicators

Our focus is on continuous indicators of individual modal variability. We draw on previous research to specify a set of four indicators to measure modal variability (see Table 3). These indicators provide different perspectives on the phenomenon of modal variability. Two indicators are based on the Herfindahl–Hirschman Index (HHI) with the other indicators being the difference in proportion between the most commonly used mode (primary mode) and second most commonly used mode (secondary mode), and the total number of modes used.

The HHI is a commonly used measure for market concentration (Rhoades, 1993).[7] In the context of our study, it is calculated for each individual as the sum of the squared values of the share of each mode option of the total number of stages – see Eq. (1). The squaring of mode shares leads to the HHI giving a high importance to modes with large shares. Values for the HHI range from $1/N$ to one, where N is the number of mode options, but the HHI can be normalized to range from zero to one – see Eq. (2). The normalised HHI values represent the equality of distribution of mode choices across the options with a value of zero representing equality (balanced distribution) and a value of one representing concentration of mode choices on one mode option. Intuitively, this provides an appropriate way of measuring the balance of use of mode options.

$$H = \sum_{i=1}^{N} s_i^2 \tag{1}$$

$$H^* = \frac{(H - \frac{1}{N})}{(1 - 1/N)} \tag{2}$$

The normalised HHI values were generated for eight mode categories (as identified in Section 3.1) and for three mode categories: private transport (car driver, car passenger); public transport (bus, rail, taxi, other); and active transport (walk, bicycle). The HHI for eight mode categories considers a large number of mode categories and captures the balance in usage across these mode categories. However, some of the eight modes are relatively little used (rail, bicycle, taxi, other) and their use and non-use will disproportionately affect the value of the HHI. The HHI for three modes is less affected by the

[6] The data has not been weighted for non-response of adult diary respondents and is reasonably representative of the population (60% response rate).

[7] DOJ (2010) recommends use of HHI to assess market concentration when reviewing potential mergers and their threats to competition within a relevant market. Other measures of market concentration/diversity include concentration ratio, entropy index and Gini coefficient. There is no concensus in the literature on which measure is preferable and this will depend on the context and the particular data under analysis. A variant of HHI was devised by Kuhnimhof (2009) but was not found to be appropriate to our data. Their MIX index was designed to account for the problem of a small number of observations per individual (tours) compared to choice options (modes). We calculated MIX values for our data and found the distribution of values was 'lumpy' with this being a consequence of the index giving greater emphasis to the number of modes used than the frequency of use of modes. This results from it being designed to be used for integer values which is not applicable in our case where we have fractional values for number of stages (after applying weighting).

Table 1
Mode usage and primary mode.

	Mode used (at all)		Number/percentage of individuals that use a mode who use it as their primary mode	
	n	%	*n*	%
Car driver	9283	63.6	7381	79.5
Car passenger	7663	52.5	2402	31.4
Bus	3872	26.5	1149	29.7
Rail	1792	12.3	252	14.1
Walk	6280	43.0	3000	47.8
Bicycle	664	4.5	188	26.4
Taxi	1590	10.9	168	10.6
Other	817	5.6	199	24.4
Number of respondents	14,607			

Table 2
Mode combinations used (based on three categories).

	n	%
Private transport only	5518	37.8
Public transport only	661	4.5
Active transport only	290	2.0
Private and public transport	1857	12.7
Private and active transport	2919	20.0
Active and public transport	854	5.9
Private, public and active transport	2508	17.2
Total	14,607	

Table 3
Overview of indicators of variability and number of stages in total sample and analysis sample.

	Individuals in total sample			Individuals in analysis sample		
	Mean	Std. dev.	*n*	Mean	Std. dev.	*n*
Herfindahl–Hirschman Index – 8 modes	0.66	0.27	14,607	0.66	0.27	7897
Herfindahl–Hirschman Index – 3 modes	0.67	0.33	14,607	0.67	0.33	7897
Difference in proportion between primary and secondary mode	0.60	0.35	14,607	0.61	0.35	7897
Number of modes used	2.19	1.08	14,607	2.18	1.08	7897
Number of stages	17.34	9.85	14,607	16.96	9.86	7897

use/non-use of less commonly used modes and shows whether there is balanced use between private transport, public transport and active transport. The difference in mode share as a proportion between the primary and secondary mode indicates the extent of dependency on one mode (from the eight mode categories). The number of modes used provides an overall indication of the extent of modal variability but takes no account of the frequency of use of different modes.

