



Are multimodals more likely to change their travel behaviour? A cross-sectional analysis to explore the theoretical link between multimodality and the intention to change mode choice

Eva Heinen*

University of Leeds, Institute for Transport Studies, Faculty of Environment, LS2 9JT Leeds, United Kingdom

Delft University of Technology, Faculty of Technology, Policy & Management, Department of Transport & Logistics, Jaffalaan 5, 2628 BX Delft, The Netherlands

ARTICLE INFO

Article history:

Received 5 December 2016

Received in revised form 12 April 2018

Accepted 12 April 2018

Available online 30 April 2018

Keywords:

Multimodality

Intention to change

Mode choice

Behavioural change

ABSTRACT

Existing research suggests that being more multimodal (i.e. the use of more than one transport mode within a given period of time) increases the likelihood of changing travel behaviour over time. However, alternative explanations may have contributed to these findings. Many well-known psychological theories state that the actual demonstration of a behaviour is preceded by an intention to demonstrate this behaviour. Therefore, one essential step towards the determination of a causal relationship between multimodality and behaviour change is to investigate whether multimodality increases *the intention* to change.

This paper explored to what extent multimodality was associated with the intention to change the level of cycling, walking, car use, and train use. Our findings showed that the more multimodal individuals were, the more likely they intended to decrease their car use. However, most associations between multimodality and the intention to change mode choice were non-significant. This could be interpreted to mean that there is no relationship between multimodality and the intention to change. However, the significant findings for car use, and the direction of most (non-significant) associations in our analyses were intuitive. Therefore, our analyses are not conclusive on whether or not the level of multimodality is associated with the intention to change and actual behavioural change. Additional research will be necessary to test the proposed link between multimodality and behavioural change. Three lines of additional research that focus on associations between multimodality and behavioural change, multimodality and the intention to change behaviour, and variability and stability of individual behaviour over time, respectively, are particularly important.

© 2018 Elsevier Ltd. All rights reserved.

1. Introduction

Transport has negative consequences on our health, the environment and urban liveability. In particular, the dominance of the car in the transport system may contribute to this. Policies have aimed to generate a modal shift away from the car

* Address: University of Leeds, Institute for Transport Studies, Faculty of Environment, LS2 9JT Leeds, United Kingdom.

E-mail address: e.heinen@leeds.ac.uk

with initiatives that include subsidies, improving the facilities for active travel and public transport, and restrictive car access. Recently, increased policy attention has been placed on encouraging a partial shift instead of a full modal shift (EC, 2014).

In the scientific debate, the mixed use of different transport modes—referred to as multimodality, the use of more than one transport mode within a given period of time—has recently gained increased attention (e.g. Jones & Clarke, 1988; Huff & Hanson, 1986; Kuhnimhof, 2009; Nobis, 2007; Buehler & Hamre, 2015; Heinen & Chatterjee, 2015; Susilo & Axhausen, 2014; Kroesen, 2014). Despite the fact that the number of studies on multimodality is still small, various topics have been addressed. The majority of studies have either focused on the prevalence of multimodality in a geographical area such as a country (e.g. Nobis, 2007; Buehler & Hamre, 2015; Heinen & Mattioli, 2017), or have tried to identify the predictors of multimodality (e.g. Heinen & Chatterjee, 2015; Susilo & Axhausen, 2014; Kroesen, 2014; Molin, Mokhtarian, & Kroesen, 2016).

However, few studies have investigated whether variability may be a predictor *itself* of behavioural change. Two studies (Kroesen, 2014; Heinen & Ogilvie, 2016) have explicitly addressed this. Kroesen (2014) investigated the predictors of transitions between data-driven travel behaviour clusters and showed that individuals who used multiple modes compared to those that relied on one mode had a higher likelihood of changing from one travel behaviour cluster to another over time. Heinen and Ogilvie (2016) tested whether individuals who were more multimodal in their mode choice before an intervention were more likely to change their share of trips made entirely by car, partially by active travel and partially by public transport when facing an intervention. They concluded that a higher level of multimodality at baseline was significantly associated with changes in all mode shares. More importantly, they also found a significant interaction effect between the exposure to an intervention and multimodality for an increase in active travel and a decrease in car use, implying that individuals who had more variable behaviour at baseline were more receptive to the intervention.

Despite the fact that these results provide an indication that the level of multimodality may be a predictor of travel behaviour change, two other mechanisms may also explain these findings, both of which are related to the possibility that the predictor and outcome may not be independent. First, changes in travel behaviour and variability in travel behaviour cannot always be easily separated, and measured changes may, in part, be a result of variability. A 'change in travel behaviour' refers in here to a shift towards or away from a given mode of transport over time. Variability refers to the level of variation in modes of transport used by an individual within a certain period. Second, statistical coupling (Gilthorpe, 2011) may be present between the measures of interest (change in travel behaviour on the one hand and group membership or baseline level of multimodality on the other). The first mechanism relates to the measurement of the variables, whereas the second relates to the mathematical calculation. Both mechanisms may result in the measurement of a significant association between multimodality and change in travel behaviour, even if such an association is not present in reality (i.e. a type-1 error).

One essential step towards a better understanding the relationship between multimodality and changes in travel behaviour is to investigate the relationship between multimodality and the intention to change. Many well-known psychological theories state that the actual demonstration of a behaviour is preceded by an intention to show this behaviour (e.g. theories such as: the theory of planned behaviour (Ajzen, 1991) and the theory of reasoned action (Fishbein & Ajzen, 2010)). Theories and models based on stages of change (e.g. Prochaska, DiClemente, & Norcross, 1992; Prochaska & Velicer, 1997) also include the contemplation of new behaviour before experimentation with new behaviour. Therefore, if variability predicts the intention to change, this would offer support to the notion that previous findings are not statistical artefacts, but rather that these findings support the proposed conceptualisation (i.e. that those with higher levels of variability may be more open to change).

This study explores the association between multimodality and the intention to change mode choice. Using data collected in the Netherlands in 2015, we explored these associations between multimodality and the intention to change the level of cycling, walking, car use, and public transport use. The remainder of this paper is organised as follows. First, a short overview of the existing literature is provided, followed by a discussion of the methods. Section 4 will present the results of our analyses, which will be discussed in Section 5. A short conclusion of the research is provided in Section 6.

2. Literature review

This section will discuss three aspects of multimodality: the measurement of multimodality, predictors of multimodality, and, finally, to what extent multimodality predicts changes in travel behaviour. The focus of this paper is this last aspect, but a discussion of the wider context of the topic in the scientific research helps to understand the phenomenon, provides a perspective to how multimodality is distributed over the population, and illustrates the complexities of measuring multimodality.

2.1. Measurements of multimodality

The topic of variability of travel behaviour and multimodality (mode choice variability) specifically has received attention in the travel behaviour research literature over the past few decades. Multimodality is, broadly speaking, defined in three ways. The first definition method used to investigate multimodality is to define the use of modes in different predefined groups, such as multimodal car, monomodal car, and multimodal active travel groups (e.g. Nobis, 2007; Buehler & Hamre, 2015). The second measure is based on data-driven groups (e.g. Kroesen, 2014), whereas the third method of multimodality

characterisation is by using a continuous indicator to describe the level of variability (e.g. Heinen & Chatterjee, 2015; Susilo & Axhausen, 2014; Heinen & Mattioli, 2017). These approaches to characterising multimodality vary from each other, but also within these approaches of characterisation much variation exists. Diana and Pirra (2016) reviewed several continuous indicators, some of which are often used in studies on multimodality and others that have potential to be applied. The measures Gini, Dalton, Atkinson, entropy, and Herfindahl indices were compared and the authors concluded that none of these indicators outperformed any other in all qualities considered. They however recommend the use of a variation of the Herfindahl index, as well as two variations of the Shannon entropy. However, the guidelines for which indicator to use are not clearly agreed upon yet. Perhaps more importantly, although these indicators may be more suitable to measure multimodality correctly, the interpretability of these indicators is more difficult, which makes it harder to use them as predictors.

In addition to the index of the level of multimodality, the duration over which travel behaviour data are collected as well as how mode choice is measured differ among studies. In some surveys, the main mode is requested, whereas other surveys ask for all modes used for each trip. As a consequence of questionnaire design, some studies, therefore, are able to investigate multimodality only on a trip level, whereas others may also investigate multimodality at the stage level. These three potential differences among studies (indicator, duration, and survey question) complicate comparisons of the level of multimodality as well as the determinants and predictive power of multimodality among studies.