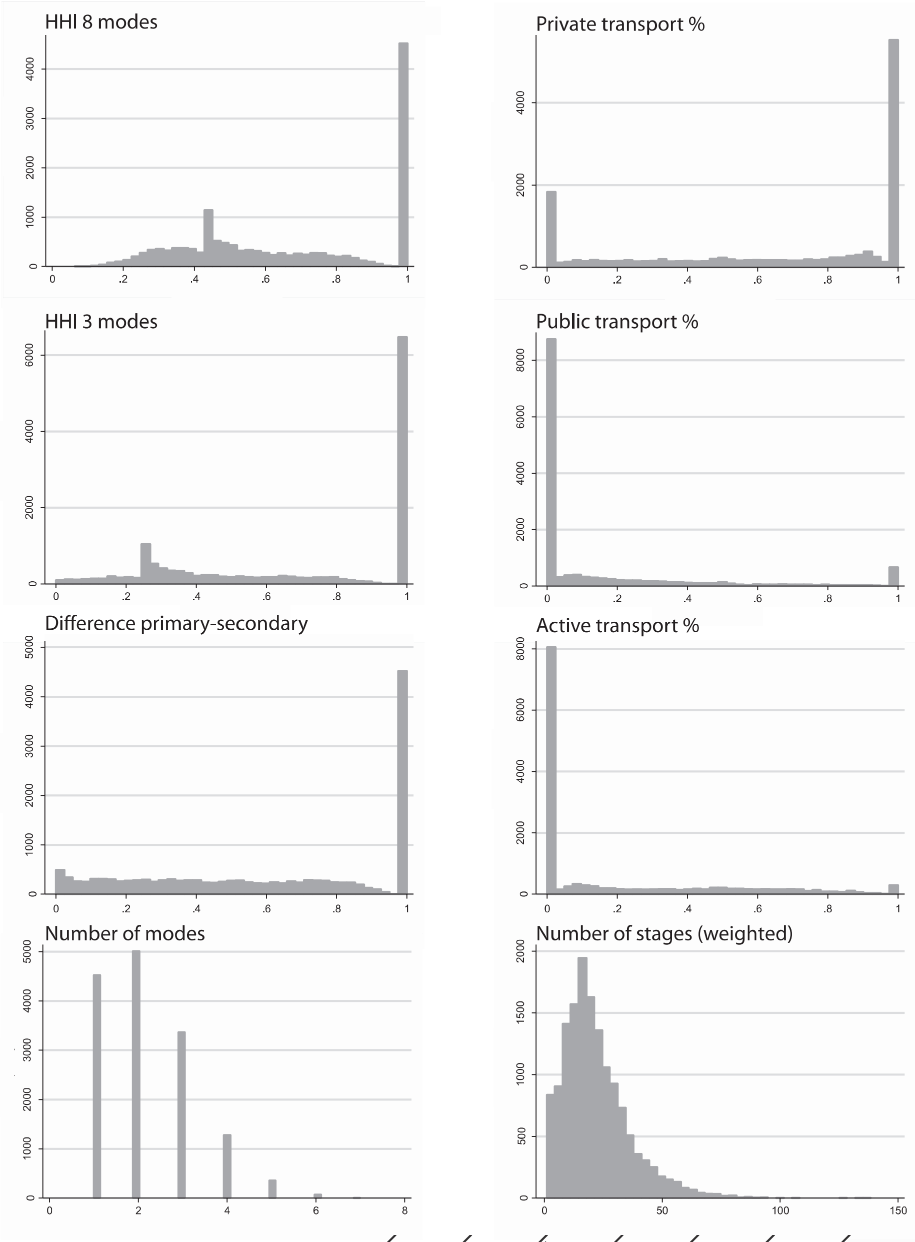
Fig. 1 presents plots of the distributions observed for the indicators, as well as the distributions for the mode share of private, public and active transport and total number of stages. Correlations are also shown for these variables at the bottom of Fig. 1. The distributions for two HHIs show a high number of extreme '1' values where only one mode is used by respondents and a relatively even spread of values lower than this, except for modest spikes at about 0.5 for HHI for 8 mode categories and 0.25 for HHI for 3 mode categories. These arise where there are two modes that dominate and have similar levels of usage.

The distribution for the difference between use of primary and secondary mode shows an even distribution of values below 1 and the distribution for the number of modes used shows most respondents used 1, 2 or 3 modes (of 8 mode categories considered). The indicators of modal variability are moderately correlated to the proportion of use of each mode category and show a strong correlation with each other.

Overall, the distributions are quite even across the range from zero to one for proportional indicators (except with peak values at one (representing single mode users)) and this reinforces the value of using the continuous variable indicators to analyse modal variability further.

3.4. Explanatory variables

The literature review showed that the association between individual modal variability and explanatory variables has been tested in a small number of studies but mostly using discrete indicators for modal variability such as multimodal



	HHindex 8 modes	HHindex 3 modes	Difference between primary and secondary mode	Number of modes use	% by private transport	% by public transport	% by active transport
HHindex 8 modes	1.00						
Hhindex 3 modes	0.84	1.00					
Difference between primary and secondary mode	0.96	0.79	1.00				
Number of modes use	-0.84	-0.73	-0.70	1.00			
% by private transport	0.44	0.54	0.41	-0.39	1.00		
% by public transport	-0.22	-0.21	-0.21	0.18	-0.66	1.00	
% by active transport	-0.37	-0.52	-0.34	0.34	-0.70	-0.08	1.00

n=14607

Fig. 1. Distributions and correlations for modal variability indicators.

Table 4
Overview of respondents in survey and analysed sample.

		Adults in survey		Adults in analysis sample	
		%	*n*	%	*N*
		100	14,607	100	7897
Capability constraints					
Mobility difficulties	No (ref)	87.8	12,827	85.6	6758
	Yes	12.1	1770	14.4	1133
	Missing values (MV)	0.1	10	0.1	6
Driving licence status[a]	No or provisional licence	26.4	3851	26.8	2114
	Yes (ref)	73.1	10,680	72.8	5752
	MV	0.5	76	0.4	31
Coupling constraints					
Gender	Male (ref)	47.7	6961	46.3	3658
	Female	52.3	7646	53.7	4239
	MV	0.0	0		
Ethnicity	White (ref)	90.5	13,215	91.7	7241
	Other	9.5	1385	8.2	650
	MV	0.0	7	0.1	6
Age	16–19	6.0	875	3.8	297
	20–29 (ref)	12.5	1830	10.9	862
	30–39	16.0	2333	16.2	1281
	40–49	18.9	2762	17.8	1406
	50–59	15.1	2199	14.5	1145
	60–69	16.4	2395	17.6	1393
	70 and above	15.2	2213	19.2	1513
	MV	0.0	0		
Having young child(ren) (<16) in the household	no (ref)	68.8	10,055	72.1	5690
	Yes	31.2	4552	27.8	2207
	MV	0.0	0		
Economic status	Full time (ref)	42.4	6187	40.3	3184
	Part time	15.2	2217	14.3	1126
	Unemployed	3.2	469	2.8	220
	Retired	28.0	4093	33.1	2610
	Student	4.3	634	2.9	232
	Home/other	6.9	1007	6.7	525
	MV	0.0	0		
Self-employed	No (ref)	89.4	13,054	89.2	7041
	Yes (current or last job)	10.6	1553	10.8	856
	MV	0.0	0		
Working from home	No (ref)	87.4	12,766	87.6	6918
	Yes	12.6	1841	12.4	979
	MV	0.0	0		
Working at more than one location	No (ref)	87.4	12,766	87.6	6918
	Yes	12.6	1841	12.4	979
	MV	0.0	0		
Authority constraints					
Settlement type	London Boroughs (ref)	12.2	1779	12.0	947
	Met built-up areas	14.6	2135	14.6	1156
	Other urban over 250 K	14.1	2057	14.2	1119
	Urban over 25–250 K	27.6	4028	27.9	2199
	Urban over 10–25 K	7.0	1019	7.1	564
	Urban over 3–10 K	8.4	1232	8.4	662
	Rural	16.1	2357	15.8	1250
	MV	0.0	0		
Housing type	Detached (ref)	28.5	4160	26.0	2053
	Semi-detached or terraced	57.4	8385	56.7	4477
	Flat or other	14.1	2062	17.3	1367
	MV	0.0	0		
Housing tenure	Owns/buying (ref)	73.8	10,775	70.9	5594
	Rents and other	26.2	3831	29.2	2302
	MV	0.0	1	0.0	1

Table 4 (*continued*)

		Adults in survey		Adults in analysis sample	
		%	*n*	%	*N*
		100	14,607	100	7897
Bus accessibility[b]	Good	36.1	5268	36.2	2862
	Medium	29.8	4358	29.3	2312
	Poor (ref)	34.1	4981	34.5	2723
	MV	0.0	0		
Rail accessibility[c]	Good	35.2	5147	35.5	2805
	Medium	30.3	4427	30.3	2390
	Poor (ref)	34.5	5033	34.2	2702
	MV	0.0	0		
Household income	Less than £25,000 (ref)	42.4	6191	50.3	3975
	£25,000–£49,999	31.7	4632	29.2	2309
	£50,000 and over	25.9	3784	20.4	1613
	MV	0.0	0		
Socio-economic status	A (highest)	25.5	3725	23.6	1861
	B	35.9	5242	38.2	3017
	C	21.7	3173	20.7	1632
	D&E (lowest) (ref)	13.3	1935	13.8	1088
	MV	3.6	532	3.8	299
Car driver status	Main driver of household car (ref)	57.1	8342	57.2	4515
	Not main driver of household car	12.0	1754	10.2	803
	Household car but non driver	13.2	1925	9.7	762
	Driver but no household car	4.3	628	5.6	440
	Non driver and no household car	13.4	1958	17.4	1377
	MV	0.0	0		
Bicycle ownership	Yes own myself	37.1	5426	34.9	2752
	No, I do not own myself (ref)	62.8	9171	65.1	5140
	MV	0.1	10	0.1	5
Public transport pass	Old age pensioner (OAP) with bus pass	25.0	3649	29.3	2317
	Season ticket holder	5.2	760	4.9	384
	No pass (ref)	63.6	9285	60.0	4741
	Other	6.3	913	5.8	455
	MV	0.0	0		

[a] Driving license status is captured by the car driver status variable where the categories 'Household car but non driver' and 'non driver and no household car' represent individuals without a driving licence. It is therefore redundant in a regression model containing car driver status and has been excluded from the models presented in the paper.

[b] Bus accessibility is constructed based on the service level and the accessibility. For bus accessibility 'good' indicates a walking time of less than 7 min and a service at least every 15 min and 'medium' indicates a walking time of less than 7 min and a service at least every 30 min (but not every 15 min).

[c] Rail accessibility is constructed based on the service level and the accessibility. For rail accessibility 'good' corresponds with access time by foot/bus of less than 14 min to a station (to either train or light rail) and frequent rail service the entire day and 'medium' with an access time of less than 27 min (but not less than 14 min) to a station and frequent rail service the entire day.

car-public transport users and only tested using a limited number of explanatory variables. Pas (1987) theorised that intrapersonal variability in trip making is influenced by motivations and constraints for travel. According to Hägerstrand (1970), individuals are limited in their spatial (travel) behaviour by three main types of constraints: capability, coupling and authority constraints. We conceive that modal variability is influenced by similar constraints. We conceptualize the following contextual factors as possible explanatory variables (see Table 4 for descriptive statistics for these variables):

Capability constraints:

- Physical mobility constraints (e.g. mobility difficulties, driving licence possession) – these influence capabilities of participating in certain activities as well as the ability to use certain modes.

Coupling constraints:

- Social role constraints (e.g. gender, ethnicity, age, having a child in the household) – these influence role responsibilities, activity requirements and time availability.
- Work constraints (e.g. economic status, self-employment, working location) – these influence the amount and pattern of commuting required and the time remaining to participate in other activities which may influence the opportunity to use multiple modes.

Authority constraints:

- Accessibility constraints (e.g. settlement type, housing type, housing tenure, access to public transport) – these influence distance required to travel to destinations and physical context for these journeys, as well as transport options available.

- Economic constraints (e.g. income, social-economic status) – these influence economic resources available for mobility.
- Mobility resource constraints (e.g. car access, having a public transport pass/season ticket, bicycle ownership) – these influence opportunity and commitment to use particular transport modes.

3.5. Model specification

The three scalar and one integer modal variability indicators (HHI for 8 modes; HHI for 3 modes; difference in mode share as a proportion between the primary and secondary mode; number of modes used) were selected as dependent variables for multiple regression modelling.