2.2. Predictors of multimodality

Various studies have investigated the predictors of variability (e.g. Nobis, 2007; Buehler & Hamre, 2015; Heinen & Chatterjee, 2015; Susilo & Axhausen, 2014; Kroesen, 2014; Scheiner, Chatterjee, & Heinen, 2016; Molin et al., 2016). Although some findings are unique to only few studies, and some findings are contradictory, overall, it appears that multimodality is more prevalent among women and in areas with higher population densities. Unimodal car users are, on average, more likely to be male, white, fulltime employees, individuals with young children, car owners, and (less often) students. Age results appear to vary among countries. Additionally, life events have been shown to predict changes in multimodality (Scheiner et al., 2016). For example, if a child moves out, this increases the multimodality of their parents, as does leaving the labour market. Entering the labour market reduces the level of multimodality, whereas improvements in public transport increase the level of multimodality and vice versa, as do reductions in car parking.

2.3. Multimodality as a predictor of behavioural change

Two recent papers did not investigate predictors of variability, but examined to what extent variability itself was a predictor of behaviour. Heinen and Ogilvie (2016) investigated the impact of baseline variability in mode choice on the likelihood of travel behaviour change. They used three indicators of variability: the Hirfindel–Hirschman index (HHI), the number of different modes of transport used over a week, and the proportion of trips made by the main (combination of) mode(s) based on self-reported commute journeys over a seven-day period. Using data from a cohort study in Cambridge ($n = 450$), they tested the influence of baseline variability on behaviour change, both independently and as an interaction effect with exposure to the intervention. They concluded that variability predicted changes in mode share for active travel, car travel, and public transport. Commuters with higher baseline variability were also more likely to increase their active mode share and decrease their car mode share in response to the intervention (as an interaction effect).

In another study, the predictors of transitions between data-driven travel behaviour clusters were investigated (Kroesen, 2014). The clusters were based on three variables: the number of car trips, the number of public transport trips, and the number of bicycle trips. The author's results showed that individuals who used multiple modes compared to those that relied on one mode had a higher likelihood of changing from one cluster to another cluster over time. In particular, individuals who mainly relied on a bicycle or mainly relied on a car were the least likely to change. He also reported that transitions were predicted by individual characteristics and experiencing certain life events, in particular age, the residential environment, moving house and changing jobs.

Although these two studies suggest that being more multimodal increases the likelihood of behavioural change over time, these measurements could be explained differently, as discussed in the introduction. In the remainder of this paper, we will therefore investigate the relationship between multimodality and changing travel behaviour, by exploring the relationship between multimodality and the intention to change travel behaviour, which is theoretically a concept or phase before actual behavioural change. Additionally, as our search of the literature revealed that a consensus has not yet been reached on which indicator to use for multimodality, we therefore decided to explore this relationship by indices as well as determined groups.

3. Method

3.1. Setting and data collection

Data were collected in Utrecht, the Netherlands (approximately 335,000 inhabitants). The city of Utrecht is the fourth largest in the Netherlands, and is home to a university and other higher educational institutions. The city is centrally located in the Netherlands with Utrecht Central station serving as the main train station in the nation's train network.

Questionnaire data were collected by post in June 2015. Municipality data were used to randomly approach individuals over 18 years of age and living in several areas of the city. To avoid biasing recruitment and responses, the study was presented to participants as a study on travel behaviour and travel behaviour change. The aim of investigating specific predictors of behaviour and behavioural change was not made explicit to potential respondents. One-thousand-sixty-two individuals completed the online survey.

3.2. Outcomes

The outcome measures were the intention to change mode choice for several transport modes. This information was obtained by asking ‘to what extent do you intend to increase or decrease the use of the following modes (in the coming years)?’. We measured this intention on a seven-point scale for five modes: car, train, bus, bicycle, and walking. Given the distribution of the answers, we grouped the answers into ‘intend to decrease’, ‘intend not to change’, and ‘intend to increase’. We considered car use, bicycle use, walking, and train use in this paper (Table 1), given they had the largest variation in responses.

3.3. Covariates

The following covariates were obtained in the questionnaire and considered in our analysis: gender, age, education level, income, being a student, living alone, car availability, bicycle availability, presence of children in the household, being Dutch, and commute distance (Appendix A). Several additional variables had been measured but were not considered in the final models given their correlations with other independent variables: living with family, living with others (not family), working, and possessing a driving license.

Table 1
Summary statistics of numerical indicators.

		Trip-based indicators		Stage-based indicators		OM_PI
		Number of modes used	Highest share	HHI	Number of modes used	
Sex	Male	1.81	86.90	0.67	2.16	0.22
	Female	1.80	85.90	0.65	2.16	0.23
Dutch	No	1.75	86.81	0.68	2.05	0.21
	Yes	1.81	86.26	0.66	2.17	0.23
Children at home	No	1.83	86.09	0.65	2.19	0.23
	Yes	1.73	87.00	0.69	2.04	0.20
Living alone	No	1.81	86.25	0.66	2.19	0.23
	Yes	1.79	86.38	0.66	2.11	0.22
Student	No	1.81	86.37	0.66	2.15	0.22
	Yes	1.79	85.69	0.65	2.20	0.24
Working	No	1.89	83.85	0.67	2.12	0.22
	Yes	1.79	86.79	0.66	2.17	0.23
Holding a driver license	Yes	1.84	85.63	0.65	2.18	0.23
	No	1.50	91.43	0.69	1.97	0.20
Car availability	Yes, always	1.79	86.37	0.71	1.97	0.19
	Yes, mostly	2.07	81.81	0.62	2.31	0.25
	Yes, sometimes	1.91	86.45	0.55	2.61	0.30
	No, never	1.59	88.53	0.65	2.13	0.23
Bicycle availability	Yes, always	1.80	86.3	0.66	2.16	0.23
	Yes, mostly	2.62	78.46	0.51	2.69	0.32
	Yes, sometimes	2.17	83.97	0.54	2.50	0.30
	No, never	1.47	90.00	0.80	1.63	0.13
Pre-tax personal income	Not answered	1.80	87.05	0.72	1.99	0.19
	Less than half normal wage (<€17,000 a year)	1.73	86.09	0.66	2.17	0.23
	Between half and normal wage (€17,300–34,600)	1.75	87.38	0.66	2.14	0.22
	Between normal and twice normal wage (€34,600–69,200)	1.81	86.34	0.64	2.20	0.24
	More than twice normal wage (>€69,200)	2.06	82.98	0.63	2.25	0.24
All		1.80	86.30	0.66	2.20	0.23
n=		882	882	882	882	882

In bold and italic: significant differences.

3.4. Predictors

Given the debate in the literature whether to use an index or whether groups are more insightful to measure multimodality, we calculated both indices as well as determined groups, which were predefined as well as data-driven. These groups and predictors were based on self-reported travel diary. Individuals were asked to report their mode choice to and from work for a 14-day period in which respondents were asked to report all modes used during each trip (see also Heinen, 2016). Given that we use multimodality as a predictor, we gave preference to indicators that were more intuitive and widely used.

We calculated five indicators, which comprised three measures of variability at the stage level (a stage is a part of a trip; for example, a trip involving both cycling and bus travel would be composed of two stages, one by bicycle and one by bus) and two measures of variability at the trip level (based on the mode or combination of modes of transport used for the entire trip). Variability at the stage level reflects the variation in all possible modes used, independent of whether these are used in combination with other modes and independent of the length of each stage. Variability at the trip level reflects the variation in the mode or combination of modes used between trips, and considers each combination of modes as a unique choice. We selected the variables that were easiest to interpret.

The first measure at the trip level was the number of different modes/modal combinations used in all trips. The second measure at the trip level was the highest share of a mode/modal combination use. Three indicators were calculated based on the modes used in the trip stages. The first of these indicators was a count variable of the number of different modes used in all legs. This is a very intuitive measure of the variety of modes being used. However, as it does not take the level of variation into account, we considered two other measures. The second indicator was an index, the Hirfindel–Hirschman index (HHI). The HHI, a measure of market concentration, which is one of the most commonly applied measures of mode choice variability (Heinen & Chatterjee, 2015; Susilo & Axhausen, 2014; Scheiner et al., 2016), is calculated as the sum of the squared values (S) of the share of each mode within all commuting trips (Rhoades 1993). A normalised index ranges from 0 to 1, where the closer to 1 the more one mode dominates an individual's travel (see Heinen & Chatterjee, 2015 for formulas). The third was one of the indicators recommended by Diana and Pirra (2016): OM_PI, which is based on the Shannon Entropy. OM_PI is appropriate when considering a set number of travel means, independent on whether an individual has access to it (Diana & Pirra, 2016). Given the large number of modes we considered (10), this likely applies. The indicators 'number of modes' and OM_PI are indices of variability and higher values correspond with a greater level of multimodality, whereas HHI is an index for concentration where higher values correspond with less multimodality.