The number of modes used is a count variable and Poisson models were estimated for this indicator. The other three indicators take fractional values between zero and one. Fractional response models have been developed for handling proportions data in which zero and one values may appear as well as intermediate values (Papke and Wooldridge, 1996). We have used the fractional logit model which entails a logit transformation of the response variable and assumes the response variable follows the binomial distribution. Poisson and fractional logit models were estimated using Stata.[8]

We estimated 'full' models containing all but one of the explanatory variables shown in Table 4. Having a driver licence was excluded as this was entirely captured by car driver status. Five sensitivity tests were performed: (s1) including all adult respondents (thus not randomly selecting one adult per household); (s2) only including individuals with five stages or more; (s3) excluding socio-economic status (as this variable has a substantial number of cases with missing values); (s4) including the number of stages as a covariate; (s5) separate models with the three different types of constraint. The coefficient estimates in the full models for each indicator were also compared to unadjusted estimates for the coefficients (i.e. testing only one independent variable at a time).

4. Results

This section provides an account of the results of the regression analyses which are presented in Table 5. Reported are the coefficients (coef.) with 95% confidence intervals (95%CI) and significance levels. Also presented are the average marginal effects (dy/dx) for the fractional logit models and incidence-rate ratios (IRR) for the Poisson model.

An average marginal effect of 0.1 for a particular variable category indicates that belonging to that category predicts a + 0.1 higher score on the outcome. The average marginal effect is calculated (by default) in Stata for categorical variables by taking the category of interest (e.g. female) and setting all cases in the sample data to the category of interest (female) and finding the mean change in the outcome variable compared to all cases being set to reference category (male). An incidence-rate ratio in a Poisson model represents the factor by which the outcome variable is predicted to increase for the category of interest compared to the reference category.

Goodness of fit (GoF) statistics of the full models are included in the lower part of Table 5. The statistics are log pseudo likelihood, AIC (Akaike information criterion) and BIC (Bayesian information criterion) for fractional logit models and log pseudo likelihood and pseudo R^2 for Poisson model. They are also presented for empty models which contain no independent variables. The difference in log pseudo likelihood value between the empty models and full models is significant in all models.

4.1. HHI for eight mode categories

Having mobility difficulties predicts a higher HHI value with an average predicted increase of 0.1. This indicates that this capability constraint reduces modal variability.

Being female (social role coupling constraint) strongly predicts increased modal variability with an average predicted decrease of HHI by 0.05. In contrast with the unadjusted model, non-white ethnicity is predicted to decrease modal variability. Being between 60 and 70 years old, or over 70 years old, compared to being between 20 and 29 decreases modal variability. Of the work coupling constraints, compared to working full-time, working part-time and being retired predict increased modal variability. Being self-employed and workplace location are not significantly associated with the level of modal variability.

Many authority constraints are significantly associated with modal variability. As regards accessibility constraints, living in a smaller settlement predicts decreased modal variability compared to living in London, and in general the smaller the settlement size the lower the level of modal variability. Housing type and tenure are not significantly associated with differences in modal variability. Bus and rail accessibility also do not predict differences in modal variability for the HHI for eight modes. With economic constraints, a household income of at least £50,000 per year is associated with higher levels of modal variability compared to households earning less than £25,000, but belonging to a higher socioeconomic class shows no significant association with modal variability. The variables representing access to mobility resources are statistically significant at 99.9% level. Not being the main driver, not having a car, having a public transport pass/season ticket and owning a bicycle all predict higher levels of modal variability.

[8] Fractional logit models were estimated using Stata command of the form: *glm y x1 … xK, fam(bin) link(logit) robust.*

Table 5
Predictors of modal variability.

		HHI 8 modes		HHI 3 modes		Difference between primary and secondary mode		Number of modes used	
		Coef. (95% CI)	dy/dx	Coef. (95% CI)	dy/dx	Coef. (95% CI)	dy/dx	Coef. (95% CI)	IRR
Capability constraints									
Mobility difficulties	No (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Yes	**0.46 (0.29, 0.63)*****	**0.10**	**0.59 (0.42, 0.76)*****	**0.12**	**0.48 (0.32, 0.64)*****	**0.11**	**−0.17 (−0.22, −0.12)*****	**0.84**
Coupling constraints									
Gender	Male (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Female	**−0.22 (−0.32, −0.11)*****	**−0.05**	−0.06 (−0.17, 0.05)	−0.01	**−0.22 (−0.32, −0.11)*****	**−0.05**	**0.07 (0.04, 0.11)*****	**1.08**
Ethnicity	White (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Other	**0.24 (0.04, 0.44)***	**0.05**	**0.26 (0.06, 0.46)***	**0.05**	**0.21 (0.02, 0.41)***	**0.05**	**−0.14 (−0.20, −0.08)*****	**0.87**
Age	16–19	0.11 (−0.25, 0.46)	0.02	0.18 (−0.18, 0.53)	0.04	0.11 (−0.24, 0.46)	0.02	−0.04 (−0.15, 0.07)	0.96
	20–29 (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	30–39	0.05 (−0.15, 0.24)	0.01	−0.02 (−0.22, 0.18)	0.00	0.04 (−0.15, 0.23)	0.01	−0.01 (−0.07, 0.05)	0.99
	40–49	0.09 (−0.11, 0.28)	0.02	−0.02 (−0.22, 0.18)	0.00	0.08 (−0.11, 0.27)	0.02	−0.03 (−0.09, 0.03)	0.97
	50–59	0.09 (−0.12, 0.30)	0.02	−0.07 (−0.28, 0.14)	−0.01	0.02 (−0.18, 0.23)	0.01	−0.06 (−0.13, 0.00)	0.94
	60–69	**0.45 (0.16, 0.75)****	**0.10**	**0.48 (0.18, 0.79)****	**0.10**	**0.42 (0.15, 0.70)****	**0.10**	**−0.18 (−0.28, −0.09)*****	**0.83**
	70 and above	**0.64 (0.32, 0.97)*****	**0.14**	**0.68 (0.34, 1.01)*****	**0.14**	**0.62 (0.31, 0.93)*****	**0.14**	**−0.28 (−0.38, −0.18)*****	**0.75**
Having young child(ren) (<16) in the household	No (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Yes	0.06 (−0.08, 0.20)	0.01	0.03 (−0.11, 0.17)	0.01	0.07 (−0.07, 0.20)	0.01	−0.02 (−0.06, 0.02)	0.98
Economic status	Full time (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Part time	**−0.24 (−0.40, −0.08)****	**−0.05**	**−0.27 (−0.43, −0.10)****	**−0.05**	**−0.25 (−0.41, −0.10)****	**−0.06**	**0.08 (0.03, 0.13)****	**1.09**
	Unemployed	−0.26 (−0.58, 0.05)	−0.06	**−0.38 (−0.69, −0.07)***	**−0.08**	−0.24 (−0.55, 0.07)	−0.05	0.08 (−0.02, 0.18)	1.09
	Retired	**−0.22 (−0.43, −0.01)***	**−0.05**	**−0.27 (−0.49, −0.06)***	**−0.06**	**−0.23 (−0.43, −0.03)***	**−0.05**	**0.07 (0.00, 0.13)***	**1.07**
	Student	−0.33 (−0.72, 0.05)	−0.07	−0.36 (−0.75, 0.03)	−0.07	**−0.39 (−0.77, 0.00)***	**−0.09**	0.09 (−0.03, 0.21)	1.10
	Home/other	−0.11 (−0.34, 0.12)	−0.02	−0.15 (−0.39, 0.08)	−0.03	−0.12 (−0.34, 0.10)	−0.03	0.02 (−0.06, 0.09)	1.02
Self-employed	No (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Yes (current or last job)	0.12 (−0.06, 0.30)	0.03	0.08 (−0.11, 0.26)	0.02	0.12 (−0.05, 0.30)	0.03	−0.05 (−0.11, 0.00)	0.95
Working from home	No (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Yes	−0.03 (−0.20, 0.13)	−0.01	−0.08 (−0.24, 0.09)	−0.02	−0.03 (−0.19, 0.13)	−0.01	0.03 (−0.02, 0.08)	1.03
Working at more than one location	No (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Yes	−0.06 (−0.38, 0.26)	−0.01	−0.02 (−0.35, 0.32)	0.00	−0.05 (−0.36, 0.27)	−0.01	0.02 (−0.08, 0.12)	1.02
Authority constraints									
Settlement type	London Boroughs (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Met built-up areas	**0.21 (0.01, 0.41)***	**0.05**	**0.25 (0.05, 0.46)***	**0.05**	**0.22 (0.02, 0.41)***	**0.05**	**−0.09 (−0.15, −0.03)****	**0.91**
	Other urban over 250 K	0.19 (−0.02, 0.39)	0.04	0.18 (−0.02, 0.39)	0.04	0.17 (−0.03, 0.37)	0.04	**−0.10 (−0.16, −0.03)****	**0.91**
	Urban over 25–250 K	**0.28 (0.09, 0.46)****	**0.06**	**0.28 (0.09, 0.47)****	**0.06**	**0.27 (0.09, 0.45)****	**0.06**	**−0.13 (−0.19, −0.07)*****	**0.88**
	Urban over 10–25 K	**0.35 (0.09, 0.60)****	**0.07**	**0.36 (0.10, 0.62)****	**0.07**	**0.36 (0.11, 0.61)****	**0.08**	**−0.17 (−0.25, −0.09)*****	**0.84**
	Urban over 3–10 K	**0.35 (0.10, 0.60)****	**0.08**	**0.34 (0.09, 0.59)****	**0.07**	**0.35 (0.10, 0.59)****	**0.08**	**−0.16 (−0.24, −0.09)*****	**0.85**
	Rural	**0.36 (0.13, 0.60)****	**0.08**	**0.46 (0.22, 0.70)*****	**0.10**	**0.34 (0.11, 0.57)****	**0.08**	**−0.19 (−0.27, −0.12)*****	**0.82**
Housing type	Detached (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Semi-detached or terraced	−0.03 (−0.17, 0.10)	−0.01	−0.13 (−0.26, 0.01)	−0.03	−0.05 (−0.17, 0.08)	−0.01	0.01 (−0.03, 0.05)	1.01
	Flat or other	−0.16 (−0.35, 0.03)	−0.04	**−0.30 (−0.49, −0.11)****	**−0.06**	−0.16 (−0.35, 0.02)	−0.04	**0.06 (0.00, 0.12)***	**1.06**
Housing tenure	Owns/buying (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Rents and other	0.11 (−0.03, 0.24)	0.02	0.07 (−0.07, 0.20)	0.01	0.11 (−0.02, 0.24)	0.02	−0.04 (−0.08, 0.00)	0.96
Bus accessibility	Good	−0.02 (−0.16, 0.11)	−0.01	−0.02 (−0.16, 0.12)	0.00	−0.01 (−0.14, 0.12)	0.00	0.01 (−0.04, 0.05)	1.01

(*continued on next page*)

Table 5 (*continued*)