Table 1 shows the mean values for the numeric indicators of multimodality by socio-economic group. This table reveals that several groups had higher levels of multimodality than other groups, but the overall differences were small. For example, individuals who were employed generally rely more on one mode, indicated by a higher value of the highest mode share. Individuals with children at home showed less variable mode choice behaviour, which is indicated by a higher HHI. In general, individuals who did not own a car were more multimodal. An opposite trend was present for bicycle ownership: individuals who owned a bicycle were generally more multimodal. Individuals with a higher income (more than twice the mode) appeared to be more multimodal at a trip level, but only small differences were present at a stage level. These findings largely correspond with existing studies.

Second, we predefined modality groups. We considered unimodal car users (UMcar) (i.e. individuals who used only a car for every trip), UM cyclists (UMbike), multimodal users who relied on a single combination of modes (UM/MM one mode) (i.e. individuals who always used the same (combination of) mode(s) for each trip, but not only the bicycle or only the car), and other multimodal users (MM) (i.e. individuals who varied their modal use between trips). The last group included individuals who alternated a single mode (i.e. those who sometimes used car and sometimes used a bicycle), as well as individuals with any other multimodal pattern.

Third, we conducted cluster analyses on the individual mode shares based on the following variables: the share of trips made entirely by car, the share of trips made entirely by bicycle, the share of trips made entirely on foot, the share of trips made entirely by public transport, the share of trips partly made by car (using a car together with another mode in a trip), the share of trips partly made by bicycle, the share of trips partly made on foot, and the share of trips partly made by public transport. We used k-means clustering and explored the results varying the number of clusters (6, 5, 4, 3 and 2 clusters). The optimal number of clusters using the Calinski–Harabasz criterion was three. However, these three clusters could roughly be described as 'mainly unimodal car', 'mainly unimodal bicycle', and 'mainly multimodal'. These clusters do not discriminate well between the level of multimodality as well as the modes used. Given that we are interested in investigating the relationship between multimodality and intention to change, and not to reveal the optimal number of clusters, we decided to explore the clusters with three, four, and five groups as dependent variables. The first presented grouping revealed five clusters. Cluster 5.1 mainly consisted of individuals who solely used a car and cluster 5.2 mainly of individuals who only used a bicycle. Cluster 5.3 was a relatively small cluster and consisted of individuals who predominantly walked or used public transport for the entire trip. Cluster 5.4 and 5.5 both consisted of mostly multimodal individuals. The former included individuals who used all kind of modes except a car, whereas the latter contained multimodals who also used a car. We also considered a cluster analyses that revealed four groups. Cluster 4.1 contained mostly car only users and cluster 4.2 mostly bicycle-only users. Cluster 4.3 was very diverse group with many individuals who used a large variety of modes, whereas cluster 4.4 contained individuals who did not use a car, but used a variety of other transport modes. The last cluster analyses revealed three clusters. Cluster 3.1 contained individuals with high shares of trips made using a car alone. Individuals in

cluster 3.2 mostly had a high share of trips made using a bicycle alone and cluster 3.3 contained individuals with mostly evinced a mixed modal use.

The clusters and groups that mostly contained only car or only bicycle use (clusters 5.1, 5.2, 4.1, 4.2, 3.1, 3.2, and the groups only car and only bike) had very low scores for the numeric indicators of multimodality. In contrast, the multimodal clusters, and, in particular, clusters 5.5 and 4.4, had very clear multimodal patterns with relatively many modes being used, at both the stage and trip level (Table 2). The clusters and groups differed significantly in composition in several ways (Appendix B). Men were more likely to be in the car only groups and clusters. Individuals who work also appeared to be more likely to only use a car compared to those not working. A relatively large share of individuals in only-car groups were part of the higher income group and students were less likely to be in this group. The segments that rely heavily on a bicycle contained a higher share of students, lower-income individuals, and those who always have a bicycle available. Individuals in such groups were on average less likely to have a car available, and less likely to be working. Most multimodal clusters/-groups were in between the two main unimodal clusters/groups. Individuals in such groups only sometimes had a bicycle and car available more often instead of always or never, and some multimodal groups were less likely to have children at home.

3.5. Analyses

The primary aim of this paper was to test whether the individual level of multimodality is associated with the intention to change one's mode choice. For this, we estimated several multinomial logistic regression analyses, with 'no intention to change' as a reference category. The dependent variables were the intention to change the level of car use, the intention to change the level of bicycle use, the intention to change the frequency of walking, and the intention to change the level of train use. The multivariate analyses were stepwise adjusted by first including the measure of multimodality, second also adding age and gender, and third including all other covariates. Each covariate was tested independently on every outcome variable and only adjusted for if $p < 0.25$ in the unadjusted models.

4. Results

The next sections focus on the key questions of this paper, and will subsequently address whether multimodality predicts the intention to change car use, bicycle use, walking, and train use. The tables only present the estimates of the associations between multimodality and the intention to change in the maximally adjusted models. The reference category in all analyses is 'no intention to change', and the clusters and groups are compared to the cluster/group that can be described as (predominantly) car alone. The results of all the multivariate models on the same dependent variable are presented in one table, however, the predefined groups, each indicator and each cluster were modelled separately (i.e. in different multivariate statistical models).

Table 2
Relationship between clusters, predefined groups and modal shares.

	Clusters												Predefined groups			MM
	5.1	5.2	5.3	5.4	5.5	4.1	4.2	4.3	4.4	3.1	3.2	3.3	Only car	Only bike	UM/MM one mode	
Share UM car*	89.65	4.07	5.50	2.47	5.38	89.75	4.70	2.49	5.66	79.06	4.05	2.91	100	0	0	23.69
Share UM bicycle	5.78	90.63	9.49	2.69	6.50	4.36	83.80	2.71	6.27	5.45	88.92	3.57	0	100	0	39.92
Share UM walk	0.44	0.50	43.81	0.19	2.15	0.71	4.23	0.19	4.01	5.83	1.31	1.03	0	0	4.97	4.16
Share UM PT	0.45	0.71	19.14	0.26	0.39	1.21	1.93	0.26	1.19	2.65	1.00	0.52	0	0	1.66	2.70
Share MM car**	1.54	1.27	2.21	1.24	28.25	1.54	1.24	1.25	27.03	2.36	1.61	11.47	0	0	10.53	6.58
Share MM bike	2.07	2.81	2.95	90.15	36.57	2.04	2.58	90.75	35.36	2.24	2.80	70.15	0	0	70.52	19.54
Share MM walk	2.14	2.10	4.39	58.03	78.85	2.17	2.00	58.42	75.21	3.46	2.54	66.97	0	0	70.03	18.11
Share MM PT	1.85	2.55	4.05	93.21	37.57	1.88	2.48	93.16	36.96	2.17	2.85	72.03	0	0	74.82	18.63
Numbers of modes used trip	1.52	1.59	2.15	2.02	2.71	1.51	1.61	2.03	2.76	1.61	1.62	2.27	1	1	1.59	2.81
Highest share	89.65	90.63	77.04	83.07	72.94	90.48	89.35	82.96	71.99	88.02	89.48	79.90	100	100	89.39	69.57
HHI	0.82	0.82	0.66	0.28	0.31	0.83	0.81	0.28	0.32	0.80	0.81	0.29	1	1	0.35	0.45
OM_PI	0.11	0.12	0.22	0.48	0.46	0.49	0.45	0.11	0.12	0.13	0.13	0.47	0	0	0.42	0.36
Number of modes used stages	1.58	1.63	2.08	3.39	3.39	1.58	1.66	3.40	3.36	1.68	1.68	3.36	1	1	2.98	2.98
n=	231	351	40	153	107	228	388	152	114	267	363	252	154	213	181	334

* UM = Unimodal. This indicate that an entire trip is made by this mode only.