		HHI 8 modes		HHI 3 modes		Difference between primary and secondary mode		Number of modes used	
		Coef. (95% CI)	dy/dx	Coef. (95% CI)	dy/dx	Coef. (95% CI)	dy/dx	Coef. (95% CI)	IRR
	Medium	0.00 (−0.13, 0.14)	0.00	0.00 (−0.13, 0.14)	0.00	0.01 (−0.12, 0.14)	0.00	0.00 (−0.04, 0.04)	1.00
	Poor (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Rail accessibility	Good	−0.06 (−0.20, 0.07)	−0.01	−0.09 (−0.22, 0.05)	−0.02	−0.06 (−0.19, 0.07)	−0.01	0.04 (−0.01, 0.08)	1.04
	Medium	0.00 (−0.13, 0.13)	0.00	−0.05 (−0.19, 0.08)	−0.01	0.00 (−0.12, 0.13)	0.00	0.00 (−0.04, 0.05)	1.00
	Poor (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Household income	Less than £25,000 (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	£25,000–£49,999	−0.09 (−0.22, 0.04)	−0.02	−0.02 (−0.15, 0.11)	0.00	−0.11 (−0.24, 0.02)	−0.03	0.03 (−0.01, 0.07)	1.03
	£50,000 and over	**−0.31 (−0.46, −0.15)*****	**−0.07**	**−0.23 (−0.39, −0.07)****	**−0.05**	**−0.32 (−0.47, −0.16)*****	**−0.07**	**0.12 (0.07, 0.17)*****	**1.13**
Socio-economic status	A (highest)	−0.16 (−0.34, 0.02)	−0.03	−0.11 (−0.29, 0.07)	−0.02	−0.13 (−0.30, 0.05)	−0.03	**0.10 (0.04, 0.16)*****	**1.11**
	B	−0.13 (−0.29, 0.02)	−0.03	−0.16 (−0.31, 0.00)	−0.03	−0.13 (−0.28, 0.03)	−0.03	**0.08 (0.03, 0.13)****	**1.09**
	C	0.02 (−0.15, 0.20)	0.00	0.07 (−0.11, 0.25)	0.01	0.03 (−0.14, 0.20)	0.01	−0.01 (−0.07, 0.04)	0.99
	D&E (lowest) (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Car driver status	Main driver of household car (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Not main driver of household car	**−0.25 (−0.42, −0.09)****	**−0.05**	**−0.34 (−0.51, −0.18)*****	**−0.07**	**−0.25 (−0.41, −0.09)****	**−0.06**	**0.09 (0.04, 0.14)*****	**1.10**
	Household car but non driver	−0.12 (−0.30, 0.07)	−0.02	**−0.65 (−0.83, −0.46)*****	**−0.13**	−0.15 (−0.33, 0.03)	−0.03	0.01 (−0.05, 0.07)	1.01
	Driver but no household car	**−0.39 (−0.62, −0.17)****	**−0.08**	**−0.57 (−0.80, −0.35)*****	**−0.12**	**−0.42 (−0.65, −0.20)*****	**−0.10**	**0.11 (0.04, 0.18)****	**1.12**
	Non driver and no household car	**−0.33 (−0.50, −0.17)*****	**−0.07**	**−0.61 (−0.77, −0.44)*****	**−0.13**	**−0.37 (−0.53, −0.21)*****	**−0.08**	**0.10 (0.04, 0.15)*****	**1.10**
Bicycle ownership	Yes own myself	**−0.28 (−0.39, −0.16)*****	**−0.06**	**−0.34 (−0.45, −0.22)*****	**−0.07**	**−0.26 (−0.37, −0.15)*****	**−0.06**	**0.13 (0.10, 0.17)*****	**1.14**
	No, I do not own myself (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Public transport pass	OAP with bus pass	**−0.64 (−0.87, −0.41)*****	**−0.14**	**−0.84 (−1.09, −0.60)*****	**−0.17**	**−0.66 (−0.88, −0.45)*****	**−0.15**	**0.24 (0.17, 0.31)*****	**1.27**
	Season ticket holder	**−0.68 (−0.91, −0.45)*****	**−0.15**	**−0.87 (−1.11, −0.64)*****	**−0.18**	**−0.84 (−1.07, −0.60)*****	**−0.19**	**0.24 (0.17, 0.31)*****	**1.27**
	No pass (ref)	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
	Other	**−0.31 (−0.53, −0.10)****	**−0.07**	**−0.47 (−0.68, −0.25)*****	**−0.10**	**−0.30 (−0.51, −0.09)****	**−0.07**	**0.15 (0.09, 0.22)*****	**1.16**
Constant		1.03 (0.67, 1.40)***		1.31 (0.94, 1.69)***		0.82 (0.47, 1.18)***		0.67 (0.56, 0.79)***	1.96
n		7589		7589		7589		7589	
		In full model:	In empty model:	In full model:	In empty model:	In full model:	In empty model:	In full model:	In empty model:
Log pseudo likelihood=		−3596.5	(−3756.14)	−3758.2	(−4006.54)	−4021.3	(−4202.58)	−11493.1	(−11793.28)
AIC[a]=		0.96	(1.00)	1	(1.06)	1.07	(1.11)		
BIC[a]=		−64486.94	(−64560.73)	−63129.17	(−63025.70)	−62991.96	(−63022.52)		
Pseudo r2								0.03	0.00

Values in bold are significant.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

[a] Higher BIC scores represent a better model fit. Lower AIC scores represent a better model fit.

4.2. HHI for three mode categories

We will only describe the main differences in the results compared to HHI for eight categories. Whereas the direction of effect is similar, women are not significantly more variable than men with the HHI for three modes. In contrast, living in a flat compared to detached housing, and owning a household car without being a driver (compared to being the main driver) predict a significant increase in variability in the model for HHI for three modes.

Some constraints are stronger predictors of variability measured with the HHI for three modes than eight modes. For example, the predicted effects for living in rural area and not being the main driver of the household car, being a driver but not having a household car and being a non-driver with no household car (compared to being the main driver of a household car) are more pronounced, whereas it is less pronounced for having a household income of at least £50,000.

The overall fit of the model is lower than HHI for 8 categories, but the difference in log pseudo likelihood value between the empty model and full model is greatest for HHI for 3 modes which suggests the independent variables provide the greatest explanation for this indicator.