** MM = multimodal. This indicate that trip is made by use of more than one mode.

Cluster 5.2: Mostly only bicycle; Cluster 5.3: Mostly only walk or only public transport; Cluster 5.4: Using a variety of modes, but little car; Cluster 5.5: Using a variety of modes including car.

Cluster 4.2: Mostly only bicycle; Cluster 4.3: Using a variety of modes, but little car; Cluster 4.4: Using a variety of modes including car.

Cluster 3.2: Mostly only bicycle; Cluster 3.3: Using a variety of modes.

4.1. Intention to change level of car use

Table 3 shows the results of the maximally adjusted models (i.e. separate models were estimated for each indicator/-group/cluster) that estimated the association between different indicators of multimodality and the intention to change car use. The general trend among all indicators and groups is that the more multimodal individuals were, the more likely they intended to decrease their car use. The groups and multimodality indicators showed a mixture of positive and negative associations (and only non-significant) with the intention to increase car use.

In more detail, all indices showed non-significant associations with intended changes in levels of car use both before and after adjustment. Despite these non-significant results, the direction of the relative risk ratios are intuitive for the intention to decrease. For all four indicators, they showed that there is a tendency among individuals who are more multimodal to be more likely to intend to decrease their level of car use.

Analyses using clusters as the dependent variables revealed that individuals in clusters 5.5 and 4.4—i.e. the very multimodal clusters—showed a greater likelihood of intending to decrease car use. For example, individuals in cluster 5.5 compared to cluster 5.1 (predominantly car users) were 2.5 times more likely to indicate the intention to decrease car use (relative risk ratio (RRR): 2.71; 95% confidence interval (95% CI): 1.22–6.03).

The analyses on pre-defined groups revealed several significant association in the unadjusted models that remained significant in the maximally adjusted models. Compared to individuals who exclusively travelled by car all other three groups were more likely to intend to decrease their car use. For example, individuals belonging to the 'UMbike' group were three times more likely (compared to the 'only car' group) to have an intention to decrease car use (RRR: 2.96, 95% CI: 1.13–7.84), and also the other two groups were approximately three times more likely to intend to decrease car use (RRR: 3.133 and 2.545, respectively).

4.2. Intention to change levels of bicycle use

Table 4 shows the results of the maximally adjusted multivariate models that tested the association between indicators of multimodality and the intention to change bicycle use. Although many associations between multimodality and the intention to decrease bicycle use were significant in the unadjusted models (including the stage-based indicators, all predefined groups and many clusters), these attenuated and became non-significant in the maximally adjusted models. For an increase in cycling levels, only some clusters were significantly associated in the unadjusted models, but these also attenuated and became non-significant in the maximally adjusted models.

Table 3

Intention to change the level of car use.

			Intention to decrease		Intention to increase	
			RRR	95% CI	RRR	95% CI
Indicators	Trip based	Number of modes used	1.167	[0.988–1.378]	0.913	[0.765–1.090]
		Highest share	0.990	[0.978–1.002]	0.997	[0.986–1.009]
	Stage based	HHI	0.685	[0.310–1.514]	0.924	[0.451–1.895]
		OM_PI	1.733	[0.550–5.460]	1.243	[0.445–3.468]
		Number of modes used	1.118	[0.928–1.347]	1.029	[0.871–1.215]
Clusters (ref: Mostly only car (i.e. cluster 5.1. 4.1, 3.1))		Cluster 5.2	1.862	[0.882–3.931]	0.971	[0.480–1.963]
		Cluster 5.3	2.070	[0.581–7.370]	0.478	[0.132–1.736]
		Cluster 5.4	1.103	[0.455–2.677]	0.800	[0.352–1.817]
		Cluster 5.5	2.716*	[1.223–6.034]	1.059	[0.477–2.352]
		Cluster 4.2	1.544	[0.735–3.241]	0.912	[0.454–1.835]
		Cluster 4.3	1.006	[0.415–2.438]	0.761	[0.336–1.722]
		Cluster 4.4	2.664*	[1.212–5.852]	1.065	[0.481–2.359]
		Cluster 3.2	1.354	[0.687–2.671]	1.146	[0.591–2.221]
		Cluster 3.3	1.178	[0.597–2.325]	0.991	[0.512–1.917]
Predefined groups (ref: UM car)		UM bike	2.959*	[1.133–7.729]	0.983	[0.433–2.230]
		UM/MM one mode	3.133*	[1.253–7.835]	0.701	[0.310–1.583]
		MM	2.545*	[1.101–5.883]	0.969	[0.480–1.957]

Each measurement of multimodality was separately tested (whilst adjusting for covariates) on the intention to change.

Maximally adjusted model for the intention to change the level of car use.

Reference is no intention to change the level of car use.

The analyses are adjusted for: gender, having children living at home, living alone, being a student, working, commute distance, car availability, bicycle availability, education, income, BMI, and age.

RRR = relative risk ratio; 95% CI = 95% confidence interval.

* $p < 0.05$.

In bold: significant associations.

Cluster 5.2: Mostly only bicycle; Cluster 5.3: Mostly only walk or only public transport; Cluster 5.4: Using a variety of modes, but little car; Cluster 5.5: Using a variety of modes including car.

Cluster 4.2: Mostly only bicycle; Cluster 4.3: Using a variety of modes, but little car; Cluster 4.4: Using a variety of modes including car.

Cluster 3.2: Mostly only bicycle; Cluster 3.3: Using a variety of modes.

The associations between the continuous indicators of multimodality and the intention to change cycling suggest (although they are non-significant) that individuals who were more multimodal were less likely to decrease their cycling levels. The strength of the associations was less strong for an increase in cycling, but the results suggest that individuals with higher levels of multimodality may be more likely to intend to increase cycling. The associations found for the clusters also suggest that compared to individuals who (primarily) only use a car (the control group) other clusters are less inclined to decrease their bicycle use. There is a tendency for individuals who were more multimodal to be more likely to increase cycling. For the predefined groups, the maximally adjusted models suggest that compared to individuals who only use the car (UMcar), the other groups (UMBicycle, UM/MM one mode, MM) are all less likely to intend to decrease their cycling levels.

4.3. Intention to change levels of walking

Although all associations of the numerical indicators were non-significant in the maximally adjusted models, these results suggest that individuals with higher levels of multimodality were less likely to have an intention to decrease walking. The associations of the numerical indicators with an intention to increase walking hardly deviated from 1, meaning that the level of multimodality was not associated with a higher likelihood of intending to increase walking (Table 5).

These analyses revealed that individuals in cluster 5.3 were more likely than individuals in cluster 5.1 (predominantly car alone) to increase their levels of walking in the unadjusted models, and this association remained significant in the maximally adjusted models (RRR: 3.07; 95% CI: 1.14–8.30). This indicates that individuals in cluster 5.3 (mostly only walking or only using public transport) were three times more likely to have an intention to increase walking.

In the predefined groups, no significant associations were found. The results suggest that compared to individuals who only use a car, the other three groups have a higher intention to increase their level of walking and are also less likely to intend to decrease walking, except for the 'MM one mode', possibly because this group includes individuals who walk frequently.

4.4. Intention to change levels of train use

Finally, in Table 6, the associations between the multimodality and intention to change levels of train use are presented. None of the numerical multimodal indicators were significantly associated with intentions to change train use, neither in the unadjusted or the adjusted models. In contrast, several clusters showed a lower likelihood to decrease the level of train use. For example, individuals in cluster 5.2 (predominantly bicycle users) compared to cluster 5.1 (predominantly car users) were half as likely to intend to decrease train travel (RRR: 0.45; 95% CI: 0.22–0.93). Similarly, individuals in cluster 3.2 (predom-

Table 4
Intention to change the level of bicycle use.

			Intention to decrease		Intention to increase	
			RRR	95% CI	RRR	95% CI
Indicators	Trip based	Number of modes used	0.742	[0.400–1.376]	1.037	[0.911–1.180]
		Highest share	0.996	[0.969–1.024]	0.996	[0.987–1.004]
	Stage based	HHI	2.421	[0.449–13.060]	0.675	[0.396–1.151]
		OM_PI	–1.349	[–3.876–1.177]	0.500	[–0.522–0.206]
		Number of modes used	0.749	[0.461–1.218]	1.067	[0.939–1.212]
Clusters (ref: Mostly only car (i.e. cluster 5.1, 4.1, 3.1))	Cluster 5.2		0.265	[0.046–1.529]	0.790	[0.472–1.323]
	Cluster 5.3		0.624	[0.052–7.467]	1.161	[0.418–3.226]
	Cluster 5.4		0.110	[0.009–1.375]	0.800	[0.441–1.451]
	Cluster 5.5		1.173	[0.235–5.860]	1.313	[0.704–2.449]
	Cluster 4.2		0.243	[0.044–1.325]	0.689	[0.413–1.151]
	Cluster 4.3		0.095	[0.008–1.197]	0.700	[0.384–1.277]
	Cluster 4.4		1.006	[0.199–5.076]	1.307	[0.700–2.439]
	Cluster 3.2		0.323	[0.071–1.474]	0.793	[0.489–1.285]
	Cluster 3.3		0.562	[0.135–2.348]	0.946	[0.575–1.556]
	Predefined groups (ref: UM car)					
		UM bike	0.390	[0.061–2.483]	0.862	[0.462–1.606]
		UM/MM one mode	0.480	[0.085–2.724]	1.369	[0.732–2.560]
		MM	0.507	[0.106–2.434]	1.403	[0.812–2.424]

Each measurement of multimodality was separately tested (whilst adjusting for covariates) on the intention to change.

Maximally adjusted model for the intention to change the level of car use.

Reference is no intention to change the level of car use.

The analyses are adjusted for: gender, having children living at home, being a student, working, car availability, bicycle availability, education, income, being Dutch, and age.

RRR = relative risk ratio; 95% CI = 95% confidence interval.

* $p < 0.05$.

In bold: significant associations.

Cluster 5.2: Mostly only bicycle; Cluster 5.3: Mostly only walk or only public transport; Cluster 5.4: Using a variety of modes, but little car; Cluster 5.5: Using a variety of modes including car.

Cluster 4.2: Mostly only bicycle; Cluster 4.3: Using a variety of modes, but little car; Cluster 4.4: Using a variety of modes including car.

Cluster 3.2: Mostly only bicycle; Cluster 3.3: Using a variety of modes.

Table 5

Intention to change the level of walking.

			Intention to decrease		Intention to increase	
			RRR	95% CI	RRR	95% CI
Indicators	Trip based	Number of modes used	0.885	[0.619–1.266]	1.001	[0.874–1.148]
		Highest share	1.008	[0.984–1.031]	1.001	[0.991–1.010]
	Stage based	HHI	3.544	[0.856–14.68]	0.945	[0.525–1.699]
		OM_PI	0.186	[0.024–1.471]	0.974	[0.417–2.276]
		Number of modes used	0.836	[0.591–1.184]	0.980	[0.851–1.129]
Clusters (ref: Mostly only car (i.e. cluster 5.1. 4.1, 3.1))		Cluster 5.2	1.262	[0.384–4.147]	1.102	[0.664–1.831]
		Cluster 5.3	–	–	3.069*	[1.136–8.297]
		Cluster 5.4	0.455	[0.108–1.918]	0.869	[0.487–1.551]
		Cluster 5.5	0.151	[0.017–1.354]	1.102	[0.605–2.009]
		Cluster 4.2	1.001	[0.317–3.161]	1.218	[0.735–2.020]
		Cluster 4.3	0.485	[0.118–1.987]	0.855	[0.476–1.535]
		Cluster 4.4	0.142	[0.016–1.269]	1.264	[0.697–2.290]
		Cluster 3.2	1.472	[0.460–4.708]	0.995	[0.612–1.618]
		Cluster 3.3	0.362	[0.105–1.255]	0.886	[0.551–1.427]
Predefined groups (ref: UM car)		UM bike	1.761	[0.442–7.014]	1.121	[0.596–2.108]
		UM/MM one mode	0.281	[0.048–1.635]	1.461	[0.813–2.627]
		MM	1.251	[0.369–4.237]	1.433	[0.823–2.494]

Each measurement of multimodality was separately tested (whilst adjusting for covariates) on the intention to change.

Maximally adjusted model for the intention to change the level of car use.

Reference is no intention to change the level of car use.

The analyses are adjusted for: gender, having children living at home, living alone, working, commute distance, bicycle availability, education, income, BMI, and being Dutch.

RRR = relative risk ratio; 95% CI = 95% confidence interval.

* $p < 0.05$.

In bold: significant associations.

Cluster 5.2: Mostly only bicycle; Cluster 5.3: Mostly only walk or only public transport; Cluster 5.4: Using a variety of modes, but little car; Cluster 5.5: Using a variety of modes including car.

Cluster 4.2: Mostly only bicycle; Cluster 4.3: Using a variety of modes, but little car; Cluster 4.4: Using a variety of modes including car.

Cluster 3.2: Mostly only bicycle; Cluster 3.3: Using a variety of modes.

inantly bicycle users) compared to cluster 3.1 (predominantly car users) were also half as likely to have this intention (RRR: 0.44; 95% CI: 0.23–0.88). However, individuals in cluster 4.4 (using a variety of modes including car) were found to be more than twice as likely compared to cluster 4.1 (predominantly car) to intend to increase train travel (RRR: 2.22; 95% CI: 1.00–4.93), which is in contrast to the numeric indicators that show a tendency of a lower likelihood to increase train use with higher levels of multimodality.

5. Discussion

This paper explored to what extent multimodality was associated with the intention to change travel behaviour. Although existing research suggests that baseline multimodality may predict changes in travel behaviour, alternative explanations are possible, such as mathematical coupling, regression to the mean, and the measured change actually being variability. To overcome these issues, this paper investigated the influence of multimodality on an important precedent of behavioural change: the intention to change behaviour. Specifically, this paper explored to what extent multimodality was associated with the intention to change the level of cycling, walking, car use, and public transport use.

Our findings showed that the more multimodal individuals were, the more likely they intended to decrease their car use. The analyses on the pre-defined groups revealed that compared to individuals who exclusively travelled by car all other three groups were more likely to intend to decrease their car use. Similarly, compared to the clusters with heavy car users, members of other groups were less likely to intend to decrease their bicycle and train use (but these findings were mostly non-significant). This may imply that individuals who only travel by another mode, or alternate their commute mode choice, may be more inclined to reduce their car use even further. In addition, this may indicate that individuals who rely (mainly) on a car for transport are more likely to intend to decrease other modes of transport, resulting in an even greater car dependency. These findings also support the idea that multimodality may increase the likelihood of changing behaviour towards more healthy and sustainable alternatives.

Our analyses did not provide conclusive evidence that the level of multimodality is associated with the intention to change. Most adjusted models, except the models on the intention to change car use, revealed non-significant associations. However, in many models, the directions of the associations were clear as well as intuitive and the non-significance may have been a result of (unexpected) insufficient statistical power (see also below). Based on the current analyses, we are therefore unable to conclusively corroborate or disapprove the suggested conceptualisation that multimodals are more open to change (Heinen & Ogilvie, 2016; Kroesen, 2014). This is important when designing interventions: if those individuals with

Table 6

Intention to change the levels of train use.

			Intention to decrease		Intention to increase	
			RRR	95% CI	RRR	95% CI
Indicators	Trip based	Number of modes used	1.017	[0.869–1.190]	0.881	[0.722–1.076]
		Highest share	0.992	[0.981–1.003]	1.008	[0.995–1.020]
	Stage based	HHI	0.845	[0.401–1.779]	1.143	[0.542–2.410]
		OM_PI	1.128	[0.389–3.268]	0.711	[0.241–2.100]
		Number of modes used	1.007	[0.849–1.195]	0.901	[0.749–1.084]
Clusters (ref: Mostly only car (i.e. cluster 5.1, 4.1, 3.1))	Cluster 5.2		0.450*	[0.218–0.928]	1.842	[0.873–3.889]
	Cluster 5.3		1.488	[0.428–5.174]	2.462	[0.669–9.064]
	Cluster 5.4		0.491	[0.210–1.145]	1.226	[0.507–2.965]
	Cluster 5.5		0.879	[0.404–1.912]	2.192	[0.976–4.925]
	Cluster 4.2		0.498	[0.246–1.007]	1.565	[0.744–3.292]
	Cluster 4.3		0.461	[0.198–1.072]	1.073	[0.443–2.598]
	Cluster 4.4		0.822	[0.379–1.786]	2.222*	[1.001–4.934]
	Cluster 3.2		0.444*	[0.225–0.876]	1.290	[0.652–2.554]
	Cluster 3.3		0.522	[0.268–1.018]	1.264	[0.635–2.515]
Predefined groups (ref: UM car)	UM bike		0.603	[0.256–1.422]	1.903	[0.789–4.590]
	UM/MM one mode		0.960	[0.428–2.152]	2.162	[0.914–5.112]
	MM		1.178	[0.597–2.324]	1.297	[0.582–2.891]

Each measurement of multimodality was separately tested (whilst adjusting for covariates) on the intention to change.