4.3. Difference in proportion of use between primary and secondary mode

Again, differences are noted compared to the results for HHI for eight mode categories. Given the very high correlation between these outcome variables major differences are not expected. The only additional significant variable was being a student compared to working full-time: Being a student is predicted to reduce the difference between use of primary and secondary mode. Moreover, the predicted effect of being a driver but not owning a household car is associated with a reduced difference between primary and secondary mode at a 99.9% significance level instead of a 99% significance level for HHI for eight modes.

4.4. Number of modes used

Several variables are additional significant predictors of number of modes used compared to HHI for eight modes. Living in an urban area over 250 K compared to living in London predicts that fewer modes are used, whereas living in a flat compared to detached housing and being in the two highest socio-economic groups (A or B compared to D/E) are associated with more modes being used.

Some constraints are associated with modal variability with greater certainty (i.e. a higher significance level). For example, not being white, being between 60 and 69 and not being the main driver of the household car are associated with a difference in number of modes used at a 99.9% significance level. Additionally, all categories in the settlement type variable have stronger significance levels.

4.5. Sensitivity tests

The sensitivity tests showed that the results reported above are robust. The results for the full models when estimated for the entire NTS sample over 16 years old, for the sample restricted to individuals with five or more stages and with the inclusion of number of stages as an additional independent variable largely corresponded with the reported results. A few changes in significance levels were observed in variables that were borderline (non-)significant in the presented models. Changes in the direction of effect were rare and only occurred for coefficient estimates close to zero.

For example, in the estimation on the entire sample several variables were significant whereas they were not previously (which is expected with a larger sample size), including living in a urban area over 250 K, living in a flat, renting a home and owning a household car but not being a driver for HHI for eight modes; living in a urban area over 250 K and being in socio-economic group B for HHI for three modes; living in an metropolitan built-up area, living in a flat, owning a house and owning a household car but not being a driver for the difference between use of primary and secondary mode; being between 40 and 49 years old, being between 50 and 59 years old, being unemployed, being self-employed and renting a home for the number of modes used. Being unemployed was no longer significant for HHI for three modes and difference in use of primary and secondary mode.

The sensitivity test including number of stages as an additional independent variable showed that an increase in the number of stages predicted an increase in modal variability. This indicates that people who travel more have greater opportunity to use different modes (all else being equal), but the inclusion of this variable did not affect the estimates of other coefficients.

Compared to unadjusted models (testing one independent variable at a time) only the prediction for ethnicity changed in direction, i.e. whereas in full models being non-white predicted lower modal variability, the opposite effect was predicted in unadjusted models. This suggests that ethnicity is collinear with other explanatory variables (such as living in larger settlement) and once these other explanatory variables are included in the model it is found that ethnicity has the opposite predicted effect (i.e. non-whites living in large settlements have lower modal variability than whites).

4.6. Summary of results and interpretation

We first summarise results that are common across the indicators and then identify differences. Comparisons are made to results of other research but it should be reiterated that we opted to use continuous measures of modal variability, which capture the magnitude of variability in mode use, while most other research has used discrete indicators of modal variability (i.e. whether individuals are multimodal or not) and therefore differences can be expected.

Increased modal variability is predicted for individuals without mobility difficulties (capability constraint); females (for three of four indicators), white ethnicity and adults under 60 years of age (social role constraints); working part-time or being retired (work constraints); living in larger urban settlement (accessibility constraint); higher household income (economic constraint); not having car access, having public transport pass/season ticket and owning bicycle (mobility resource constraints).

As with findings for Germany (Nobis, 2007), but not US (Buehler and Hamre, in press-b), being female is associated with greater modal variability. This result applies after accounting for economic status and car access. One hypothesis is that females have more household responsibilities which require visiting a larger of different destinations and consequently making use of more transport modes. As with findings for US, but not Germany, older people are associated with lower modal variability. In the context of GB and US this could be explained by older people having difficulty in using certain modes (such as bicycles) due to unsupportive environments. Working full-time is associated with lower modal variability which was also found in Germany and US and can be explained by commuting travel tending to involve a single transport mode and working full-time leaving little time for other travel.

Larger urban settlements offer more destinations at a wider range of distances and more transport alternatives, so the finding that they predict greater modal variability is intuitive and is consistent with results for Germany and US. The finding that higher income predicts greater modal variability (after accounting for car access) is consistent with findings from Germany and US and can be explained in different ways. These individuals will have more economic freedom to travel long distances and use the transport modes they wish and they may participate in a larger variety of activities at different destinations. We additionally found being in a higher socio-economic group predicted that more modes were used which may relate to the living environments of these groups supporting the use of more transport modes.

Being the main driver of a car predicts reduced modal variability (consistent with findings from Germany and US). Those with regular access to a car generally use it as their main form of mobility. In contrast, having a public transport pass or season ticket predicts increased modal variability. This may involve a commitment to use public transport for certain travel but a need to use other modes of transport where public transport is less suitable. Owning a bicycle also predicts higher levels of modal variability which implies that bicycle owners have willingness and/or necessity to use other modes.

There are some differences between the indicators in the results. For example, being female predicts higher levels of variability except for the HHI for three modes. This indicates that woman use a larger variety of sub-modes (e.g. car driver and car passenger, bus and train, walk and cycle), but do not have any greater variability than men in their use of modes across the three main mode categories.

Larger size of settlement predicts increased modal variability in all indicators which indicates that living in London is particularly associated with use of a large range of mode options (i.e. multiple public transport options). Good rail and bus access does not predict greater modal variability after accounting for settlement size which shows that settlement size is a more important characteristic of where people live in explaining their use of different modes. Car access predicts decreased modal variability with all four indicators but it is notable that the effect is strongest for HHI for 3 modes which implies that it particularly encourages a less balanced use of private transport, public transport and active transport.