Maximally adjusted model for the intention to change the level of car use.

Reference is no intention to change the level of car use.

The analyses are adjusted for: gender, having children living at home, living alone, being a student, working, commute distance, car availability, bicycle availability, education, income, BMI, being Dutch, and age.

RRR = relative risk ratio; 95% CI = 95% confidence interval.

* $p < 0.05$.

In bold: significant associations.

Cluster 5.2: Mostly only bicycle; Cluster 5.3: Mostly only walk or only public transport; Cluster 5.4: Using a variety of modes, but little car; Cluster 5.5: Using a variety of modes including car.

Cluster 4.2: Mostly only bicycle; Cluster 4.3: Using a variety of modes, but little car; Cluster 4.4: Using a variety of modes including car.

Cluster 3.2: Mostly only bicycle; Cluster 3.3: Using a variety of modes.

higher levels of variability were more inclined to change when confronted with an intervention, this would offer opportunities for two-staged interventions.

Our descriptive analyses revealed a strong association between car availability and the level of multimodality. Individuals who always have a car available had, on average, lower levels of multimodality. Between the modality groups, either predefined or revealed by cluster analyses, many differences were revealed. Men, individuals who work, individuals with above-average incomes, and car owners were more likely to be in the 'car only' groups. Those groups that heavily rely on a bicycle contained, on average, more students, individuals with lower incomes, and individuals in possession of a bicycle. The stronger relationship between socio-economic characteristics and multimodality groups than the level of multimodality may indicate that the levels of multimodality are less affected by socio-economic characteristics than the use of (the combination of) certain modes.

The existing literature on multimodality has not been conclusive as to which measure is most appropriate to use. We therefore used three measures of multimodality: indices, predefined groups, and data-driven groups obtained by factor analyses. The selection for a particular index or grouping strategy was important in this study, illustrated by the difference in strength of the revealed associations. However, all these measures have limitations. For example, the indices are likely to best represent the level of multimodality. However, they can be easily affected by certain characteristics in the data resulting in peaks (see also [Susilo & Axhausen, 2014](#); [Heinen & Chatterjee, 2015](#); [Diana & Pirra, 2016](#)) and consequently affect the results. The interpretation of the clusters and groups may have other difficulties. The clusters potentially include individuals with a large variety in their modal mix. This large variety in such clusters may consequently result in large varieties in intentions. This may explain the sometimes less clear direction of effects in the analyses. The predefined groups face other shortcomings as this measure of multimodality is most closely related to the use of certain modes. As a result, the groups correspond most closely to mode choice and may therefore link to discussions around habit and mode choice (e.g. [Verplanken, Aarts, Knippenberg, & Moonen, 1998](#); [Aarts, Verplanken, & Knippenberg, 1998](#)). As a result, analyses with predefined groups may just report on whether the use of a current mode increases or decreases the intention for future use. Thus, we recommend conducting analyses with multiple measures, similar to the approach used in this paper. Nevertheless, all measures are intended to measure something slightly different, and if one is interested in the level of multimodality, it may be best to use an index, although the results should be checked with predefined groups and/or clusters.

This paper investigated the intention to change travel behaviour rather than actual change. Actual behavioural change may be a result of various factors, including intention to change. However, research has revealed that changes in the built environment and life events may also have an effect on travel behaviour and thereby result in behavioural changes

(Clark, Chatterjee, Melia, Knies, & Laurie, 2014; Heinen, Panter, Mackett, & Ogilvie, 2015; Panter, Heinen, Mackett, & Ogilvie, 2016; Scheiner et al., 2016). The observation of Scheiner et al. (2016) that life events may result in changes in level of multimodality is also important in this context. Given that life events may change travel behaviour, they are likely to also impact on levels multimodality, which is measured by the use of modes and their intensity of use. From a policy perspective, behavioural change could be caused by life events, which may simultaneously increase the level multimodality. This increase in multimodality may then possibly increase the likelihood of changing travel behaviour, as suggested by Heinen and Ogilvie (2016) and Kroesen (2014). However, this increase may not result due to changes in intention to change.

Discriminating between behavioural change and variability is difficult. If we only have two measurements without any intervention, we cannot (easily) discriminate, unless we know the 'natural' level of variability, i.e. the prevalence and extent of variation in mode choice. The focus of this paper on intention to change instead of actual change partly removes this problem. However, it introduces another issue, as an intention does not necessarily result in consequent behaviour. Experimental studies may offer alternative possibilities, as they intend to effectuate a change in behaviour, and a measured change can be conceptually be attributed to the intervention. Monitoring levels of multimodality/variability in the population will also contribute to a better understanding of the potential size of its effect.

This paper is the first to explore an essential step towards the determination of a causal relationship between multimodality and travel behaviour change by investigating whether multimodality is also associated with *the intention* to change travel behaviour, a missing piece in the puzzle. The strengths of this study include its consideration of several measures of multimodality (indices, predefined groups, and data-driven groups) as well as multiple outcome measures of intention to change mode choice. Nevertheless, this study also has several limitations. Too limited statistical power may explain the limited number of significant associations in the multivariate analyses. In particular, the limited number of respondents who indicated an intention to reduce walking or cycling may explain the non-significant findings for these modes. The study design has shown sufficient power for similar analyses, but variations in the outcome and predictor variables were lower than anticipated. In addition, the sample is not representative of the entire population of the city of Utrecht or the Netherlands and caution needs to be taken when these findings are transferred to another context. Nevertheless, the correlates of multimodality appear to be similar to previous studies. Moreover, travel behaviour and intention to change is self-reported, which may result in an attentional or unintentional incorrect reporting of actual travel behaviour. Respondents may be willing to provide socially desirable answers, although the format of a survey (and consequent anonymity of the respondent), make this less likely than in more personal types of data collection such as interviews. Another shortcoming is that individuals who do not use a certain mode are unable to reduce the use of this mode, and therefore are very unlikely to intend to do so. We measured multimodality based on commuting behaviour, whilst we measure the intention to change in general. This allows one to intend to reduce use of a mode, even if not used, although this is limited by the fact that the level of multimodality is only based on commuting trips.

Additional research will be necessary to test the proposed link between multimodality and behavioural change. Three lines of research are particularly important in this vein. First, additional research is necessary to corroborate or disprove the connection between multimodality and behavioural change. Second, similar to this study, research will be necessary to show not only associations between multimodality and changes in mode choice, but also antecedents of such changes in choices, such as intention to change. Finally, another line of research that may be pursued is to test the stability of multimodality over time. Knowing how stable/variable an individual's behaviour is would help us to understand the extent of individual variability and thereby better distinguish natural travel behaviour variability when measuring travel behaviour change. Experimental studies would contribute to this understanding further, as they aim for a direction in effect, and consequently measured change in that direction could, to some extent, be more firmly attributed to an intervention. In addition to investigating the link between multimodality and behaviour change further, it would also be noteworthy to investigate how levels of car use can be decreased for multimodal individuals. To this end, it would be interesting to determine whether the level of multimodality differs by trip purpose, and in which cases multimodal use employs the car.

6. Conclusion

This paper explored to what extent multimodality was associated with the intention to change travel behaviour. Our findings showed that the more multimodal individuals were, the more likely they intended to decrease their car use. However, the associations between multimodality and the intention to change other modes of transport were non-significant. This may imply that there is no relationship between multimodality and the intention to change. However, the significant findings for car use, and the direction of most (non-significant) associations in our analyses were intuitive. Therefore, although this paper has not been able to provide support for the previously reported findings that multimodality may correspond with higher levels of behavioural change in mode choice, it does not disconfirm it either. Additional research will still be necessary to explore this putative relationship.

Acknowledgement

EH was funded by The Netherlands Organisation for Scientific Research, VENI-Grant (016.145.073). Thanks are due to the anonymous reviewers appointed by this journal, whose comments greatly improved the paper.

Appendix A. Overview of data

		n	%	Mean	St. Dev.
Intention to change car use	Decrease	180	20.4		
	No change	452	52.3		
	Increase	250	28.3		
Intention to change bicycle use	Decrease	35	4.0		
	No change	391	44.3		
	Increase	456	51.7		
Intention to change levels of walking	Decrease	43	4.9		
	No change	470	53.3		
	Increase	369	41.8		
Intention to change levels of train use	Decrease	191	21.7		
	No change	494	56.0		
	Increase	197	22.3		
Trip-based indicators					
Number of modes used		882		1.8	1.3
Highest share		882		86.3	19
Stage-based indicators					
HHI		882		0.66	0.33
OM_PI		882		0.23	0.23
Number of modes used		882		2.20	1.30
Predefined groups					
UM car		154	17.5		
UM bike		213	24.2		
UM/MM one mode		169	19.2		
MM		346	39.2		
Clusters					
Cluster 5	5.1: Mostly only car	231	26.2		
	5.2: Mostly only bicycle	351	39.8		
	5.3: Mostly only walk or only public transport	40	4.5		
	5.4: Using a variety of modes, but little car	153	17.4		
	5.5: Using a variety of modes including car	107	12.1		
Cluster 4	4.1: Mostly only car	228	25.9		
	4.2: Mostly only bicycle	388	44.0		

(continued on next page)

Overview of data (continued)

		n	%	Mean	St. Dev.
Cluster 3	4.3: Using a variety of modes, but little car	152	17.2		
	4.4: Using a variety of modes including car	114	12.9		
	3.1: Mostly only car	267	30.3		
	3.2: Mostly only bicycle	363	41.2		
	3.3: Using a variety of modes	252	28.6		
Socio-economic characteristics					
Age		871		41.1	13.3
Sex	Male	310	35.3		
	Female	569	64.7		
Dutch nationality	Yes	803	92.7		
	No	63	7.3		
Received higher education	Yes	530	84.5		
	No	97	15.5		
Children at home	Yes	199	22.6		
	No	683	77.4		
Living alone	Yes	319	36.2		
	No	563	63.8		
Student	Yes	89	10.1		
	No	793	89.9		
Working	Yes	734	83.2		
	No	148	16.8		
Holding a driver license	Yes	770	88.1		
	No	104	11.9		
Car availability	Yes, always	419	47.7		
	Yes, mostly	112	12.8		
	Yes, sometimes	155	17.7		
	No, never	192	21.9		
Bicycle availability	Yes, always	841	95.7		
	Yes, mostly	13	1.5		
	Yes, sometimes	6	0.7		
	No, never	19	2.2		
Pre-tax personal income	Not answered	110	12.7		
	Less than half normal wage (<€17,000 a year)	134	15.4		
	Between half and normal wage (€17,300–34,600)	223	25.7		
	Between normal and twice normal wage (€34,600–69,200)	330	38.0		
	More than twice normal wage (>€69,200)	72	8.3		

Appendix B. Cluster and group membership

		5.1	5.2	5.3	5.4	5.5	4.1	4.2	4.3	4.4	3.1	3.2	3.3	Predefined groups			Uses combination
		Mostly UMcar	Mostly UMbike	Mostly UMother	MM-exclcar	MMall	Mostly UMcar	Mostly UMbike	MM-exclcar	MMall	Mostly UMcar	Mostly UMbike	MM	Only car	Only bike	UM/MM one mode	
Age		42.8	41.0	46.3	38.0	40.6	42.7	41.5	37.9	41.1	43.7	40.7	39.0	42.2	41.3	40.0	41.2
Sex	Male	42.90%	32.10%	35.00%	30.30%	36.40%	43.00%	32.40%	29.80%	36.80%	41.60%	31.90%	33.50%	46.80%	30.30%	36.70%	32.30%
	Female	57.10%	67.90%	65.00%	69.70%	63.60%	57.00%	67.60%	70.20%	63.20%	58.40%	68.10%	66.50%	53.30%	69.70%	63.30%	67.70%
Dutch	No	7.90%	7.00%	5.30%	6.60%	8.50%	7.60%	7.10%	6.60%	8.00%	7.70%	6.80%	7.60%	6.60%	9.60%	8.40%	5.50%
	Yes	92.10%	93.00%	94.70%	93.40%	91.50%	92.40%	92.90%	93.40%	92.00%	92.30%	93.20%	92.40%	93.40%	90.40%	91.60%	94.50%
Children at home	No	70.60%	78.10%	90.00%	77.80%	85.00%	69.70%	79.40%	77.60%	86.00%	72.70%	78.20%	81.30%	70.60%	78.10%	90.00%	77.80%
	Yes	29.40%	21.90%	10.00%	22.20%	15.00%	30.30%	20.60%	22.40%	14.00%	27.30%	21.80%	18.70%	29.40%	21.90%	10.00%	22.20%
Living alone	No	63.60%	65.50%	40.00%	64.10%	67.30%	64.00%	63.40%	63.80%	64.90%	60.70%	65.00%	65.50%	63.00%	65.30%	60.80%	65.00%
	Yes	36.40%	34.50%	60.00%	35.90%	32.70%	36.00%	36.60%	36.20%	35.10%	39.30%	35.00%	34.50%	37.00%	34.70%	39.20%	35.00%
Student	No	97.00%	85.50%	87.50%	90.80%	88.80%	96.90%	85.80%	90.80%	88.60%	97.40%	84.80%	89.30%	97.40%	83.10%	91.20%	90.10%
	Yes	3.00%	14.50%	12.50%	9.20%	11.20%	3.10%	14.20%	9.20%	11.40%	2.60%	15.20%	10.70%	2.60%	16.90%	8.80%	9.90%
Working	No	9.10%	21.40%	42.50%	11.10%	16.80%	9.20%	22.90%	11.20%	18.40%	12.40%	22.30%	13.50%	8.40%	23.50%	12.70%	18.60%
	Yes	90.90%	78.60%	57.50%	88.90%	83.20%	90.80%	77.10%	88.80%	81.60%	87.60%	77.70%	86.50%	91.60%	76.50%	87.30%	81.40%
Holding a driver license	Yes	99.60%	82.70%	82.50%	84.90%	87.90%	99.60%	82.80%	84.80%	87.70%	97.40%	82.70%	86.10%	99.30%	78.20%	83.40%	91.80%
Car availability	No	0.40%	17.30%	17.50%	15.10%	12.10%	0.40%	17.20%	15.20%	12.30%	2.60%	17.30%	13.90%	0.70%	21.80%	16.60%	8.20%
	Yes, always	89.50%	33.20%	37.50%	20.90%	47.70%	89.40%	33.70%	21.10%	48.20%	84.90%	32.70%	30.20%	92.20%	27.80%	26.50%	51.50%
	Yes, mostly	8.30%	16.60%	5.00%	9.80%	16.80%	8.00%	15.80%	9.90%	15.80%	7.20%	16.90%	12.70%	6.50%	14.60%	9.40%	16.30%
	Yes, sometimes	1.70%	19.20%	17.50%	35.30%	21.50%	2.20%	18.90%	34.90%	21.10%	3.80%	18.80%	30.60%	0.70%	21.20%	32.60%	15.10%
Bicycle availability	No, never	0.40%	30.90%	40.00%	34.00%	14.00%	0.40%	31.60%	34.20%	14.90%	4.20%	31.60%	26.60%	0.70%	36.30%	31.50%	17.20%
	Yes, always	92.60%	98.90%	89.70%	97.40%	91.60%	91.60%	98.40%	98.00%	91.20%	92.00%	98.90%	94.80%	91.40%	99.10%	93.40%	96.70%
	Yes, mostly	1.30%	0.90%	2.00%	2.00%	2.80%	1.80%	0.80%	2.00%	2.60%	1.50%	0.80%	2.40%	1.30%	0.50%	2.80%	1.50%
	Yes, sometimes	1.30%	0.00%	0.00%	0.00%	2.80%	1.30%	0.00%	0.00%	2.60%	1.10%	0.00%	1.20%	1.30%	0.00%	1.10%	0.60%
Pre-tax personal income	No, never	4.80%	0.30%	7.70%	0.70%	2.80%	5.30%	0.80%	0.00%	3.50%	5.30%	0.30%	1.60%	5.90%	0.50%	2.80%	1.20%
	Not answered	10.10%	15.10%	17.90%	7.80%	15.20%	11.20%	14.20%	7.90%	17.00%	11.90%	14.60%	10.80%	11.30%	18.10%	9.40%	11.60%
	Less than half normal wage	6.60%	20.60%	28.20%	16.30%	11.40%	6.70%	21.00%	16.40%	12.50%	8.00%	21.60%	14.30%	4.60%	22.90%	13.90%	16.50%
	Between half and normal wage	21.60%	25.50%	35.90%	30.10%	24.80%	21.00%	27.00%	30.30%	24.10%	23.80%	25.50%	27.90%	24.50%	26.70%	30.60%	22.90%
Intention to change car use	Between normal and twice normal wage	48.50%	32.80%	15.40%	38.60%	40.00%	47.80%	32.00%	38.20%	38.40%	44.40%	32.50%	39.00%	47.00%	29.00%	40.00%	38.40%
	More than twice normal wage	13.20%	6.10%	2.60%	7.20%	8.60%	13.40%	5.80%	7.20%	8.00%	11.90%	5.90%	8.00%	12.60%	3.30%	6.10%	10.70%
	Decrease	13.90%	22.20%	32.50%	20.90%	23.40%	14.00%	22.40%	21.10%	25.40%	17.20%	22.00%	21.40%	11.00%	20.20%	26.50%	21.60%
	No change	63.60%	46.70%	42.50%	47.70%	47.70%	63.20%	46.90%	48.00%	46.50%	60.70%	46.60%	48.00%	61.70%	49.30%	45.90%	50.60%
Intention to change bicycle use	Increase	22.50%	31.10%	25.00%	31.40%	29.00%	22.80%	30.70%	30.90%	28.10%	22.10%	31.40%	30.60%	27.30%	30.50%	27.60%	27.80%
	Decrease	8.20%	1.40%	10.00%	0.70%	5.60%	8.80%	2.10%	0.70%	5.30%	8.60%	1.40%	2.80%	10.40%	1.90%	2.80%	3.00%
	No change	41.10%	48.70%	35.00%	50.30%	31.80%	40.40%	48.20%	50.70%	30.70%	39.30%	48.50%	43.70%	43.50%	53.50%	42.00%	40.10%
	Increase	50.60%	49.90%	55.00%	49.00%	62.60%	50.90%	49.70%	48.70%	64.00%	52.10%	50.10%	53.60%	46.10%	44.60%	55.20%	56.90%
Intention to change levels of walking	Decrease	8.20%	4.60%	2.50%	3.90%	0.90%	8.80%	4.10%	3.90%	0.90%	7.50%	4.40%	2.80%	9.10%	4.70%	2.20%	4.50%
	No change	55.00%	53.00%	35.00%	58.80%	49.50%	54.80%	51.80%	59.20%	47.40%	51.70%	52.90%	55.60%	56.50%	55.90%	52.50%	50.60%
	Increase	36.80%	42.50%	62.50%	37.30%	49.50%	36.40%	44.10%	36.80%	51.80%	40.80%	42.70%	41.70%	34.40%	39.40%	45.30%	44.90%
	Decrease	29.90%	17.40%	30.00%	15.00%	24.30%	22.80%	30.30%	15.10%	18.80%	29.60%	18.50%	17.90%	28.80%	15.50%	18.20%	24.30%
Intention to change levels of train use	No change	58.00%	58.10%	32.50%	60.80%	46.70%	46.50%	56.60%	61.20%	56.40%	53.60%	57.60%	56.40%	58.40%	57.80%	53.60%	55.10%
	Increase	12.10%	24.50%	37.50%	24.20%	29.00%	30.70%	13.20%	23.70%	24.70%	16.90%	24.00%	25.80%	13.00%	26.80%	28.20%	20.70%