5. Conclusions

5.1. Summary of findings

This study shows that the majority of the adult population in GB (69% of the adults who made at least one trip) is multimodal over their weekly travel. This is in line with the findings of Nobis (2007) for Germany and Buehler and Hamre (in press-b) for US and shows that multimodality is ubiquitous. We opted to use continuous indicators for our analysis of intrapersonal modal variability rather than the categorical indicators that have mostly been used up to now. The HHI represents the balance of usage of modes within an individual and therefore best reflects the variability in mode use. We applied it to an eight mode grouping and three mode grouping. The HHI for three modes has the advantage that it covers mode categories that are applicable in different spatial contexts and enables results to be compared between contexts. As the HHI is affected by grouping of modes, it is recommended to test the differences between several groupings. The other indicators provide additional insights and should also be used if possible. The continuous indicators offer a useful addition to discrete indicators. In future research, a combination of discrete and continuous indicators could provide a comprehensive picture of variability of individual mode choice. For example, taking primary car users (a discrete group) and looking at a continuous measure of their modal variability would provide useful insights on what circumstances encourage car users to also use other modes.

Taking inspiration from Hägerstrand (1970), we conceived that modal variability is determined by different types of mobility constraints. Our analysis showed that the factors associated with reduced modal variability, across all indicators used were having mobility difficulties, being aged over 60, being non-white, working full-time, living in smaller settlement, lower household income, having regular access to a car, having no public transport pass/season ticket and not owning a bicycle. Being male, not being unemployed or a student and not living in a flat were also associated with reduced modal variability, but not for all indicators used.

These findings are largely consistent with those from studies in Germany and US (although we used different indicators). One finding that differs between countries is that older people are associated with lower modal variability in GB and US, but greater variability in Germany, which may be explained by the built environment and transport system in Germany better supporting older people using different mode options.

5.2. Limitations and research recommendations

This paper focused on individual-level variability in transport mode usage and contributed to the existing literature by analysing variability with continuous measures of modal variability, testing a large set of independent variables derived from theory and using data from a national travel survey of a country that has received not much attention thus far in this topic area. However, our study has several shortcomings. We selected four indicators of variability but more (continuous and discrete) indicators could be considered. The indicators we used are relatively easily interpretable, but all are affected by the grouping of the mode categories used. Another limitation of our study is the limited number of explanatory variables tested. Given the data available we were only able to test the role of objective factors. Findings from research on modality styles (e.g. Lavery et al., 2013) show that subjective factors (such as attitudes) play a role, although it should be recognised that these are not necessarily independent of the objective factors included in our analysis (they may themselves be influenced by objective factors or vice versa). It would be of value in future research to test the additional explanation that subjective factors can offer.

The literature review highlighted there has been only limited analysis of the variability of mode choice for specific travel purposes. The indicators we used to study all travel could also be adopted to look at specific travel purposes, although this would benefit from longer period data than one week. (It would also be of value to extend analysis of all travel to longer periods to reveal whether the variability found for one week captures the variability over, say, a month.) The challenge here is data collection. Developments in passive monitoring measurement tools may enable longer period data collection.

Also of interest would be to find out whether intrapersonal modal variability is stable over the long term. Most longitudinal studies of travel behaviour concentrate on usage of a single mode. For example, Heinen et al. (2011) assessed seasonal variation in bicycle use over a year and Chatterjee (2011) assessed how bus use over a six-month period was affected by the introduction of a bus rapid transit system. One recent study by Kroesen (2014) has investigated whether multimodality is stable using the German MOP. His analysis first involved cluster analysis to identify six segments based on their modal behaviour in terms of number of trips per week by car, public transport and bicycle. He then used transition analysis to examine stability of cluster membership two years later. He found that single mode clusters are most stable and multimodal clusters are most changeable and the most likely transitions are intermediate ones such as between strong car users and multimodal clusters, rather than extreme ones from strong car users to strong public transport users. We suggest it would also be worthwhile to examine stability of modal behaviour over the long term using continuous indicators of modal variability (such as the ones used in this paper) and to assess how modal variability is influenced by external changes to the transport system (e.g. public transport improvements) and internal changes to individuals over their life course (e.g. home moves).

5.3. Policy implications

Our research increases understanding of intrapersonal mode choice variability and the factors that influence this. This is increasingly important as policy efforts are made to encourage use of a wider variety of modal options to increase efficiency and sustainability of transport and improve quality of life. Future desirable scenarios for urban transport put forward a vision of a more balanced mix of transport options being provided and used than currently (EC, 2014). If these are to come to fruition then the multimodal user will need to become the norm rather than exception. Diana and Mokhtarian (2009b) report that individuals who rely strongly on one mode would like to bring more balance in their 'modal consumption', and thus increase their variability. Variability in behaviour may allow individuals to be more flexible when an unplanned disruption takes place in the transport system or to more quickly adapt to socio-technical transitions. Our research provides insights to support a change in perspective in transport policy from encouraging people to replace the use of one mode with another to encouraging people to make a change to their relative use of different transport modes.

Our findings show that modal variability is lower for those living in smaller settlements which suggests that priority should be given to facilitating walking, cycling and public transport use outside of major cities. They also show that modal variability is strongly associated with mobility capabilities and resources. Those with mobility difficulties have lower modal variability which highlights the risk that this limits their mobility opportunities. Having ready personal access to a car restrains use of multiple modes, while owning a public transport pass/season ticket or owning a bicycle has the opposite effect. This implies that encouraging people to invest in non-car transport resources is key to moving towards more balanced mobility.

Acknowledgements

EH has been funded for her work at Delft University of Technology by the Dutch Research Council, VENI-Grant (016.145.073).

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