In bold: significant differences.

Appendix C. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.trf.2018.04.010>.

References

- Aarts, H., Verplanken, B., & Knippenberg, A. (1998). Predicting behavior from actions in the past: Repeated decision making or a matter of habit? *Journal of Applied Social Psychology*, 28(15), 1355–1374.
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50, 179–211.
- Buehler, R., & Hamre, A. (2015). The multimodal majority? Driving, walking, cycling, and public transportation use among American adults. *Transportation*, 42, 1081–1101.
- Clark, B., Chatterjee, K., Melia, S., Knies, G., & Laurie, H. (2014). Life events and travel behaviour: Exploring the interrelationship using UK household longitudinal study data. *Transportation Research Record*, 2413, 54–64.
- Diana, M., & Pirra, M. (2016). A comparative assessment of synthetic indices to measure multimodality behaviours. *Transportmetrica A: Transport Science*, 12(9), 771–793. <https://doi.org/10.1080/23249935.2016.1177133>.
- EC (2014). Do the right mix. European Commission's Sustainable Urban Mobility Campaign. European Commission Directorate-General for Mobility and Transport. <<http://www.dotherightmix.eu/campaign/do-the-right-mix>>.
- Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behavior: The reasoned action approach*. New York, NY: Psychology Press.
- Gilthorpe, M.S. (2011). Chapter 4. Mathematical coupling and regression to the mean in the relation between change and initial value. In: *Statistical thinking in epidemiology*. Chapman and Hall/CRC. Print ISBN: 978-1-4200-9991-1. eBook ISBN: 978-1-4200-9992-8. <https://0-doi-org.wam.leeds.ac.uk/10.1201/b11045>.
- Heinen, E. (2016). Identity and travel behavior: A cross-sectional study on commute mode choice and intention to change. *Transportation Research Part F: Traffic Psychology and Behaviour*, 43, 238–253.
- Heinen, E., & Mattioli, G. (2017). Does a high level of multimodality mean less car use? An exploration of multimodality trends in England. *Transportation*, 1–34.
- Heinen, E., & Chatterjee, K. (2015). The same mode again? An exploration of mode choice variability in Great Britain using the National Travel Survey. *Transportation Research Part A*, 78, 266–282.
- Heinen, E., & Ogilvie, D. (2016). Variability in baseline travel behaviour as a predictor of changes in commuting by active travel, car and public transport: A natural experimental study. *Journal of Transport and Health*, 3(1), 77–85.
- Heinen, E., Panter, J., Mackett, R., & Ogilvie, D. (2015). Changes in mode of travel to work: A natural experimental study of new transport infrastructure. *International Journal of Behavioral Nutrition and Physical Activity*, 12.
- Huff, J. O., & Hanson, S. (1986). Repetition and variability in urban travel. *Geographical Analysis*, 18, 97–114.
- Jones, P., & Clarke, M. (1988). The significance and measurement of variability in travel behavior. *Transportation*, 15(1–2), 65–87.
- Kroesen, M. (2014). Modeling the behavioral determinants of travel behavior: An application of latent transition analysis. *Transportation Research Part A*, 65, 56–67.
- Kuhnimhof, K. (2009). Measuring and modeling multimodal mode use in the longitudinal section. In *Paper presented at the meeting of the transportation research board 88th annual meeting*, Washington, D.C., USA.
- Molin, E., Mokhtarian, P., & Kroesen, M. (2016). Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch Travelers. *Transportation Research Part A*, 83, 14–29.
- Nobis, C. (2007). Multimodality – Facets and causes of sustainable mobility behavior. *Transportation Research Record*, 2010, 35–44.
- Panter, J., Heinen, E., Mackett, R., & Ogilvie, D. (2016). Impact of new transport infrastructure on walking, cycling, and physical activity. *American Journal of Preventive Medicine*, 50, e45–e53.
- Prochaska, J. O., & Velicer, W. F. (1997). Misinterpretations and misapplications of the transtheoretical model.
- Prochaska, J. O., DiClemente, C. C., & Norcross, J. C. (1992). In search of how people change: Applications to the addictive behaviors. *American Psychologist*, 47, 1102–1114. PMID: 1329589.
- Rhoades, S. A. (1993). The Herfindahl-Hirschman index. *Federal Reserve Bulletin*, 79, 188–189.
- Scheiner, J., Chatterjee, K., & Heinen, E. (2016). Key events and multimodality: A life course approach. *Transportation Research Part A: Policy and Practice*, 91, 148–165.
- Susilo, Y. O., & Axhausen, K. W. (2014). Repetitions in individual daily activity-travel-location patterns: a study using the Herfindahl-Hirschman Index. *Transportation*, 41, 995–1011.
- Verplanken, B., Aarts, H., Knippenberg, A., & Moonen, A. (1998). Habit versus planned behaviour: A field experiment. *British Journal of Social Psychology*, 37(1), 111–128.